YOUNG LIVES STUDENT PAPER

Is Blood Thicker than Water? An Analysis of Social Capital as a Risk-Sharing Mechanism in Children's Development in India

Dhruv Chadha

June 2011

Paper submitted in part fulfilment of the requirements for the degree of MSc in Economics for Development at the University of Oxford, UK.

The data used come from Young Lives, a longitudinal study of childhood poverty that is tracking the lives of 12,000 children in Ethiopia, India (Andhra Pradesh), Peru and Vietnam over a 15-year period. **www.younglives.org.uk**

Young Lives is core-funded from 2001 to 2017 by UK aid from the Department for International Development (DFID) and co-funded by the Netherlands Ministry of Foreign Affairs from 2010 to 2014. Sub-studies are funded by the Bernard van Leer Foundation and the Oak Foundation.

Young Lives
An International Study of Childhood Poverty

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Acknowledgements

The author would like to thank Dr. Christopher Ksoll at the Centre for the Study of African Economies (CSAE) of the University of Oxford for his continuous guidance and support in completing this thesis. Additionally, Dr. Francis Teal and Professor Stefan Dercon of the University of Oxford also provided invaluable thoughts, suggestions and contributions. Lastly, I would like to thank Mrs. Ivica Petrikova for her moral support and encouragement in the completion of this paper.

Abstract

This essay evaluates the role of social capital as a risk-coping device in rural communities of India's Andhra Pradesh state. Focusing on health outcomes among children between the ages of 1 and 9, I test whether social capital serves as an insurance mechanism and helps households minimize the negative impact of income shocks. Negative shocks considered are of two types: individual-household level shocks and common (or aggregate) shocks affecting more than one household. Death or serious illness in the family is an example of the former, while crop failure and droughts are examples of the latter category. Similarly, social capital is also of two types: associational and trust-based. Associational social capital is derived from one's network of family and close friends, while trust (or civic-cooperation) social capital is a measure of how involved the citizenry is in local political and civic issues. The econometric methods used include fixed effects, pooled-OLS and a Hausman-Taylor specification. I find that while aggregate shocks do not have a negative impact on children's development, individual household shocks do. Moreover, associational social capital helps mitigate the impact of these shocks and appears to be serving an insurance role, while trust-based social capital does not have a similar impact. A second result of importance is that within associational social capital, smaller networks of 1-5 family members appear to better mitigate risk compared to larger networks. Similarly, family networks comprised of influential members of the community help more relative to those without influence. These results are presented with the caveat that there is likely to be significant endogeneity in group formation in an environment where shocks are correlated with each other over time. While the statistical techniques used are aimed at overcoming this problem of self-selection into groups, some residual bias likely persists.

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I. Introduction

Poor people in developing countries often face risks that are systematically different and greater than those faced by other people around the world. Rural areas in these countries are often agriculturally oriented and hence production and consumption are susceptible to weather, health, crop-related and other income shocks (Rosenzweig, 1988; Townsend, 1994). As a result, households often incur relatively large and unforeseen expenditures such as medical costs, or are faced with the prospect of significant losses in income and consumption possibilities. Faced with such uncertainty, people adopt risk-mitigating strategies. This is corroborated by the empirical evidence that although household income in developing countries varies greatly, consumption is relatively smoother (Townsend, 1994; Jacoby and Skoufias, 1997; Fafchamps and Lund, 2003).

This observation merits an examination of the mechanisms through which risk-sharing is achieved, especially since market-based instruments are often not available in these regions. As Rosenzweig (1988: 1150) notes, 'information and moral hazard problems inherent in agricultural production ... make the provision of insurance by private, profit-seeking agents unlikely. These areas are also likely to be characterized by the lack of formal credit markets.' Additionally, opportunities to save are also limited because assets that return a positive yield after accounting for price volatility (characteristic in developing regions) are typically lacking (Besley, 1995). While savings in the form of holding stocks, say of food, is possible, this too is fraught with difficulties such as destruction through flooding or theft.

The presence of consumption smoothing despite the lack of formal insurance options points to the existence of informal options. In the literature, these options have taken the form of labour market arrangements such as sharecropping, informal credit and insurance arrangements, and social networks among others (see for examples: Bardhan, 1984; Rosenzweig, 1988; Besley, 1995; Becker, 1981; and White, 1969).

In this thesis, I focus specifically on the role of social capital as a risk-sharing device. Concentrating on children's health outcomes in rural areas of India's Andhra Pradesh state, I investigate whether having a higher degree of social capital can help mitigate the impact of negative income shocks, and if so, what type of social capital is most beneficial and what types of shocks does it help insure against.

The thesis proceeds as follows. The second section reviews the existing literature on risk-sharing and social networks. The third section builds on the existing research and links social capital and children's health outcomes. The fourth section discusses the methodology and the fifth presents an overview of the data. The sixth section details how the issue of endogenous group formation is resolved in this essay. Finally, the last two sections display the results of the econometric analysis and present issues for further consideration.

II. Literature Review

1. Risk-Sharing and Insurance

A large number of papers have shown that although income in rural areas of developing countries tends to be volatile, consumption is much smoother. Of these, Townsend's (1994) seminal paper is perhaps the best known. In his paper, Townsend shows that 'household consumptions are not much influenced by contemporaneous own income, sickness, unemployment, or other idiosyncratic shocks such as rainfall' (1994: 539). Other examples include Paxson's (1992) work on farmers in Thailand, Jacoby and Skoufias' (1997) study on child school attendance in India and Fafchamps and Lund (2003) who finds that rural Filipino households are able to smooth consumption when faced with income shocks.

Additionally there is a general consensus that this smoothing is not achieved through market-based insurance instruments which are typically lacking in rural areas of developing countries. This premise holds for the communities of Andhra Pradesh (in India) under study in my thesis as well. For example, in round 2 of the survey data used, the most common types of aggregate shocks experienced by households were drought and crop failure. When asked if insurance payments formed part of the response to these shocks, only 4.2% answered in the affirmative for droughts and 2.3% for crop failure. Similarly, in round 1, when asked if insurance payments formed part of the response to the 'worst shock' experienced by a household, only 2 out of 871 households experiencing a shock answered yes[1].

2. Groups and Social Networks

Given the absence of formal markets, consumption smoothing suggests the presence of informal insurance institutions. Stiglitz (1990), in his *peer monitoring view*, was among the first to articulate how social ties might substitute for market-based mechanisms. He proposed that individuals who repeatedly interact in geographically proximate nonmarket environments are

[1] This question is not asked in round 3 of the survey

able to exploit a comparative advantage in monitoring and enforcing informal arrangements. Thus, while market-based mechanisms might fail in these settings, group-based and informal mechanisms might still prosper. This importance of geographical and group and kinship ties in overcoming market failures are also highlighted in Fafchamps (1992) and Moore (1994). In addition to their ability to substitute for market-based mechanisms, social networks are viewed as being important as close associates constitute an important asset for poor people, one that can be called upon in difficult times (Woolcock and Narayan, 2000; Dordick, 1997).

If one accepts that groups can substitute for market failures, insurance in this case, it is natural to consider the size of groups best suited to correct imperfections. Gertler and Gruber (2002) and Ligon et al. (2002) show that efficient risk-sharing ties are built at the community level. However, Genicot and Ray (2003) argue for smaller groups as informal arrangements are limited by incentive constraints, as they are legally non-binding and rely on voluntary participation. Fafchamps and Lund (2003) and Murgai et al. (2002) support this argument, reasoning that group size might be limited due to higher costs of maintaining ties in larger groups.

3. Social Capital

It is important to differentiate between social groups and social capital. The concept of social capital has become important in the academic realm since the publication of Putnam's *Making Democracy Work* (1993), which compares the social structures and economic performance of Italy's northern and southern regions. Defined as the value derived from connections within and between social networks, Putnam finds that social capital plays a positive role in explaining the better performance of economic and political institutions in northern Italy.

As discussed in Olson (1982), Putnam (1993), and Knack and Keefer (1997), social capital is of two major kinds: *associational* and *civic cooperation and trust*. Associational social capital is derived through one's networks of family and friends, or through membership of self-help, religious, sports and other groups. This definition is similar to the phenomenon described in the previous section and as noted, can substitute for market failure and serve as an insurance mechanism. On the other hand, *civic cooperation and trust* is a measure of how involved the citizenry is in local political and civic issues. Coleman (1990: 300-301) writes that ‘authority relations, relations of trust, and consensual allocations of rights which establish norms’ can be viewed as resources for individuals. We have already seen how one’s social networks might substitute for market-based insurance mechanisms and help mitigate risk in the previous section. Civic cooperation and trust too can serve this purpose. ‘Cooperative norms act as constraints on narrow self-interest, leading individuals to contribute to the provision of goods (not provided by the market) of various kinds’ (Knack and Keefer, 1997: 1254). As a result, societies with high levels of trust are less reliant on other, more formal institutions to help enforce contracts and economic agreements.

In examining the role of social capital on economic performance, trust and civic cooperation is generally shown to have a positive impact (Putnam 1993, Olson 1982, Knack and Keefer 1997). On the other hand, the role of associational activity is less clear and there is greater debate surrounding its impact. Knack and Keefer (1997) along with Olson (1982) show that it is negatively correlated with growth, while Putnam (1993) finds the opposite result.

III. Linking Risk-Sharing, Social Capital and Children's Health

This thesis examines the role of social capital in helping households cope with adverse income shocks, with children's health as the outcome variable of interest. To my knowledge, very few studies have examined the link between social capital and health, with Carter and Maluccio (2003) being an exception. Examining stunting in South African children, the authors reject the conventional risk-sharing finding on consumption smoothing. Additionally, they find that households in communities with more social capital – defined as 'networks, norms, and trust that enhance the incentive compatibility of noncontractual or legally unenforceable exchange' (Carter and Maluccio, 2003: 1148) – are better able to cope with shocks. My analysis differs from the aforementioned paper in two notable aspects. First, in their paper access to social capital is considered at the level of the community. In this essay, the data allows me to examine household-level social capital. Second, I *compare* different forms of social capital to see whether *associational social capital* or *civic cooperation and trust* is more beneficial. This analysis is not present in Carter and Maluccio (2003).

So, which of the two – associational and civic – types of social capital would we expect to help better insure against risk? One argument is centred on the size of group fostered by each type of social capital. Arguably, associational social capital, which typically consists of one's family and friends, involves smaller and more closely bound groups than social capital derived from civic cooperation and trust, which usually exists at a broader community-wide level. Then, following Gertler and Gruber (2002) and Ligon et al. (2002) who favour risk-sharing in larger groups, we might expect civic cooperation and trust to matter more.

Conversely, following Genicot and Ray (2003) and others, moral hazard, adverse selection, informational asymmetries and the lack of enforcement are likely to be less pronounced among family members and close friends than among villagers who share little in common. In this case, one might expect associational social capital, reflected in smaller groups that lend themselves to easier monitoring, to be more beneficial. However, it is also possible that close social networks might face jointly higher risks. For example, an occupational-based group of farmers is likely to be subjected to the same drought (or other agricultural shock), thereby diminishing the positive impact of group membership if everyone in the group is negatively impacted at the same time.

Hence, on the basis of theory it is unclear which type of social capital will matter more. Perhaps individual shocks are better insured through one's close family and friends due to the lack of informational asymmetries, as 'shocks that are easily and unambiguously observed should be better insured than shocks for which false claims are possible' (Fafchamps, 1992; Ligon 1998), whereas common shocks could be better insured at the community level as everyone 'pitches in'. However, the opposite could easily be true if a large proportion of the community is negatively impacted by a shock and thus is in no position to help each other, or if the individual shock, perhaps a death in the family, reduces the amount of associational social capital a household can rely on. Overall then, comparing the two forms of social capital is an empirical issue, as is determining the type of shock against which they help insure.

Having linked social capital to risk-sharing, it is also necessary to link risk-sharing to children's health, the outcome of interest here. In the insurance literature, risk-sharing is most commonly studied with regards to its impact on consumption. As shown in the health and health economics literature, nourishment, or food consumption, is a key input of children's health (see for example: Strauss and Thomas, 1998; Duflo, 2000; Burgard, 2002). Additionally, height and weight, which are important indicators of health, respond negatively to food consumption shocks. Stunting, or deficiencies in height, and wasting, or deficiencies in weight, are often precipitated by household crises where the family food supply is limited and food intake is relatively low (WHO, 2006). Given that these situations are prone to occur in risky environments, it is not difficult to extend the traditional risk-sharing framework focused on consumption, to food consumption, which directly affects children's health.

In conclusion, in this thesis I investigate the role of social capital as a risk-sharing mechanism. While social capital is expected to help mitigate the negative consequences of income shocks, the mechanism through which this occurs is not clear *a priori*. By comparing different forms of social capital, I aim to contribute to the debate surrounding the importance of associational vs. cooperation- and trust-based social capital, focusing – somewhat uniquely – on children's health as my outcome of interest.

IV. Methodology

1. Theoretical Framework

The theoretical framework I use builds on Townsend's (1994) efficient risk-sharing framework and is adapted from Dercon and Krishnan (2003). In their paper, Dercon and Krishnan examine whether food aid helps smooth consumption by reducing the impact of negative shocks in Ethiopia.

Risk-sharing tests analyze whether consumption (or income) outcomes observed in a risky environment are consistent with what would have been observed if full market-based insurance mechanism existed before the shock(s) had occurred. In other words, the test investigates if income shocks can help explain the change in consumption patterns. If risk is shared perfectly, as under complete markets, individual consumption should be unaffected by shocks in income, though aggregate consumption might vary at the village level (Dercon and Krishnan 2003, Fafchamps and Lund 2003). Typically, while consumption smoothing is supported, these tests reject perfect risk-sharing in favour of partial risk-sharing in a number of contexts (see: Townsend, 1994; Hayashi et al., 1996; Dercon and Krishnan, 2000; Fafchamps and Lund, 2003).The expectation here is that negative income shocks adversely impact households. However, as in Carter and Maluccio (2003), having social capital is expected to mitigate this effect in households, relative to households without social capital.

More formally, let a community consist of *N* households, with each household *j* having time-separable expected utility defined over instantaneous utility $u(c_{ts}^{j}; z_{ts}^{j})$ where c^{j} is a single consumption good and z_{ts}^{j} are taste shifters, varying across households; and *T* are the number of periods *t*, and *S* are the states *s*. The economy is endowment-based, with endowments in each period assumed to be risky. If all households efficiently share risk, the optimization problem can be represented from the point of view of a social planner who allocates weights θ_j to each household and maximizes the weighted sum of expected utilities in each period and state. At period 0, this can be written as:

$$max \sum_{j=1}^{N} \theta_j \sum_{t=0}^{T} \sum_{s=1}^{S} \pi_s u(c_{ts}^{j}; z_{ts}^{j}) \qquad (1)$$

in which π_s is the probability of state *s* occurring. The budget constraint at the community level can be written as:

$$\sum_{j=1}^{N} c_{ts}^{j} \leq \sum_{j=1}^{N} e_{ts}^{j} \qquad (2)$$

which states that aggregate consumption *c* over all *N* households in the community must not be greater than the aggregate endowment *e* of these households. From this, the first order condition for optimal consumption in a household *j* at time *t* can be derived to be:

$$\theta_j u_c^j\left(c_{ts}^j; z_{ts}^j\right) = \lambda_{st} \qquad (3)$$

where λ_{st} is defined as the multiplier on the community level budge constraint in each period and state and $u_c^j\left(c_{ts}^j; z_{ts}^j\right)$ denotes the marginal utility of consumption of household *j*.

Given that λ_{st} only depends on aggregate consumption, the above implies perfect risk-sharing; the growth path of weighted marginal utilities of all households is the same and is influenced only by the changes in community-level resources. Hence, the ratio of marginal utilities is the same, i.e. relative marginal utilities between households are constant (Dercon and Krishnan, 2003).

2. Empirical Model

Following from the theoretical framework, risk-sharing is empirically tested via the following model. Utility $u_c^j\left(c_{ts}^j; z_{ts}^j\right)$ is assumed to follow a CRRA formulation[2]:

$$u_c^j\left(c_{ts}^j; z_{ts}^j\right) = z_t^j\left[\frac{(c_t^j)^{1+\gamma} - 1}{1+\gamma}\right] \qquad (4)$$

Differentiating, taking logs and allowing for measurement error ε_t^j, equation (3) becomes:

$$lnc_t^j = \frac{1}{\gamma}\ln\lambda_t - \frac{1}{\gamma}\, lnz_t^j - \frac{1}{\gamma}\, ln\theta_j + \varepsilon_t^j \qquad (5)$$

The above equation is used to test risk-sharing in the face of income shocks. The advantage of using shocks to income over just income is that many income changes are predictable and responses to them are already reflected in current consumption patterns. On the

[2] The subscript *s* is dropped following Dercon and Krishnan (2003)

other hand, shocks – provided that they are independent of current consumption levels – enable better testing of risk-sharing. As argued by Udry (1995) and Dercon and Krishnan (2000), most negative events such as death, illness and agricultural shocks reasonably satisfy independence.

A modified version of equation (5), presented below, forms the basis of much empirical work on risk-sharing.

$$lnc_t^j = \beta Z_t^j + \delta Y_t^j + \varphi_1 SC_t^j + \varphi_2 (SC * Y)_t^j + \vartheta^j + \varepsilon_t^j \qquad (6)$$

C_t^j is the consumption in household *j*, Z_t^j are the control variables and Y_t^j are shocks that affect income such as illness, death, and crop failure. Additionally, I also include SC_t^j as the measure of social capital (either associational or civic cooperation/trust) and $(SC * Y)_t^j$ as the interaction of income shocks and social capital. Both of these are specific to my research and are not typically included in risk-sharing models. Finally, ϑ^j are time-invariant control variables such as the fixed portion of resources, Pareto weights and other household characteristics that do not evolve.

3. Specifying Health

As discussed in the previous section, it is relatively straightforward to extend the above analysis, from consumption, to nutrition and child health. However, since health can be specified differently to consumption in empirical models, the specification used here incorporates elements from the health economics literature to build on equation (6).

As noted in Strauss and Thomas (2008), the health production function can be modelled as:

$$H = H(N; A, B_H, D, \mu) \qquad (7)$$

in which *H* are health outcomes such as height, body mass or physical function, *N* are health inputs, for example nutrition and use of health services, *A* are socio-demographic characteristics such as gender and ethnicity, *B* are parental characteristics including their health endowment, and *D* is the public health infrastructure[3].

[3] For examples on static health production functions in the development economics literature see Schultz, 1984, 2005; Behrman and Deolalikar, 1988; Strauss and Thomas, 1998 among others

Combining equations (6) and (7) gives a testable formulation for a static health production function which incorporates social capital as a risk-sharing device. This can be represented as:

$$h_t^j = \beta_1 N_t^j + \beta_2 A_t^j + \beta_3 B_t^j + \beta_4 D_t^j + \delta Y_t^j + \varphi_1 SC_t^j + \varphi_2 (SC * Y)_t^j + \vartheta^j + \varepsilon_t^j \qquad (9)$$

where health of children, h_t^j, is now the outcome of interest and the control variables Z_t^j from equation (6) have been expanded to explicitly control for determinants of health such as nutrition, household characteristics and environmental circumstances. As before, Y_t^j and SC_t^j represent negative income shocks and social capital respectively, while $(SC * Y)_t^j$is the interaction between social capital and shocks. ϑ^j is the time-invariant, household-specific component of the error, while ε_t^j is the time-varying part.

If efficient risk-sharing occurs at the community-wide level, we would expect the coefficient on household-shocks Y_t^j, given by δ, to be 0 as consumption would depend on the level of group resources instead. As idiosyncratic shocks would not affect consumption under perfect-risk sharing, group membership would not matter as there would be no insurance role for social capital (or other informal mechanisms for that matter). Hence, in this case the coefficient on $(SC * Y)_t^j$, given by φ_2, would be 0 as well. However, as discussed, perfect risk-sharing is not supported in the literature. Thus, we would expect the coefficient on the shock variables to be negative, reflecting losses due to adverse events. With regards to the coefficient on $(SC * Y)_t^j$, which is the interaction of social capital with shocks, we would expect it to be positive, reflecting the fact that social capital mitigates negative outcomes among households experiencing a shock. In other words, the impact of a shock on a household with no social capital would be δ, and is expected to be negative – given the absence of perfect risk-sharing. On the other hand, the impact on a household with social capital would be $\delta + \varphi_2$, and is expected to be less than δ, since φ_2 should be positive.

V. Data and Descriptive Statistics

Rural communities in India's Andhra Pradesh state offer a good environment to study the impact of social capital as a risk-coping device. Andhra Pradesh is the third largest producer of food grains in India and employment is predominantly agriculturally focused. Hence both production and consumption are susceptible to idiosyncratic weather shocks. Additionally, almost 75% of the state's population resides in rural areas that are characterized by underdevelopment in formal insurance markets. In this atmosphere of risk and uncertainty, informal insurance mechanisms assume greater significance. The data for my thesis comes from three surveys conducted on a panel of approximately 2000 households through the Young Lives research project. The availability of detailed data on shocks is relatively unique, especially when taken together with the information on social capital, which is available at the household level.

Table 1 below reports descriptive statistics for the control variables. On the basis of equation (7), these include *socio-demographic characteristics* including a dummy for sex of the child (1 being boys and 0 girls), age in months and the number of rooms in the house and asset ownership (the sum of TV, radio, fan, bike, and fridge ownership) to measure economic status. They also include *parental characteristics* – through mother's years of education – a significant determinant of children's health outcomes across much empirical work and the *public health and infrastructural environment*, modelled through access to electricity and toilets (as a proxy for sanitation). Additionally, inputs to health status such as the birth size of the child and whether the child was born prematurely are also included. Moreover, average expenditure on food and on non-food items is also included. In the survey, food expenditure covers the previous two weeks and non-food expenditure the past 30 days (both of these measures have been annualized)[4]. Hence, they are not expected to be adjusted for any positive or negative shocks, unless these shocks occurred in the very recent past or have a long-term impact. Nonetheless, given the potential correlation between expenditures and unobserved shocks that have a long-lasting

[4] Food expenditure includes expenditure on pulses, bread, vegetables, salt, and oil and the value of own food consumed, if any (i.e., produced by the household). Non food expenditure includes personal care, fuel, public transport, cleaning materials, electricity, festivals, clothing, medical and entertainment

impact, equation (7) is also estimated without the controls for expenditure to avoid any bias from endogeneity among these variables.

Table 1. Descriptive Statistics for Control Variables

Variable	Mean	Std Deviation	Obs.	Min	Max
Child's gender	1.53	0.50	6028	0	1
Child's age (months)	57.37	34.87	5850	2.30	106.32
Number of rooms in house	2.06	1.23	5950	0	16
Asset ownership	1.62	1.22	5950	0	5
Access to electricity	0.88	0.32	6030	0	1
Access to toilets	0.34	0.47	6030	0	1
Annual food expenditure (Rs.)[5]	14245	15878	3675	487	323286
Annual non-food expenditure (Rs.)	15305	12119	3823	644	175033
Birth size°	2.93	0.91	5870	1	5
Was the child born prematurely?	0.09	0.28	6030	0	1
Mother's years of education	4.39	6.09	5836	0	29

Source: Author's calculations based on Young Lives data
Note: ° Birth size is the caregiver's perception, with 1 being the largest and 5 being the smallest

Descriptive statistics for health, associational and trust/civic social capital and negative income shocks are presented in Table 2 below. The children under study here are 1yrs old, 5 yrs old and 9 yrs old in rounds 1, 2 and 3 respectively of the survey. Following Strauss and Thomas (1998, 2008), anthropometric z-scores of children's height, also known as height-for-age scores, are used as the primary outcome of interest. Child height has proven to be an informative indicator of nutritional status, as height reflects accumulated investments in child nutrition (Duflo, 2000; WHO 2006). However, height is a long-term indicator of nutritional status and might not change in response to one-off events such as income shocks (Falkner and Tanner, 1986; Waterlow, 1988). With this in mind, I also use children's weight-for-age z-scores as a secondary outcome of interest. Weight varies more in the short run and helps provide a more current indicator of nutritional status (Strauss and Thomas, 1998; WHO, 2006). However, weight-for-age is a challenging measure to use, as under certain circumstances, wasting (i.e., deficiencies) can be restored rapidly (WHO, 2006). Hence the impact of a negative shock may not be discernable in the data and might depend on the timing of the survey. Nonetheless, in the absence of other measures it provides an important way to analyze current responses to shocks in

[5] The smaller number of observations is due to expenditure data only being available in rounds 2 and 3

addition to providing a robustness check for the results obtained using height-for-age[6]. Finally, a key virtue of both these indicators is that there is no systematic measurement error that is correlated to the respondent's characteristics. As a result, any bias in estimated effects tends towards zero, (Strauss and Thomas, 1998). In the data, the mean height-for-age is -1.3, while the mean weight-for-age is -1.7. For both measures, z-scores below -2 are characteristic of deficiencies: stunting (height) and wasting (weight). Hence, although mean scores are above this benchmark, the children in this sample do not appear to be particularly healthy.

With regards to income shocks, two different measures are included following the literature. These are common shocks, which affect more than one household at a given time, and individual shocks, which only affect a single household. Only those variables for which data is available for all three rounds are considered. The variables that meet this criteria are *crop failure* as the common shock (has the household suffered from crop failure), and *family problems* as the individual shock (death or illness in the household). As Table 2 shows, the incidence of individual shocks is 23%, while the incidence of common shocks is slightly lower, at 16%.

Finally, social capital is also of two kinds: associational and civic-cooperation-based. Associational social capital is measured by *family and friends* outside the household. Households are coded as having family-based social capital if their response to the question *what would your household do in case of hard times* is 'ask family outside the household for help'. Similarly, households that answer 'ask friends and neighbours for help' are said to have friendship-based social capital. Together, they comprise *family and friends*, which is the key variable used in the regressions. Trust-based social capital is recorded through *civic cooperation*, a measure of whether the household has joined with others in the community to address a particular issue and whether they have contacted local authorities about problems in the community. This variable captures social capital as individuals in civic-oriented societies initiate contact each other on issues with implications for the welfare of the broader-community. Conversely, individuals from communities where civic cooperation is lacking interact mostly for private gain (Knack and Keefer 1997, Putnam 1993). A secondary measure, *trust*, which inquires whether the household

[6] Theoretically, weight-for-height, a measure that combines height-for-age and weight-for-age, is probably the best outcome to look at (WHO, 2006). However, per WHO guidelines, this variable is only calculated for children up till the age of 60 months which makes it untenable to use in this analysis.

believes that a majority of people in their community would try to take advantage of them if they got the chance, is used for robustness.

Table 2. Descriptive Statistics for Outcome, Shocks, and Social Capital

Variable	Mean	Std Deviation	Obs.	Min	Max
Outcomes					
Height-for-age (z-score)	-1.25	1.33	5527	-11.02	12.02
Weight-for-age (z-score)	-1.71	1.07	5921	-5.73	3.22
Shocks´					
Death or illness in household	0.23	0.42	3940	0	1
Crop Failure	0.16	0.36	3940	0	1
Associational social capital°					
Family	0.08	0.26	2010	0	1
Friends	0.06	0.23	2010	0	1
Family and Friends	0.13	0.34	2010	0	1
Trust/Civic social capital					
Civic Cooperation	0.31	0.46	2008	0	1
Trust	0.58	0,49	2003	0	1

Source: Author's calculations based on Young Lives data. ´° The smaller number of observations for shocks is because the variables are restricted to rounds 2 and 3. Similarly, social capital data comes from round 1 only

From Table 2, we can see that 8% of households have family social capital, 6% have friendship-based social capital, and 13% have both[7]. On the other hand, civic social capital is much higher, with 31% of households having participated in resolving community-based problems, and 58% of households trusting others not to take advantage of them. This very high average level of trust is the reason that it is used as a secondary variable (primarily for robustness). For instance, Knack and Keefer (1997), who measure trust using cross-country macro surveys, find that on average 36% of people agree that most other people can be trusted. Hence, in this sample, there appears to be a positive response bias regarding trust.

Finally, Table 3 below presents descriptive statistics of how social capital varies by shock. For each value of a shock, 0 and 1, descriptive statistics on the mean and number of observations of the 5 measures of social capital discussed above are presented. Additionally,

[7] The discrepancy is from rounding error

there is a t-test to check whether measures of social capital are significantly different for households that have experienced shocks versus those that have not. These variables capture how households that experience a negative shock differ from those that don't experience such an event with respect to their levels social capital.

Table 3. Descriptive Statistics for Interactions of Social Capital and Shocks

Variable	**Shock = 0**		**Shock = 1**		**T-test for difference**[8]
	Mean	Obs.	Mean	Obs.	
Family problems					
Family[a]	0.08	3026	0.06	914	5%
Friends[a]	0.06	3026	0.05	914	Insignificant
Family and friends[a]	0.14	3026	0.11	914	10%
Civic cooperation[c]	0.31	3021	0.33	913	Insignificant
Trust[c]	0.58	3015	0.57	909	Insignificant
Crop failure					
Family[a]	0.08	3320	0.03	620	1%
Friends[a]	0.06	3320	0.05	620	Insignificant
Family and friends[a]	0.14	3320	0.08	620	1%
Civic cooperation[c]	0.30	3315	0.37	619	1%
Trust[c]	0.58	3306	0.54	618	10%

Source: Author's calculations based on Young Lives data. [a,c] *Refer to associational and civic-social capital*

Examining the statistics for family problems, we see that associational social capital is marginally higher among families that *don't* experience a shock, whereas there is no difference in the levels of civic social capital. Given that we would expect social capital to be positively correlated with shocks if these variables were endogenous (see next section), this offers some evidence that unobserved shocks do not bias the results. Similarly, for crop failure, both types of social capital are higher among households not experiencing shocks (with the exception of civic cooperation). Again, this offers some evidence that these variables may not be endogenous *if* being shock-prone promotes higher group participation (to overcome adverse effects).

Finally, regarding the interaction between shocks and social capital, since both are dummy variables, the interaction terms too can only take a value of either 0 or 1. Hence, if household A and B suffer from crop failure, the crop failure variable takes a value of 1 for both. Then, if household A has family social capital and household B does not, the interaction term

[8] Indicates significance level when statistically different

takes a value of 1 for household A and 0 for B. In this way, the coefficient of the interaction term is telling us how much better household A does relative to B, owing to having a greater amount of social capital.

VI. Endogeneity and Empirical Techniques

Before turning to an examination of the regression results, it is important to note what the possible sources of bias are in this study and how they are being controlled for. To begin with, in panel data estimation, OLS estimators may be biased due to the endogeneity resulting from the correlation between explanatory variables and time-invariant omitted variables. This has been shown to be true in a variety of contexts (see, for examples: Cheng and Wall, 2002; and McPherson and Trumbull, 2008). In my thesis, it is possible that unobserved and fixed household characteristics are correlated with network formation and community action, or with exposure to shocks. Given this, following Dercon and Krishnan (2003) and Carter and Maluccio (2003), the first estimation technique used is household fixed-effects, which eliminates bias due to time-invariant unobservable variables. However, as has been noted in the literature, fixed-effects regressions (and other differencing approaches), while correcting for the correlation between explanatory variables and time-invariant omitted variables, exacerbate measurement error bias which can often be greater than the endogeneity-bias being corrected (Wooldridge, 2006). Keeping this in mind, results from pooled-OLS regressions are also presented. Following Pitt and Khandker (1998) who argue that unmeasured village attributes might also be correlated with risk and social capital variables, community effects are controlled for in the pooled-OLS. Such correlation might arise if agricultural shocks are a function of geographical location or if group formation depends on the socio-ethnic composition of a particular community.

Secondly, a potential source of endogeneity is self-selection into groups, especially if shocks are correlated with each other over time. In this case, past unobserved shocks could be correlated with network formation and community action, as at-risk households develop informal insurance mechanisms in response to their circumstances. Social capital could hence be endogenous with respect to omitted variables that are predictive of risk. In the literature, it is common to argue that using pre-determined levels of social capital, selection on observables and fixed effects jointly control for this type of bias (Fafchamps and Lund, 2003; Carter and Maluccio, 2003).

In my sample, there is evidence of some autocorrelation regarding the shocks under investigation. Over the three time periods, sample autocorrelation coefficients range from 0.09 – 0.10 for family problems. For crop failure, these are slightly higher, ranging from 0.19 – 0.31. As noted by Fafchamps and Lund (2003) who find sample autocorrelation between -0.25 and 0.01 in their data, '(this is) hardly evidence of autocorrelation'[9]. However, given that Fafchamps and Lund (2003) find negative autocorrelation, while in my data there is positive autocorrelation – the potential for endogeneity from self-selection exists.

To correct for this bias, an instrumental variables (IV) approach would be ideal. Unfortunately, this is exceedingly difficult with my data, especially with regards to finding suitable instruments for social capital, a point also made in Carter and Maluccio (2003). Given the potential endogeneity of instruments considered – household size and dad's literacy (for associational and trust-based social capital respectively) – and the increased inefficiency associated with weak instruments, the IV approach is unsuitable here. This is especially true as IV estimates in themselves are always biased and are superior to OLS only from a consistency standpoint, an argument that is hard to make when faced with weak instruments as with my data.

In lieu of using instrumental variables, two techniques are used to overcome potential issues surrounding selection. First, the measure of social capital used is fixed and comes from round 1 of the data; i.e. it is not 'allowed' to respond to shocks in round 2 and 3. Using social capital from rounds 2 and 3 would create greater potential for bias as it would be more likely to be correlated with both shocks that occurred preceding these rounds of the survey and other omitted variables linked with risk. Second, the shocks investigated are from rounds 2 and 3. Hence, given that social capital is measured *before* the realization of these shocks, we know that it is likely to be uncorrelated with omitted variables linked with these shocks. Together, these techniques should reduce much of the bias from endogenously determined social capital.

Overall, given that fixed effects remove bias associated with time-invariant household characteristics, the relatively weak autocorrelation within shocks, the fact that those experiencing

[9] Additionally, as shown previously in table 3, shocks and social capital do not appear to be positively correlated in the data

shocks are not more likely to have social capital and the regression techniques discussed – I believe that any residual endogeneity due to time-varying unobservables that could be improved upon through instrumenting is small. In this way, results obtained through fixed effects are not likely to be significantly more biased than those obtained through instrumental variables.

Apart from bias arising from selection, another potential source of bias is measurement error with regards to shock data (Dercon and Krishnan, 2003). One way to correct for this is to use various other measures of shocks as robustness checks. In my sample, while it is possible to find such measures for aggregate shocks, there is no variable apart from family problems that sufficiently addresses idiosyncratic household shocks and is available in all three rounds. Hence, although I control for measurement error in crop failure by using drought as an alternate measure, I am unable to do the same for death or illness in the family.

Finally, the above strategies all utilize the fixed-effects estimator. However, fixed effects itself has a drawback, in that time-invariant variables cannot be included in the regression specification. This is disadvantageous in my model of health as many independent variables that likely explain current health outcomes, such as family characteristics (for e.g., mother's education) and past health outcomes (such as premature birth) are time-invariant, and hence are omitted in a fixed-effects regression. To overcome this problem, another estimator used is the Hausman-Taylor method, developed as an alternative to fixed and random effects. The Hausman-Taylor method allows for the inclusion of time-invariant variables without biasing the estimation of time-varying variables. The main assumption of this method is that one or more explanatory variable is correlated with the error term. By specifying these explanatory variables as being 'endogenous', the method removes this correlation by instrumenting these variables using their deviation from their mean value. The selection of variables to be specified as endogenous relies on economic intuition and the model in use (Hausman and Taylor, 1981). Here, as argued, social capital is potentially correlated with household characteristics, hence is specified as being endogenous.[10] By eliminating the correlation between the error term and explanatory variables – the Hausman-Taylor method overcomes the problems associated with the random effects model. Additionally, as already noted, it also allows for the inclusion of time-

[10] Note that social capital is believed not to be endogenous in the fixed effects specification as the differencing process eliminates bias arising from household fixed effects. On the other hand, it may be correlated with household characteristics in a random-effects specification (which underlies the Hausman-Taylor approach)

invariant regressors. In this way, it combines some of the most appealing characteristics of the fixed and random effects techniques and is used here to substantiate the results obtained from fixed effects estimates[11].

VII. Regression Results

The first set of results using fixed effects with robust standard errors are reported in Table 4 below. Columns (1)-(4) model the individual household-level shock, family problems. Columns (5)-(8) model the aggregate-level shock, crop failure. The control variables, while mostly insignificant, have the expected sign across the specifications[12]. Looking at the coefficients of the shock variables, in columns (1)–(4), family problems have a negative impact on a child's height-for-age, with the results significant at the 5%-10% level on average. In other words, households are unable to insure fully against death or illness, as evidenced by the detrimental impact on child height. This conforms to the empirics on risk-sharing, as complete insurance is rejected. However, interestingly, this result does not hold in the case of crop failure. We see that in each of the four specifications reported below in columns (5)–(8), crop failure does not significantly impact on height-for-age. Hence, the aggregate shock *seems* to be insured at the community-wide level. One possible explanation is that during a drought or crop failure, when a large group of people is affected within a community, there is a greater incentive for them to work together in resolving their difficulties. Additionally, it is conceivably easier for the government to attempt to help out in such instances as well, whereas it may not be feasible for public intervention to target specific household problems.

Next, examining the impact of social capital, we see that the coefficient of the interaction term in column (2) is positive and has a p-value of 0.105. Hence, although marginally insignificant at conventional levels, it suggests that associational social capital helps mitigate the negative impact of death and illness. On the other hand, in column (3), trust-based social capital

[11] For a detailed discussion on the Hausman-Taylor method and its use relative to fixed- and random-effects see McPherson and Trumbull, 2008

[12] As noted, past unobservable shocks may be correlated with expenditures if such shocks have a long-term impact. To allow for potential endogeneity resulting from this, the specifications in columns (1) – (8) are estimated without the expenditure terms. This does not impact the estimates. Additionally, dropping these variables might result in omitted variable bias, hence the preferred specification is one in which they are included. Separately, given that health inputs might evolve due to insurance – the regressions below are also estimated without these inputs. However, this too does not materially impact the estimates.

is highly insignificant and does not appear to serve as a risk insurance mechanism. Column (4), in which both measures are included, supports this interpretation. Associational social capital – one's network of family and friends outside the household – has a positive coefficient significant at the 10% level, while civic-cooperation based social capital is again insignificant.

Table 4. Shocks and Social Capital Impact on Height-for-Age

	Family Problems				Crop Failure			
Variable	**Shock Impact (1)**	**Family & Friends (2)**	**Civic Coop. (3)**	**Combined (4)**	**Shock Impact (5)**	**Family & Friends (6)**	**Civic Coop. (7)**	**Combined (8)**
Child's age	0.039 (0.032)	0.039 (0.032)	0.039 (0.032)	0.039 (0.032)	0.037 (0.032)	0.037 (0.032)	0.037 (0.032)	0.037 (0.032)
Child's age^2	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Number of rooms (in the house)	0.021† (0.014)	0.021† (0.014)	0.022† (0.014)	0.022† (0.014)	0.022† (0.014)	0.022† (0.014)	0.023* (0.014)	0.023* (0.014)
Asset ownership count	0.039 (0.028)	0.038 (0.028)	0.039 (0.028)	0.039 (0.028)	0.038 (0.028)	0.038 (0.028)	0.039 (0.028)	0.039 (0.028)
Electricity	-0.013 (0.056)	-0.012 (0.056)	-0.019 (0.056)	-0.018 (0.056)	-0.015 (0.056)	-0.015 (0.056)	-0.022 (0.057)	-0.022 (0.057)
Toilets	0.097 (0.075)	0.097 (0.075)	0.095 (0.076)	0.095 (0.076)	0.098 (0.075)	0.098 (0.075)	0.096 (0.076)	0.096 (0.076)
Food expenditure	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Non-food expenditure	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Wave	-1.712*** (0.653)	-1.720*** (0.653)	-1.720*** (0.657)	-1.728*** (0.657)	-1.669*** (0.654)	-1.669*** (0.654)	-1.656*** (0.658)	-1.656*** (0.658)
Family problem	-0.063** (0.034)	-0.079** (0.034)	-0.073† (0.048)	-0.089* (0.051)				
Crop failure					-0.009 (0.049)	-0.009 (0.052)	0.049 (0.073)	0.049 (0.075)
Family and friends interaction°		0.120† (0.073)		0.121* (0.073)		0.002 (0.109)		0.002 (0.104)
Civic Coop. interaction			0.024 (0.066)	0.023 (0.066)			-0.091 (0.093)	-0.091 (0.093)
R^2 within	0.058	0.059	0.058	0.059	0.057	0.057	0.057	0.057
Observations	3249	3249	3235	3235	3249	3249	3235	3235

***significant at the 1% level, **significant at the 5% level, *significant at the 10% level, † significant at the 15% level

Note: Numbers not in parentheses are coefficients, numbers in parentheses are standard errors. °Measures of social capital are from round 1, hence they are omitted in a fixed effects regression by virtue of being constant

Crop failures, as previously noted, seem to be insured against at the community-wide level. In this case, we would not expect the interaction terms with social capital to be significant, either positively or negatively. This is because the impact of shocks, if insured at the broad village level, should not be lessened through one's social capital. This is corroborated in columns (5) – (8) in which none of the social capital terms are significant. On the basis of this set of results, individual household-level shocks have a negative impact and do not appear to be fully insured against, while aggregate common do not have a negative impact. This is true also when drought is used as the aggregate shock instead of crop failure and when weight-for-age is used as the outcome measure instead of height-for-age[13].

Moreover, associational social capital *does* appear to be serving an insurance purpose. To confirm this, the specifications in columns (2) and (3) in Table 4 above, with family problems as the shock measure, are re-run using pooled-OLS and the Hausman-Taylor method. The results are presented in Table 5 on the next page. In the pooled-OLS, columns (1) and (2), we again see that family problems are not fully insured against as they have an overall significant negative impact on height-for-age. Turning to the social capital terms, associational social capital in column (1) has the correct sign but is highly insignificant. Similarly, civic social capital is also highly insignificant in column (2). With regards to these results, it is worth keeping in mind that pooled-OLS is likely to be biased due to the presence of time-invariant household characteristics.

The Hausman-Taylor regressions are reported in columns (3) and (4). Family problems have a significant and negative impact on children's development at the 10% and 5% level respectively. Additionally, in column (3), the interaction between shocks and associational social capital is positive and significant at the 10% level. Hence, households who suffer from shocks are able to minimize the negative consequences through their network of family and friends. Conversely, those with civic social-capital are unable to insure against such shocks in the same way, as evidenced by the insignificant coefficient on trust in column (4).

[13] Results using weight-for-age instead of height-for-age have marginally lower levels of significance while those using drought are almost identical to those with crop failure. These are not reported due to space considerations

Table 5. Shocks and Social Capital Impact on Height-for-Age (2)[14]

	Pooled-OLS		Hausman Taylor		First Difference	
Variable	**Family and Friends (1)**	**Trust (2)**	**Family and Friends (3)**	**Trust (4)**	**Family and Friends (5)**	**Trust (6)**
Sex	-0.140*** (0.038)	-0.135*** (0.038)	-0.126*** (0.044)	-0.117*** (0.044)		
Child's Age	-0.021 (0.033)	-0.021 (0.034)	-0.019 (0.017)	-0.022 (0.018)	-0.093*** (0.031)	-0.092*** (0.031)
Child's Age^2	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.001*** (0.000)	0.001*** (0.000)
Number of rooms	0.025* (0.015)	0.026* (0.015)	0.037*** (0.011)	0.027** (0.012)	0.057*** (0.022)	0.058*** (0.022)
Total assets	0.110*** (0.021)	0.108*** (0.021)	0.051*** (0.014)	0.048*** (0.014)	0.050* (0.031)	0.053* (0.031)
Birth size	0.092*** (0.021)	0.092*** (0.021)	0.103*** (0.024)	0.100*** (0.024)		
Premature	-0.126** (0.065)	-0.119* (0.066)	-0.049 (0.076)	-0.056 (0.077)		
Mother's education	0.018*** (0.003)	0.017*** (0.003)	0.025*** (0.004)	0.024*** (0.004)		
Toilets	0.296*** (0.045)	0.290*** (0.046)	0.217*** (0.036)	0.209*** (0.036)	0.043 (0.086)	0.038 (0.087)
Wave	-0.317* (0.176)	-0.311* (0.177)	-0.152 (0.170)	-0.165 (0.172)		
Family problem	-0.089** (0.046)	-0.086† (0.056)	-0.069** (0.029)	-0.061* (0.037)	-0.110† (0.076)	-0.102 (0.089)
Family and friends interaction	0.090 (0.131)		0.139* (0.082)		0.282† (0.177)	
Civic Coop. interaction		-0.043 (0.087)		-0.028 (0.062)		0.072 (0.126)
R^2	0.102	0.100			0.039	0.037
Observations	3199	3185	3257	3176	1538	1532

***significant at the 1% level, **significant at the 5% level, *significant at the 10% level, † significant at the 15% level

Note: Numbers not in parentheses are coefficients, numbers in parentheses are standard errors. Community, electricity and expenditures are not significant across all specifications, hence are not reported in the table above

Finally, columns (5) and (6) present the result of a first-difference specification in which the sample has been restricted to waves 1 and 2, when the children under study were aged 1 and 5 respectively. This is done following WHO recommendations to limit

[14] Robust standard errors used where appropriate. Regressions in columns (1) – (4) are also run with weight-for-age as the outcome measure as a robustness check. The results are similar to the ones reported above, albeit with higher p-values

the analysis of height measures to children between 0-5 years old, to account for the importance of environmental factors that are important determinants of height in early childhood (WHO, 1986; Duflo, 2000). Examining these results, we see that in column (5), family problems have a negative impact on height-for-age with a p-value of 0.148, which is marginally insignificant. Similarly, associational social capital appears to be once again serving a risk-insurance role, as evidenced by its positive coefficient and p-value of 0.111. On the other hand, civic based social capital does not appear to help households mitigate risk, as its coefficient in column (6) is highly insignificant. One reason for the reduced significance of these results might be the smaller sample size of this specification, as using a first-difference specification with only two rounds halves the number of observations[15].

Overall, across a variety of specifications, two key results stand out. First, individual shocks, measured by deaths and illness in the family, are not fully insured against and have a negative impact on children’s development. Conversely, common shocks – crop failure and drought in this case, do not have a similar impact and appear to be insured against at the community level. Given that in the literature common shocks have been consistently found to have a negative impact, this result could potentially be due to measurement errors in the aggregate shock variables. Second, in the case of individual shocks, where there is scope for informal mechanisms to help mitigate risk, associational social capital appears to be beneficial while civic- and trust-based social capital does not.

This result vis-à-vis the role of associational social capital merits further attention, especially as the mechanism of how associational social capital is helping insure against risk remains unclear. Specifically with regards to the earlier discussion on group size, one would like to know whether efficient risk-sharing is influenced by group size. For instance, it is not evident whether a household that relies on a large number of friends and neighbours is better able to minimize the adverse consequences of a shock relative to a household that relies on a smaller number of close associates. As noted, Genicot and Ray (2003) and Fafchamps and Lund (2001) support smaller groups, while

[15] Similar results are obtained when using weight-for-age as the outcome and confining the data to rounds 2 and 3 only. Given that height stabilizes after age 5, changes in weight and hence weight-for-age capture health and nutritional outcomes among children from the age of 5 onwards (WHO, 1986)

Gertler and Gruber (2002) and Ligon et al. (2002) favour larger groups. Finding smaller groups to be more beneficial supports the notion that incentive constraints and monitoring are important in networks. Conversely, larger groups may be more beneficial if having a higher number of diversified connections is better suited to risk-sharing.

I use information on the number of relatives of a household to determine the degree of *family and friendship-based* social capital it has. Hence, if a family that relies on associational social capital has 1-5 relatives living in the community outside their household, it is placed in the 'small family' category. In other words, such a household is said to rely on a smaller, more compact network of associates to help insure against risky outcomes. Similarly, families with 6-10 relatives are included in the 'medium family' category. Lastly, having more than 10 relatives in the community and being reliant on family social capital places a household in the 'large family' category. If the results support Gertler and Gruber (2002) and Ligon et al. (2002), we would expect the large family variable to be positive and significant compared to the other categories. On the other hand, if smaller groups are better able to mitigate-risk, we would expect the opposite. The results are presented in columns (1) and (2) of Table 6 below.

Column (1) models the impact of group size on height-for-age, using family problems as the shock variable. Examining the results of the regression, family problems again negatively impact height-for-age. With regards to social capital, we see that households using social networks to minimize risk are *better served by smaller groups* – compared with no family (the omitted category) and with larger groups. The small family variable is positively signed and significant at the 10% level. On the other hand, medium family, while positively signed, is insignificant and has a smaller coefficient than small family. Lastly, the large family variable is actually negatively signed. This evidence indicates that gains from associational social capital might diminish when connections are loosely formed (as in larger groups). Although a t-test for the equality of coefficients is only marginally significant at the 10% level, it does appear that risk-sharing is more effective in smaller groups. This is possibly due to repeated interactions of group members, easier monitoring of shocks and adverse consequences, or lower costs of maintaining group ties. As such, this result supports Genicot and Ray (2003) and Fafchamps and Lund (2003). Interestingly, in column (2) which models the impact of group size using crop failure as the shock – small family is omitted due to a lack of observations. In other words, those households that experience crop failure and rely on associational social capital *only* rely on medium to large groups. Given the importance of the small family variable from the first regression, this could be one reason why associational social capital is not found to have an impact during a crop failure.

Columns (3) and (4) build on these results by examining whether households with associational social capital are helped if their network is composed of influential community members. Hence, while group size is a horizontal measure of social capital, having relatives who are influential can be thought of as a vertical measure. While 'influential' is not specifically defined in the data, vertical networks have been interpreted as connections between citizens and the political elite in the literature (Caeyers and Dercon, 2011). Furthermore, these can assume importance in the face of shocks as the distribution of aid and relief measures are often influenced by social and political connections (Caeyers and Dercon, 2011). The measure of 'some influential relatives' is created akin to the group size variable, with households relying on social capital coded as having influential relatives if any of their relatives in the community are thought to be influential. Similarly, 'no influential relatives' implies that households with associational social capital do not have influential family members. In the results in column (3) below, family problems again have a negative impact on height-for-age. Moreover, having influential relatives has a positive impact, significant at the 10% level. This is consistent with the literature and our expectations that associational social capital is better able to mitigate risk when it consists of influential community members. Indeed, this positive result holds even with crop failure as the shock measure in column (4). Conversely, households with no influential relatives are negatively impacted under both types of shocks. This result indicates that there are winners and losers in the aid distribution process following shocks, with 'connected' households apparently better able to guarantee their own wellbeing and security[16].

Together, the results of this analysis paints a picture that suggests that social capital is most beneficial in households that rely on smaller and closer-knit groups.

[16] The results in columns (1) – (4) of table 6 hold under a Hausman-Taylor specification as well. They are not reported here due to space considerations.

Additionally, there are also benefits from having family members who are perceived to be influential – politically or otherwise – in the community. While investigating the exact mechanism of how influential relatives benefit households is not within the scope of this thesis, one possibility as discussed above is through the potential influence they have on the distribution of aid and welfare in the aftermath of shocks.

Table 6. Influence of Group Size and Relatives in Mitigating Shocks' Impact on Height-for-Age[17]

	Group Size Effect		Influence Effect	
Variable	**Family Problems Fixed Effects (1)**	**Crop Failure Fixed Effects (2)**	**Family Problems Fixed Effects(3)**	**Crop Failure Fixed Effects(4)**
Number of rooms´	0.033** (0.014)	0.022† (0.014)	0.022† (0.014)	0.021† (0.014)
Total assets	0.030 (0.030)	0.038 (0.028)	0.038 (0.028)	0.039 (0.028)
Toilets	0.080 (0.067)	0.099 (0.075)	0.098 (0.075)	0.099 (0.075)
Wave	-1.523*** (0.576)	-1.663*** (0.656)	-1.762*** (0.654)	-1.677*** (0.654)
Family problem	-0.047† (0.032)		-0.048† (0.033)	
Crop failure		0.006 (0.050)		-0.086 (0.106)
Small family°	0.360* (0.210)			
Medium family°	0.046 (0.128)	0.155 (0.277)		
Large family°	-0.149 (0.181)	0.069 (0.155)		
No Influential Relatives°			-0.109 (0.089)	-0.089 (0.116)
Some Influential Relatives°			0.337* (0.195)	0.577** (0.293)
R^2 within	0.051	0.057	0.060	0.058
Observations	3492	3249	3249	3249

***significant at the 1% level, **significant at the 5% level, *significant at the 10% level, † significant at the 15% level

Note: Numbers not in parentheses are coefficients, numbers in parentheses are standard errors. ° Small family, Medium family, Large family, No Influential Relatives and Some Influential Relatives are all interaction terms with the relevant shocks (i.e., family problems and crop failure). ´ Child age, Child age^2 and electricity are highly insignificant across specifications, hence the results are not shown here.

[17] All regressions in Table 6 use robust standard errors

VIII. Conclusion

In this thesis, I have examined the role of social capital as a risk-sharing mechanism in rural communities in India's Andhra Pradesh state. The rural poor in developing countries face risks that are systematically greater than those faced by other people, and in the absence of formal markets and insurance instruments, rely on informal mechanisms such as social networks. The analysis shows that in the communities under investigation, aggregate community-level shocks measured through crop failures and droughts seem to be insured against as they do not have an adverse impact on children's height-for-age. This finding supports efficient risk-sharing at the community level as in Townsend (1994) and Udry (1994). On the other hand, household-specific shocks such as death and illness do have a negative impact on children's development and are not efficiently insured against. For such shocks, where informal insurance mechanisms have a role to play, associational social capital – one's network of family and friends outside the household – does serve a risk-mitigating role in reducing the negative impact of these shocks (as in Carter and Maluccio, 2003). Conversely, civic- and trust- based social capital matters less and does not seem to be as helpful in insuring against the adverse consequences of unfavourable events. These results are robust to the use of various outcome indicators and shock measures, as well as the use of different estimation techniques including fixed-effects and the Hausman-Taylor estimator.

Nonetheless, it is important to bear in mind the likely significant endogeneity in group formation, especially in cases when shocks are correlated over time. While such correlation does not appear to exist for observable shocks in this sample, past unobserved shocks are not taken into consideration. And although effort has been undertaken to correct for this problem through various strategies, some bias probably remains. Separately, it is also worth noting that changing investments in children's health constitutes one of possibly many other responses to income shocks. In this case, confirming the role of associational social capital as a risk-coping device requires examining its impact in specifications with a broader set of outcome variables. Lastly, the results reported are only marginally significant – some at the 10% level and some with p-values from 0.10 to 0.15. However, this might be because of a relatively small sample with only three time periods four years apart, or due to the unsuitability of some measures of shocks or social capital. Having information on a yearly basis or data on more ‘individual’ household shocks to confirm these estimates would be useful.

Despite these caveats, the results presented here carry potentially significant policy implications. Many policies are aimed at either establishing or supporting formal mechanisms to cope with risk – with employment-guarantee schemes and the development of formal credit and savings markets being two examples. However, these have the potential to crowd out informal insurance mechanisms (Dercon and Krishnan, 2003). In this case, designing policies that reinforce, not replace, existing mechanisms might be of greater value. For instance, this could involve participation in formal mechanisms being conditional on continued group membership. Attanasio and Rios-Rull (2000) investigate arrangements that enable groups to stay together by allowing group members to punish deviators through denial of access to formal insurance channels. Additionally, policies should target those with ‘poor’ social capital, given that those with ‘high’ associational social capital are seemingly better able to insure against negative outcomes. More fundamentally, if crowding out of informal market mechanisms due to public intervention takes place, those in public office must consider the impact of policy changes, intentional or not, on the social fabric of communities likely to be affected. Networks and group relations, as seen, often substitute for market failure and thus disturbing the *status quo* can have negative welfare consequences.

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