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Social capital as a coping mechanism for seasonal deprivation: the case of the *Monga* in Bangladesh

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Abstract The extreme hunger and deprivation that recurs every year in the lean season in northern Bangladesh, locally known as the *Monga*, is mainly due to the malfunctioning local labor and credit markets. Using data covering 5600 extreme poor households in the *Monga*-prone region, we investigate in detail the role of social capital in securing employment and obtaining informal loans. Correcting for the endogeneity of social capital by the heteroscedasticity-based method proposed by Klein and Vella (J Econom 154:154–164, 2010) and also by the standard IV method for a robustness check, we document that social capital plays an important role in obtaining both wage- and self-employment. We also document a weak negative effect of social capital on obtaining informal loans. We explain our results in terms of the role of horizontal and vertical components of our measures of social capital in influencing different outcomes.

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1 Introduction

Seasonality in employment and income of the rural households in developing countries is well known. Typically caused by rain-dependence in agriculture (Chaudhuri and Paxson 2002), seasonality in employment and income may sometimes be extreme enough to result in starvation and hunger. Malfunctioning of the rural labor and credit markets, which severely constrains consumption smoothing across seasons, is the primary reason behind these employment and income fluctuations (Sen 1981; Paxson 1993; Jacoby and Skoufias 1998). The *Monga* in northern Bangladesh is a unique example of such extreme seasonality.[1] It is a near-famine situation in the lean season that recurs almost every year from mid-September to mid-November and is the main cause of plummeting employment and credit opportunities for the extreme poor in the pre-harvesting period of the *Aman* crop (the main rice crop in Bangladesh) (Sen 1981; Rahman 1995; Berg and Emran 2011).[2] The contraction of the rural economic activity and the resulting lack of employment opportunities during the *Monga* not only reduce the possibility of selling labor in the spot market but also lower the proceeds of advance sales of labor in the future market to as low as 50% of those in the spot market. This situation is exacerbated by the absence of the rural credit markets, both formal and informal, thus increasing the need for effective consumption smoothing (Pitt and Khandker 2002; Amin et al. 2003). The *Monga* has been a grave policy concern for the government of Bangladesh and non-governmental organizations (NGOs).

This paper investigates the role of social capital, a non-standard factor endowment, in securing employment and informal loans for the extreme poor during the *Monga*. We interpret the improved employment and informal loan opportunities of the extreme poor during this period as indicators of their reduced exposure to hunger and famine. Consequently, our analysis adopts various employment indicators, such as wage-employment and self-employment, and loan indicators as outcome variables. Our focus on informal borrowing is predicated on the fact that the extreme poor in Bangladesh are invariably denied access to formal financial institutions (Amin et al. 2003; Mallick 2013).

[1] *Monga* is a Bengali dialect word referring to unemployment, food scarcity, hunger and starvation in northern Bangladesh. Khandker (2011) describes the *Monga* as a period of virtual economic inactivity and seasonal food deprivation, which sometimes rises to the level of famine.

[2] In studying the 1974 famine in Bangladesh, Sen (1981) documented that, at the peak of the *Monga*, employment dropped to as low as 10% of the previous three-month average. Wage laborers and several service providers (such as boatmen and petty traders) whose livelihood depends on daily wages suffered the most. This resulted in a decline of "entitlement" of food, causing starvation and death. As much as 45% victims of the famine were day laborers, while small farmers (owning less than 0.5 acre of land) constituted a further 39%.

The extreme poor comprise 25% of the population in Bangladesh and 40% of the population in the northern districts. Given their weak economic potential and almost nonexistent physical or human capital, or other form of productive assets, the extreme poor are the most vulnerable to the *Monga*. A comparison between the extreme poor and the average poor, who are typically targeted by NGOs, is instructive in illustrating the plight of the extreme poor (see Table 6 of Appendix). While an average NGO-borrower poor person owns approximately 87 decimals of land, an extreme poor person owns only 4 decimals. The latter is no more than a homestead; 47% of the extreme poor own no land at all. The value of the dwelling house (excluding land), which can be considered as a proxy for non-land asset value, is approximately 8000 and 1200 Taka for the NGO-targeted poor and extreme poor, respectively. Moreover, although the average poor can borrow through microfinance programs, the extreme poor are excluded from these schemes because of their lack of creditworthiness. The extreme poor also lack human capital endowment. For example, the household head in an extreme poor household has only 0.53 years of schooling compared to 2.86 years for an NGO-targeted poor household. As a more existential comparison, per capita consumption for the NGO-targeted poor is 2284 calories per day, while more than 50% of the extreme poor cannot even manage food twice a day. All these features make the extreme poor the most vulnerable to the *Monga*.

Given the lack of physical and human capital, social capital is the only form of capital that the extreme poor can possibly own. The proponents of social capital argue that such assets as networks, trust, and reciprocity assist households greatly during economic hardships and shocks (Durkheim 1895; Coleman 1988; Putnam 1993). For example, social capital helps economic exchange, particularly in agrarian societies where formal institutions are largely absent (Bardhan 1984; Basu 1986). Although many useful roles played by social capital are documented (Bakshi et al. 2015 provide a review), its role in mitigating the adverse effect of the *Monga* remains unexplored in the literature.

We define social capital as social characteristics that enable an individual to benefit from information flows and to reap the market and non-market returns from interaction with others. To measure the social capital of a household, we consider three distinct types of social interactions: (i) *help* received from non-relative neighbors, (ii) *invitation* received from non-relative neighbors, and (iii) participation in the *shalish* (a social system for informal adjudication of petty disputes by community members), all in the past 1 year. This information is recorded in the survey as binary responses (yes or no). Although information about repeated interactions, if any, is not available, the incidence of interactions can arguably provide a sufficient sense of whether an extreme poor household can be considered to own social capital. In our data, 27, 16, and 13% of the extreme poor households received any *invitation* and *help* and participated in *shalish*, respectively. These figures clearly demonstrate that social capital is not a resource widely available across the extreme poor but a scarce asset, like other types of economic resources. Each of the above indicators is linked to social capital theory, and, therefore, we investigate their individual roles separately. Section 3 discusses in detail that all three measures of social capital capture the horizontal social network in terms of interactions among the extreme poor; however, participation in *shalish* additionally captures the vertical social network in terms of interactions of the extreme poor with the rural elites.

Our analysis exploits rich household and village-level survey data for 5600 extreme poor households from 156 villages in three *Monga*-prone districts in northern Bangladesh. The endogeneity of social capital is a methodological challenge. One of the causes of endogeneity is omitted variables, which simultaneously affect social capital, employment, and informal borrowing during the *Monga*. We control for a multitude of explanatory variables to control for the observable characteristics, including the available physical and human capital, demographic and economic conditions at the household level, and physical infrastructure at the village level. However, unobservable characteristics, such as ability, entrepreneurship, or risk-taking behavior of the household members, may influence both the outcome variables and the level of social capital. Another source of potential endogeneity is the reverse causality, in that current employment and financial transactions may also create social capital. Measurement errors in social capital cannot be ruled out as well, because social capital is broad concept for which we use some proxies.

To address the endogeneity of social capital, we employ two alternative identification strategies. The first is a heteroscedasticity-based approach proposed by Klein and Vella (2009, 2010) that does not rely on exclusion restrictions. This is our main identification strategy. To check for robustness, we also employ the instrumental variable-based identification method, with our instrumental variable (IV) being the number of open-access resources in the neighborhood of the extreme poor. Conditional on the covariates, this IV categorizes the households into different groups with randomly varying access to social capital construction platforms, hence usefully identifying the unbiased effect of social capital (see Sect. 5.3 for details). We find that the IV results support the results based on the heteroscedasticity-based identification.

Our results document that all three measures of social capital increase the likelihood of self-employment. Given the small-scale self-employment activities undertaken by the extreme poor (see Table 8 of Appendix for a detailed list), the market for their products and services is also targeted to similar extreme poor households. Greater social capital provides better information about the market (potential customers and their locations), and, consequently, increases the profitability of self-employed activities. On the other hand, only participation in *shalish* has a significant effect on wage-employment. This result is understandable from the vertical aspect of social capital generated from participation in *shalish*. Since potential employers of the extreme poor come from the upper hierarchy in the community (rich households), rather than other extreme poor, households with networks with the upper hierarchy are more likely to be wage-employed. Quantifying the effect, participating in *shalish* increases female wage-employment during the *Monga* that can be translated into an income increase equivalent to 30 kg of coarse rice at the prevailing market price. However, social capital has a (weak) negative effect on the probability of obtaining informal loans. The reason is intuitive. Given that the higher degree of social capital increases the likelihood of both self- and wage-employment opportunities, households are less likely to resort to informal loan in times of distress during the *Monga*.

This paper makes several distinct contributions to the literature. First, to the best of our knowledge, this is the only study that investigates the role of social capital in combating the *Monga*. Second, we study the extreme poor because they are the cohort most vulnerable to the *Monga*. The facts that the extreme poor are typically illiterate and lack access to alternative sources of information, such as NGO or radio/TV, offer the major advantage that the effects of social capital are unlikely to be confounded by other sources of information. Third, we address the endogeneity of social capital through a multi-pronged approach. Prior studies on social capital have categorically ignored this problem, raising serious doubts about the reliability of their estimates.

Our work is situated in a burgeoning literature that finds a strong connection between social capital and household well-being during economic hardships. While this literature investigates the role of social capital in mitigating idiosyncratic shocks, our study explores the same effect in the context of an aggregate shock that occurs at the regional level. Our work also resembles Berg and Emran (2011), who demonstrate an important role for microfinance in reducing the adverse effects of the *Monga*. We differ from their study in terms of our focus on social capital and the extreme poor, who are typically excluded from the microfinance program.

The rest of the paper is organized as follows. Section 2 provides a background for the *Monga* problem. Section 3 discusses measurement of social capital for the extreme poor in the context of rural Bangladesh. Section 4 explains the data and descriptive statistics. Section 5 presents our estimation and identification strategies. Section 6 discusses the results based on OLS and instrumental variable estimations. Finally, Sect. 7 concludes.

2 Background and the *Monga*

Approximately 75 million people in Bangladesh live under conditions of poverty, hunger, and consumption rationing (FAO 2010). The extreme poor lack productive assets, depend on an irregular daily wage income, face severe income shocks, and are, overall, the cohort most vulnerable to hunger and food insecurity (Halder and Mosley 2004). The situation is worse in the northern part of the country, where incidence of poverty is significantly higher and income seasonality is much more pronounced. For example, in 2005 approximately 56% of the population in the greater Rangpur region[3] lived below the poverty line and 40% lived under conditions of extreme poverty (Khandker et al. 2010), while the national averages in 2006 were 40 and 28.6%, respectively (BBS 2006). The northern districts also lag behind the rest of the country in terms of other development indicators. Per capita income is as low as 71%, the share of manufacturing is only 10% (BBS 2002), and the daily wage rate is 28% lower than the national average (Khandker et al. 2010). This situation exacerbates the vulnerability of food provision for agricultural day laborers during the lean season, resulting in a famine-like situation. Households opt for advance sale of crops and labor at unfavorable terms, leading to chronic poverty. For example, a day laborer receives as little as 50% from selling advance labor as would be received in the spot market (Rahman 1995).

[3] Rangpur is one of the seven administrative divisions in Bangladesh (also a district in the same division).

The *Monga* occurs between two harvesting periods every year in five northern districts—Kurigram, Gaibandha, Lalmonirhat, Nilphamari, and Rangpur—in the Rangpur division.[4] The harvesting periods in Bangladesh are divided into two major cropping seasons—*Aus* and *Aman*. The *Aus* starts in April, and harvesting takes place in July–August. However, the main crop is *Aman*, comprising the period from July to December. The *Monga* occurs during September–November, when the stock of *Aus* runs out before the *Aman* harvesting starts in December. October–November are the hardest months for the extreme poor, due to severely reduced employment and food scarcity.[5] Since the extreme poor do not own an asset base and cannot save over the non-lean season, their ability to cope with the massive employment drop during the *Monga* is constrained significantly.

Because the local labor and credit markets either do not function properly or are absent altogether, governmental and non-governmental transfers become important for the subsistence of the extreme poor in the *Monga* region. The government, along with some NGOs, has undertaken various social safety net programs, including Vulnerable Group Feeding and Vulnerable Group Development programs, during employment and income fluctuations. Despite such efforts, 9.3 million poor, including those in the *Monga* region, are still excluded from these safety net programs (World Food Programme 2010).

3 Measuring social capital

Social capital is a broad concept and, therefore, a precise definition depends on the specific context. We define social capital as social characteristics that enable an individual to benefit from information flows and to reap the market and non-market returns from interaction with others. This definition is slightly narrower than the one espoused by Glaeser et al. (2002) and Karlan (2005).

Given our context, we measure social capital generating information flow and networking by three distinct attributes: (i) *help* from non-relative neighbors, (ii) *invitation* to visit non-relative neighbors, and (iii) participation in *shalish*, all in the last 1 year.[6] The information is recorded as a binary response; we assign a value of 1 to each "yes"

[4] See Rahman (1995), Hossain (1988), Faridi and Khalily (2008), Rahman et al. (2008), Shahriar and Khalily (2008), Khandker et al. (2010), Berg and Emran (2011), Khandker (2011). Rahman (1995) is the pioneering work on the *Monga*.

[5] This period is also termed as the *Mora Kartik*. *Mora* means "dead" in Bengali, and *Kartik* is a month in Bengali calendar (mid-October to mid-November). *Mora Kartik* implies the deadliness of the *Kartik* month.

[6] There is no clear agreement on the measurement of social capital. The literature commonly uses some proxies that track the individuals' participation in community events. The following are some examples of the proxies for social capital: Kawachi (1999)—membership in groups, civic trust, and helpfulness of others; Islam et al. (2008)—voter turnout and crime rates; Veenstra (2000)—voting, writing letters to editors, paying attention to the community, and socialization with colleagues at work; Hyyppä and Mäki (2001)—different participating activities; Campbell et al. (2002)—members of the local sporting clubs; Latkin et al. (2003)—church attendance; Gayen and Raeside (2007)—networking and social relationships; Waterkeyn and Cairncross (2005)—club membership; Guiso et al. (2004)—blood donation.

answer and a value of 0 to each "no" answer. However, information on the identity of individuals/households who either extended help, invitation to visit, or requested to participate in *shalish* to the extreme poor was not recorded.

Help includes (i) cooked food and food items, such as rice, salt, eggs, pulses, and spices, as either a gift or a loan; (ii) accompaniment to visit the doctor, hospital, and pharmacy; (iii) assistance in trading productive assets, such as cattle and trees; and (iv) information about jobs, relief, and informal loans. These types of help manifest the extreme poor's participation in the social network with compassion, support, attachment, commitment, and reciprocity, and, thus, represent a bonding relationship (Szreter and Woolcock 2004; Harper and Kelly 2003; Heaney and Israel 2002; Coleman 1988). The extreme poor usually receive help from individuals/households of similar socio-economic status. Therefore, *help* captures the horizontal social network.

Invitation is usually received from individuals or households of similar socio-economic status, thus capturing the horizontal social network. This measure is more pertinent in the current context, since the sample households consist of only the extreme poor. It needs to be stressed that, in order to be invited by non-relatives, the relationship must be both strong and based on mutual trust and recognition. *Invitation*, therefore, indicates that the individual is included and valued in the community (Baum and Ziersch 2003; Goodman et al. 1998).

Shalish is a social system designed to settle petty disputes in the community without resorting to costly legal procedures. The system reprimands and punishes an individual who violates certain norms and values of the society. The extreme poor are usually invited to participate in *shalish* by their peers to support their cause, thus representing the horizontal social network. However, unlike the other two measures, participation in *shalish* has an additional dimension. Traditionally, the rural elite, which includes rich, socially and politically influential persons, and elected local government representatives, always present in the *shalish* as power brokers and to give the final verdict. Therefore, attending *shalish* provides an opportunity for the extreme poor to interact with individuals of upper hierarchies in the community, although their interactions may not always be on equal terms. Therefore, attending s*halish* also represents a vertical social network.

It is important to bear in mind that, although both horizontal and vertical networks help disseminate information, the type of information may depend on access to the type of networks. For example, horizontal networks, in terms of interactions among the extreme poor, are less likely to provide information about potential job opportunities; rather, interactions with rich people, who are potential employers, may provide such information.

Although the data do not allow to separate out ex ante the horizontal and vertical nature of interactions, our results can still shed light on these interactions, depending on which measure of social capital influences the outcome variables.

It is important to issue a caveat that information flow and network channels of social capital may reduce moral hazard and hold-up problems and, thus, can increase one's bargaining power. We do not investigate these channels in detail, mainly because of the lack of data. For example, we do not have data on either the frequency of interactions or the durability of the relationship, which would help measure the extent to which moral hazard and hold-up problems are reduced. In addition, bargaining power is not quite a relevant concern for the extreme poor. Moreover, any potential sources of bargaining power, such as education and land ownership, is already controlled for in our estimations and, hence, are orthogonal to our social capital measurement. Therefore, we focus only on the broader channels that our measures of social capital capture.

4 Data and descriptive statistics

Data were collected in 2002 as a part of a baseline survey for BRAC's "Challenging the Frontier of Poverty Reduction/Targeting the Ultra Poor (CFPR/TUP)" program in three northern districts in Bangladesh (Rangpur, Kurigram, and Nilphamari).[7] All three districts are in the *Monga* region. The extreme poor in each village were identified through the participatory wealth ranking (PWR) exercises by the community members.[8] One-third of the program villages were randomly selected, and all extreme poor households therein were surveyed. The total sample size is 5600 households drawn from 156 villages. The collected information includes demographic characteristics; economic endowments, such as income, landholding and dwelling conditions; social capital; labor force participation; organizational membership; and village-level infrastructure. Data were collected in February–March during the post-harvest season after the *Monga*.[9] Table 8 of Appendix provides a detailed list of wage- and self-employment activities. Borrowing during the *Monga* is calculated from the information on the timing of borrowing.

The descriptive statistics on employment status, lean season borrowing, and other key variables are presented in Table 1. The number of household members employed (full time or part time) during the *Monga* is, on average, 2.15, which is 61% of the household size.[10] At first glance, it might seem that a large percentage of the household members are employed, but only an average of 1.02 household members obtain wage-employment during the *Monga*, and the proportion of self-employed is almost equal. The percentage of males who are wage-employed is higher than that of females, while the percentage of females who are self-employed is higher than that of males. The latter is due to the fact that livestock and poultry rearing are the main self-employment categories that are traditionally filled by females within the household. Only 7.7%

[7] The households were revisited in 2005 and 2008, but these panel data cannot be used to investigate the effect of social capital. The extreme poor were provided, among other assistance, support for building social capital for approximately two years. Therefore, the contribution of social capital cannot be disentangled from the program impact. Baseline data are immune to this problem.

[8] For a detailed discussion on the PWR method and the selection of households, see Matin and Halder (2007).

[9] Since data were collected in one round, consumption and income across seasons cannot be compared.

[10] We do not have disaggregated employment data, such as the number of hours a day and the number of days a month worked. It is important to note that respondents cannot recall such details of past employment. Therefore, we cannot distinguish full-time and part-time employment from the data. Information on location of employment is also not available, so we are unable to determine migration patterns during the *Monga*. However, the poor in our sample region hardly migrate, considering the associated uncertainty of finding a job in the new destination and the economic consequences of borrowing and spending money to travel to the destination (Bryan et al. 2014).

Table 1 Descriptive statistics

Variable	Mean	SD
Number of hh members employed	2.02	1.34
Number of hh members wage-employed	1.02	0.81
Number of male hh members wage-employed	0.65	0.68
Number of female hh members wage-employed	0.37	0.58
Number of hh members self-employed	1.00	1.16
Number of male hh members self-employed	0.22	0.57
Number of female hh members self-employed	0.78	0.91
Amount of loan received (Taka)	75.63	521.01
% of households received *help* from non-relative neighbors	0.16	0.37
% of households received *invitation* from non-relative neighbors	0.27	0.44
% of households attended *shalish*	0.13	0.34
Education of the household head (years of schooling)	0.50	1.68
Land owned by the household (acre)	0.04	0.14
Household size	3.67	1.74
Health condition of the household head (1 = good; 0 = otherwise)	0.42	0.49
If women can visit outside alone (1 = yes; 0 = no)	0.01	0.08
% of households with NGO membership	0.08	0.27
% of the Male household head	0.65	0.48
Age of the household head (years)	43.21	13.34
% of the married household head	0.69	0.46
If the village has electricity connection	0.75	0.43
Distance of the village from all-weather road (km)	1.92	1.82
Distance of the village from *Upazilla* (km)	7.57	4.02
Average daily male wage in the village (Taka)	43.12	7.96
Average daily female wage in the village (Taka)	29.37	6.59

of the households have NGO membership. The average age of the household head is 43 years, with 69% of them being male. Only 5% of the households have managed to receive informal loans, with the average amount of such loans being approximately 1500 Taka.[11]

5 Empirical specification and identification

In the following, we first present our empirical specification and discuss the choice of the control variables that separate the effect of social capital from other confounding factors. Social capital is likely to be endogenous, for the reasons mentioned in the Introduction. We address this problem by using two alternative methods. The first is heteroscedasticity-based identification proposed by Klein and Vella (2009, 2010), which does not require exclusion restrictions; this is our main identification strategy. The second is the conventional instrumental variables-based identification strategy with exclusion restrictions, which we employ as a robustness check.

5.1 Empirical specification

We estimate the following linear equation:

$$Y_i = \alpha + \beta S_i + \boldsymbol{\delta}'\mathbf{X_i} + \varepsilon_i, \tag{1}$$

where Y_i is a set of dependent variables, S_i is social capital, and $\mathbf{X_i}$ is a vector of control variables. In Eq. (1), our main focus is on β.

The vector of controls $\mathbf{X_i}$ includes an array of variables to aid a clean interpretation of β. These variables pertain to demographic and economic characteristics of the households, such as gender, age, education (years of schooling) and marital status of the household head, family size, amount of land owned, health condition (self-reported), women's mobility outside the home, and NGO membership. Education is intended to control for human capital, while land ownership is intended to control for physical capital. Household size controls for labor endowment of the household. A larger household size might also create more social capital, as it leads to more interactions outside the home. Age, health condition, marital status, and women's mobility outside the home often influence both employment decisions and loans received by the household. In addition to access to loans, NGO membership plays an important role in creating social capital. For example, microcredit operations are performed in peer groups, which create and extend personal networks among the members. The average annual wage rates in the village for male and female laborers capture the shadow price of labor. The developed physical infrastructure facilitates communication and economic opportunities at the village level. To account for this potential effect, we control for the village-level physical infrastructure, such as the distance of the village from the *Upazilla* (sub-district headquarters) and an all-weather road and the avail-

[11] At the 2002 exchange rate, one US dollar was approximately equal to 60 Taka.

ability of electricity. Village-level variables also account for any non-randomness in program placement, since the data came from BRAC's TUP program.

5.2 Heteroscedasticity-based identification

Our main identification strategy is a variant of the approach proposed by Klein and Vella (2009, 2010).[12] This method requires that the endogenous variable be binary. It exploits non-spherical disturbances arising in the determination of social capital. The primary intuition behind this identification is that, with substantial heteroscedasticity in the equation relating the endogenous variable to the exogenous variables, the changing variance in the residual acts as a "probabilistic shifter" of the endogenous variable. Analogous to the instrumental variables, this probabilistic shifter helps trace out the causal relationship between the dependent variable (employment or loan) and the endogenous variable (binary social capital). Consider the following equations:

$$Y_i = \alpha + \beta S_i + \boldsymbol{\delta}'\mathbf{X_i} + \varepsilon_i \tag{2}$$

$$S_i = \mu + \boldsymbol{\gamma}'\mathbf{X_i} + u_i, \tag{3}$$

where Y_i is the employment or informal borrowing during the *Monga* and S_i is the binary proxy for social capital (*help*, *invitation*, and *shalish*). The model does not satisfy the exclusion restriction. However, Klein and Vella argue that β can be estimated if the residuals u_i are heteroscedastic. Assume that residuals are heteroscedastic in the following way:

$$u_i = S_u(\tilde{X}_i)\bar{u}_i, \tag{4}$$

where $\bar{u}_i$ is the zero mean homoscedastic residuals, $\tilde{X}_i$ is a subset of (or equal to) X_i, and $S_u(\tilde{X}_i)$ is a non-constant positive function. The probability of the binary endogenous indicator is given by

$$\Pr\left(S_i^p = 1\right) = P\left(\frac{\tilde{X}_i}{S_u(\tilde{X}_i)}\right), \tag{5}$$

where $P(.)$ is the distribution function for $\bar{u}_i$. With homoscedastic errors, $S_u(\tilde{X}_i)$ is a constant, and identification depends on possible nonlinearity of the $P(.)$ function, such as Normal distribution. However, this identification is based on the nonlinearity in the tails of the distribution and, thus, relies on a small fraction of the data for identification. As such, identification based on the nonlinearity of the $P(.)$ function is, in general, deemed as not being credible. In contrast, when there is heteroscedasticity, $S_u(\tilde{X}_i)$ is not a constant function, and identification exploits data from the region where $P(.)$ is linear. Therefore, the predicted probability of Eq. (5) works as a valid instrument of the binary endogenous variable, provided that there is heteroscedasticity in the residuals (Klein and Vella 2009, 2010).

12 This method has also been employed by Berg et al. (2013).

It is instructive to discuss why the social capital equation might exhibit heteroscedasticity in the first stage. For example, gender (or marital status) of the household head is meant to capture the average difference in social capital. Male and female (or married vs. single) household heads are different groups, but there is enormous heterogeneity among each type of household head in terms of attitudes and entrepreneurship. Thus, while the discrete variables capture the mean difference across the groups, there is also a large variance in the effect, depending on which individuals from the respective groups are compared. Additionally, social capital formation, to a large extent, depends on the village-level physical infrastructure, such as roads and transportation, which exhibit great variation across villages. As in Klein and Vella (2009), we use the same $\mathbf{X_i}$ in Eqs. (2) and (3).

5.3 Exclusion restrictions-based identification

For this identification approach, our external instrument is the number of open-access resources (not to be confused with common-property resources) that extreme poor households can access in their neighborhood. These resources include (i) fallow lands, (ii) water bodies (ponds or canals), and (iii) small forests and woodlands. Fallow lands are often visited by the extreme poor for grazing cattle and collecting cow-dung to be used as fuel after drying. Water bodies, such as swamps, are visited for collecting water lilies and green leaves for food. Small forests and woodlands are visited for collecting dry leaves and fallen tree branches for fuel and firewood. These resources are privately owned, so the extreme poor cannot relocate to these places and establish ownership. Traditionally, in rural Bangladesh, the owners of the open-access resources, who are usually relatively rich, allow others to use these resources without any formal permission, as long as the property is not damaged. From the point of instrument validity, it must be emphasized that extreme poor households are not concentrated, unlike slums in the cities, in any particular part of the village. Bangladesh is very homogenous in terms of language, ethnicity, and religion, with the predominant majority being Muslims. People, even the extreme poor, unlike the (lower caste) Hindus in either India or Nepal, are not concentrated based on either caste (which is prohibited in Islam) or occupation, ruling out any selection in the probability of access to these resources. Additionally, open-access resources exhibit strong within-village variability, in that extreme poor households have variable levels of access to these areas, given their scattered locations within the village, and there are many such resources within a given settlement.

It must be stressed that access to these resources does not create, either directly or indirectly, any type of self- or wage-employment for the extreme poor. Although access to these resources supports subsistence consumption to some extent, the livelihood of the extreme poor does not depend on accessing these resources. This is clearly evident from the occupations recorded in the survey as self-employment, as listed in Table 8 of Appendix, which do not include access to any of these resources. The extreme poor interact with each other on these platforms, thus creating new relationships and cementing existing ties. The social capital of the extreme poor does not also affect the number of open-access resources, which is exogenously determined. One might raise the concern that extreme poor households can meet either potential employers or lenders in these open-access areas, because the owners of the open-access resources might also be among either the employers or the lenders in the village. This would constitute a direct channel between open-access resources and the dependent variables outside the social capital channel. Here, we must stress again that the likelihood of the extreme poor meeting either potential employers or lenders in these platforms is quite low, because the owners of these resources do not typically either visit these places or monitor others' visits. The likelihood of meeting employers or lenders in open-access resources is no different from the likelihood of meeting them at another spot in the village. Therefore, we rule out any reason for considering a direct relationship between access to open-access resources and either wage-employment or informal loans, thus violating the exclusion restriction assumption.

Nonetheless, to block other potential avenues through which access to open resources might affect the outcome variables, we employ a range of covariates in the model. Thus, conditional on the model covariates, our IV is likely to approximate a quasi-random experiment whereby the extreme poor are grouped along a single dimension in terms of their access to open areas, by which the social capital level of the extreme poor differs, given the extent of their access to these resources. Nevertheless, we take a cautious approach and interpret the results estimated by the IV method as a robustness check.

6 Results

We first present the results with OLS as benchmark; this is followed by Tobit estimations. We then present the endogeneity-corrected results. In all cases, we cluster the standard errors at the village level, given that the *Monga* is an aggregate shock and the village is the smallest unit experiencing such shocks.

6.1 OLS results

The OLS results are presented in Panel A in Table 2. The results show that *help* and *invitation* positively contribute to total employment. These are due to their effects on self-employment. We do not find a significant effect of any measure of social capital on wage-employment, except for a positive effect of *invitation* on male wage-employment. Moreover, *shalish* has no effect on any type of employment, yet it is the only measure of social capital that affects informal loans, with the effect being negative.

The choice of control variables in the estimation is important for identification. With the vector of controls, such as education, land owned, and NGO membership included in the model, the social capital variable captures those relational factors that are orthogonal to all these control variables.[13] Omitting some controls, such as the

[13] For example, higher land ownership and education would increase both information flow through social interactions (labor market information from a school friend, for example) and bargaining power [as Sen (1999) notes in *Development as Freedom*, an educated person is "taken seriously" in social interactions].

Table 2 The effect of social capital (individual measure)

Indicators	Help	Invitation	*Shalish*
Panel A: OLS regression			
Total employment	0.238 (3.04)***	0.275 (4.18)***	0.081 (1.06)
Wage-employment	0.000 (0.00)	0.063 (1.56)	− 0.003 (− 0.08)
Male wage-employment	− 0.016 (− 0.45)	0.038* (1.62)	− 0.014 (− 0.58)
Female wage-employment	0.016 (0.52)	0.025 (0.96)	0.011 (0.39)
Self-employment	0.238 (2.83)***	0.212 (3.81)***	0.085 (1.36)
Male self-employment	0.065 (1.99)**	0.064 (2.73)***	0.005 (0.19)
Female self-employment	0.173 (2.56)**	0.148 (3.15)***	0.080 (1.52)
Informal loan received	9.418 (0.48)	12.50 (0.65)	− 32.03 (− 2.13)**
Panel B: Tobit regression			
Total employment	0.252 (3.08)***	0.292 (4.20)***	0.096 (1.17)
Wage-employment	− 0.008 (− 0.12)	0.069 (1.37)	0.014 (0.28)
Male wage-employment	− 0.024 (− 0.37)	0.059 (1.56)	0.001 (0.03)
Female wage-employment	0.028 (0.32)	0.057 (0.75)	0.012 (0.15)
Self-employment	0.377 (3.12)***	0.345 (4.07)***	0.184 (1.98)**
Male self-employment	0.308 (1.91)*	0.381 (3.65)***	0.079 (0.62)
Female self-employment	0.298 (2.72)***	0.279 (3.49)***	0.186 (2.12)**
Informal loan received	288.2 (0.86)	341.8 (1.22)	− 378.6 (− 1.07)
Panel C: Probit regression			
Informal loan received (marginal effect)	0.00 880 (0.967)	0.0109 (1.360)	− 0.00 590 (− 0.658)
Observations	4353	4566	4576

Regressions include constant and all controls. Figures in parentheses are *t*-statistics clustered at the village level

***, **, *1, 5, and 10% significance levels, respectively aforementioned three, that create social capital does not change the main results in terms of sign and statistical significance of the coefficients of social capital (only its magnitude increases by 10–40%). Despite reducing the coefficient of social capital, these controls are essential not only for meaningful comparison of individuals of different types (i.e., of varying personal, family, and village characteristics) but also for preventing omitted variables from causing bias in the estimation. Moreover, those covariates are necessary for a reliable IV estimation to be able to block potential avenues for the violation of exclusion restrictions.

We next estimate the benchmark specification with Tobit, given the truncation associated with the outcome variables. Our sample comprises households with no record of either employment or loans from informal sources, which might be due either to the individuals' inability to obtain employment or loans, even if they attempted to, or simply to the weak supply side of the local economy. Since only approximately 5% of the extreme poor in the sample managed to obtain informal loans, we additionally estimate a probit model treating this outcome as binary (1 = if received any informal loan; 0 = no).

The results estimated by the Tobit model are presented in Panel B. These are qualitatively similar to those obtained with OLS, with the exceptions being that *shalish* is now not significantly related to informal borrowing but is related to (female) self-employment. As a methodological matter, the Tobit regression is efficient, but it relies on distributional assumptions. The probit results are also consistent with Tobit findings (Panel C).

Next, we investigate whether and how different combinations of social capital measures matter for the outcome variables.[14] Heterogeneity might exist among the households in terms of total endowment of social capital.[15] For example, a household may be endowed with only one measure of social capital, while others may be endowed with more, and even all, measures. Comparing the estimates across different groups, one can understand the effects of different intensities of social capital. To proceed, we first sum all three binary measures of social capital to construct an "Aggregate" measure. This measure ranges between 0 (no social capital) and 3 (maximum). Second, we create four dummies from this "Aggregate" measure—(i) households with no social capital, (ii) households with any one component of social capital, (iii) households with any two components of social capital, and (iv) households with all three components of social capital. We include the last three dummies (households with no social capital as the base category) in the regression to compare whether larger endowment of social capital has incremental effects. Finally, we construct a dummy indicating whether a household is endowed with any social capital (1 if at least one of *help*, *invitation*, or *shalish* is "yes"; 0 otherwise), which we refer to as a "Binary Aggregate."

Given that both OLS and Tobit have yielded qualitatively similar results, we now estimate these specifications by OLS. The results are presented in Table 3. Column (2) presents the results for the "Aggregate" measure. The results are in line with previous

[14] We thank an anonymous referee for this suggestion.

[15] Inequality in social capital among households might also arise in the event of an aggregate shock at the village level even households are identical in terms of other resources, such as land and human capital.

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Table 3 OLS regression: The effect of social capital (aggregate measure)

Indicators	Aggregate	No social capital versus			Binary Aggregate
		Any one component	Any two components	All three components	
	(2)	(3)	(4)	(5)	(6)
Total employment	0.175 (5.21)***	0.240 (4.11)***	0.290 (3.92)***	0.530 (3.46) ***	0.264 (4.72)***
Wage-employment	0.026 (1.36)	0.056 (1.69)*	0.039 (0.75)	0.035 (0.40)	0.051 (1.69)*
Male wage-employment	0.008 (0.61)	0.046 (1.96)*	− 0.004 (− 0.12)	− 0.015 (− 0.23)	0.031 (1.47)
Female wage-employment	0.018 (1.35)	0.011 (0.47)	0.044 (1.32)	0.050 (0.64)	0.020 (1.01)
Self-employment	0.148 (4.87)***	0.184 (3.68)***	0.250 (3.70)***	0.495 (4.55)***	0.213 (4.32)***
Male self-employment	0.035 (2.59)**	0.042 (1.92)*	0.059 (1.96)*	0.120 (1.47)	0.050 (2.43)**
Female self-employment	0.113 (4.34)***	0.141 (3.39)***	0.191 (3.24)***	0.375 (4.76)***	0.163 (3.93)***
Informal loan received	0.017 (0.00)	8.713 (0.45)	12.421 (0.46)	− 62.864 (− 2.99)***	6.452 (0.37)
Observations	4345	4345	4345	4345	4345

Regressions include constant and all controls. Figures in parentheses are *t*-statistics clustered at the village level

Aggregate social capital: Help + Invitation + *Shalish* (ranges from 0 to 3)

***, **, *1, 5, and 10% significance levels, respectively

OLS results, in that social capital has a positive effect on total and self-employment. Columns (3)–(5) report the results when three dummies for different intensities of social capital are included. The results are again similar in terms of the effect of social capital on total and self-employment, but the magnitudes of effect clearly depend on the intensities of social capital. For example, considering self-employment, the magnitude of the coefficients of social capital increases secularly from 0.184, in the case of only one component of social capital, to 0.250, in the case of two components of social capital, and to 0.495, in the case of all three components. Finally, when the Binary Aggregate index of social capital is used, the results are again consistent with the previous OLS results (column 6). The effect on informal loan is negative and significant when an individual has all three components of social capital compared with an individual with no social capital (column 5).

One important finding is that the OLS results are robust to alternative methods of aggregation of the three measures of social capital. Therefore, in our IV estimation, in addition to the three individual measures of social capital, we estimate a fourth model using the Binary Aggregate index. The reason for this is that the Klein–Vella heteroscedasticity-based identification applies to a binary and single endogenous variable. Furthermore, since we have one external instrument, we can correct the

Table 4 IV estimation Based on Klein–Vella (2010): the effect of social capital

(1) Indicators	(2) Help	(3) Invitation	(4) *Shalish*	(5) Binary Aggregate
Total employment	0.041 (9.97)***	0.023 (1.19)	0.037 (8.25)***	0.095 (7.17)***
Wage-employment	− 0.004 (− 0.13)	− 0.025 (− 0.86)	0.180 (17.65)***	0.056 (1.80)*
Male wage-employment	− 0.001 (− 0.01)	0.035 (0.92)	0.206 (12.82) ***	0.144 (1.43)
Female wage-employment	− 0.0003 (− 0.02)	− 0.090 (− 2.77)	0.263 (18.59) ***	0.003 (0.100)
Self-employment	0.228 (20.95)***	0.247 (6.83)***	0.216 (18.45)***	0.325 (12.55)***
Male self-employment	0.270 (16.23)***	0.026 (1.59)	0.281 (21.95)***	0.180 (3.36)***
Female self-employment	0.264 (19.85)***	0.319 (21.28)***	0.257 (18.23)***	0.316 (11.16)***
Informal loan	− 0.424 (− 0.63)	− 0.413 (− 0.49)	− 1.027 (− 1.98)*	0.311 (0.74)
Observations	4353	4566	4576	4345

Figures in parentheses are *t*-statistics clustered at the village level
Any social capital (binary): no social capital versus at least one component of social capital
Informal loan is binary: "biprobit" estimation; marginal effects reported
***, **, *1, 5, and 10% significance levels, respectively

endogeneity of only one variable in the case of instrumental variables-based identification.

6.2 IV results: heteroscedasticity-based identification

The results are summarized in Table 4. Columns 2, 3, 4, and 5 present the results for *help*, *invitation*, *shalish*, and the Binary Aggregate index, respectively. Greater social capital, in terms of receiving *help* from neighbors, increases the likelihood of total and self-employment (for both male and female members) but not wage-employment. Similarly, increased social capital, in terms of receiving *invitation*, increases the likelihood of self-employment, especially for the female. On the other hand, the effect of attending *shalish* is more pronounced, as *shalish* also increases the likelihood of receiving wage-employment. For example, households that have a member attending *shalish* in the last 1 year have a 18% higher likelihood of their members finding wage-employment than do households whose member did not attend *shalish*. The relevant likelihoods are 21 and 27% for male and female wage-employment, respectively, and 22% for self-employment (Table 5).

The quantitative implication of these effects for the extreme poor is very large. Assuming 45 days of wage work during the *Monga* period, and given the average daily female wage rate of 28.72 Taka, the monetary value of attending *shalish* is, on

Table 5 IV estimation based on exclusion restrictions: The effect of social capital

(1) Indicators	(2) Help	(3) Invitation	(4) *Shalish*	(5) Binary Aggregate
Total employment	0.042 (10.45)***	0.056 (5.74)***	0.039 (9.84)***	0.098 (6.63)***
Wage-employment	0.158 (7.41)***	0.043 (0.98)	0.183 (19.14)***	0.153 (2.70)***
Male wage-employment	0.214 (13.34)***	0.025 (0.93)	0.213 (14.90)***	0.225 (8.67)***
Female wage-employment	− 0.002 (− 0.10)	0.220 (6.08)***	0.268 (20.09)***	0.045 (0.76)
Self-employment	0.228 (20.31)***	0.261 (9.28)***	0.221 (19.80)***	0.326 (10.20)***
Male self-employment	0.276 (16.40)***	0.069 (0.36)	0.285 (22.91)***	0.177 (2.44)**
Female self-employment	0.260 (17.49)***	0.323 (22.90)***	0.264 (21.96)***	0.331 (8.09)***
Informal loan	− 0.944* (− 1.890)	− 0.729 (− 1.056)	0.642 (0.174)	− 0.813 (− 1.58)
Observations	4353	4566	4576	4345

Figures in parentheses are t-statistics clustered at the village level
Any social capital (binary): no social capital versus at least one component of social capital
Informal loan is binary: "biprobit" estimation; marginal effects reported
***, **, *1, 5, and 10% significance levels, respectively

average, 349 Taka (=45 * 28.72 * 0.27). Given the average price of coarse rice per kilogram at the local village market as being 11.65 Taka at the time of survey, the increased income could buy 30 kg of coarse rice (both the female wage rate and rice price are calculated from the village-level survey data).

When the Binary Aggregate index of social capital is used as the regressor, the results are very similar; a significant effect on self-employment and a weak effect on wage-employment. This is understandable, because we find above that only *shalish*, and not either *help* or *invitation*, has a significant effect on wage-employment, while all three components have a significant effect on self-employment.

In the case of informal loan, only attending *shalish* has an impact, pointing to the reduced likelihood of receiving informal loans.

6.3 IV results: identification based on exclusion restrictions

Before presenting the results, we first discuss the first stage regressions of the endogenous variables. For all individual measures of social capital and the Binary Aggregate index, the coefficient of the instrument is highly significant. For example, the coefficients (robust t-statistics) are 0.026 (3.36), 0.017 (2.00), 0.021 (2.96), and 0.025 (2.47) for *help*, *invitation*, *shalish*, and the Binary Aggregate index, respectively. The results suggest that open-access resources significantly increase social capital. The F-

statistics in these regressions are 10.55, 10.85, 10.45, and 8.38, respectively, generally satisfying the rule of thumb cut-off values.

The IV results based on the exogenous instrument are similar to the benchmark Klein–Vella (2010) IV results. In the case of self-employment and its disaggregation by gender, not only the signs and statistical significances but also the magnitudes of the estimated coefficients are very similar when using both estimation methods. However, unlike the benchmark IV results, but more in line with the OLS results, the instrumental variable-based effect of social capital on wage-employment is now positive and significant. More specifically, these are the effect of *help* on wage-employment, the effect of *help* and the Binary Aggregate index on male wage-employment, and the effect of *invitation* on female wage-employment. In the case of informal loan, the effect of *help*, as opposed to attending *shalish* in the benchmark IV estimation, is now negative and significant.

We recognize that satisfying the exclusion restriction may be difficult in practice, therefore, the results in this section are intended to be a verification tool for the reliability of the benchmark Klein–Vella (2010) IV approach. Despite the fact that these two approaches might rest on different sections of the data for information and differ in terms of statistical efficiency (i.e., Klein–Vella is less efficient than the IV method), we find that the two sets of results are largely comparable. This suggests that the violation of our exclusion restrictions is unlikely to be the case, given that the Klein–Vella method is free from such a requirement.

6.4 Discussions of the results

Our results are informative about the role of the horizontal and vertical nature of interactions in explaining the outcome variables, even though the data cannot separate out these interactions ex ante, since information on the identity of individual/household who either extended *help* or *invitation* to visit or attend *shalish* was not recorded.

We find that all three social capital components, *help*, *invitation,* and *shalish*, have a positive and significant effect on self-employment. These results can be understood by the horizontal nature of these social interactions among the extreme poor, as discussed in Sect. 3. The extreme poor constitute the market for the products and services of small-scale self-employment activities undertaken by the extreme poor. Greater interactions among the extreme poor provide better information about the market (potential customers and their locations), and, consequently, increase the profitability of these self-employed activities.

On the other hand, only participation in *shalish* has a positive significant effect on wage-employment. It is worth reiterating that, out of the three components of social capital, only attending *shalish* creates an additional opportunity for the extreme poor to interact with the upper hierarchy in the community (rich households), thus representing the vertical aspect of social capital. Since potential employers of the extreme poor come from the rich households, rather than from other extreme poor, households endowed with this vertical component of social capital are more likely to be wage-employed.

We also find that social capital has a (weak) negative effect on the probability of obtaining informal loans. Although this result is hard to further explain from the available data, it can be argued that, since greater social capital increases the likelihood of both self- and wage-employment opportunities, households are less likely to resort to informal loans in times of distress during the *Monga*.[16]

7 Concluding remarks

This paper examines the effect of an important and previously undocumented role of social capital in alleviating the adverse effects of the *Monga*, a unique type of extreme seasonality that occurs every year in the pre-harvesting period of the *Aman* crop in northern Bangladesh. The *Monga* is characterized by significantly reduced income and employment opportunities and is a result of either underdevelopment or total absence of labor and credit markets, which causes a near-famine situation for the extreme poor. This paper investigates employment and access to informal loans as two mechanisms through which social capital can help cope with hunger. The employment channel is further categorized into wage- and self-employment.

A key feature of our analytical approach is addressing the endogeneity of social capital, a problem that has been categorically ignored in the related previous work. Our main identification strategy relies on an innovative approach that exploits heteroscedasticity rather than relying on exclusion restrictions. As a robustness check, we compare the results employing the identification strategy based on exclusion restrictions. The heteroscedasticity-based benchmark results are robust to the alternative IV method. The discrepancies that we observe between our OLS estimates and those that are corrected for endogeneity raise concerns about the results of the previous literature, which left the endogeneity of social capital unaddressed.

Our analyses document that, in the absence of other forms of capital, the extreme poor households with higher levels of social capital have greater success in finding wage- and self-employment. Specifically, the vertical social network (representing an employer–employee-type relationship) in the form of participation in *shalish* plays a significant role in wage-employment. Quantifying the effect, a *shalish* participation increases female wage-employment during the *Monga* that can be translated into 30 kg of coarse rice at the local market price. In contrast, both horizontal and vertical social networks increase self-employment. We also find that social capital decreases the informal borrowing during the *Monga*, probably because households with greater social capital have better self- and wage-employment opportunities, thus relying less on informal loans to cope with the adverse effect of the *Monga*.

The *Monga* is an aggregate economic shock, and individuals with higher social capital are likely to find employment at the expense of those with lower social capital. Therefore, in the present context we do not argue for a general equilibrium effect of social capital. Recent studies demonstrate that information, combined with insurance in the form of loans to migrate outside the region for employment during the *Monga*, has a significant impact on both income and consumption (Bryan et al. 2014). Our

[16] We thank an Associate Editor of this journal for this explanation.

results indicate that social capital partially mitigates the information problem but not the insurance problem for the extreme poor, thus suggesting an area of intervention.

Appendix

See Tables 6, 7 and 8.

Table 6 Comparison of some selected socio-economic indicators between the NGO-targeted poor and the extreme poor

Socio-economic indicators	NGO-targeted poor	Extreme poor[a]
Average year of schooling of the adult members	1.85[b]	0.86
Year of schooling of the household head	2.82[b]	0.53
Amount of land owned (in acre)	0.87[b]	0.04
Value of the living room excluding land (in Taka)	7968[c]	1200
Household using toilet (%)	20[d]	13.5
Per capita calorie consumption per day	2284[c]	Only 47.5% of household can feed twice a day
Share of fish and meat in total consumption (%)	15.56[c]	5.77

[a]The authors' calculation from the dataset of this study
[b]Pitt et al. (2006)
[c]Halder (1998)
[d]Mallick (1998)

Table 7 GDP per capita in the three northern districts of Bangladesh

	Per capita GDP (nominal)		Share of manufacturing in per capita GDP (% of country average)
	In Taka	% of country average	
Kurigram	13,757	74.3	12.5
Nilphamari	13,292	71.8	9.7
Rangpur	14,936	80.7	30.1
Bangladesh	18,511	100	100

Source: Bangladesh Bureau of Statistics, *Statistical Year Book*, 2002

Table 8 List of employment during *Kartik* month

Types of employment	Percentage
Wage-employment	
Day laborer in agriculture (including those working only for food)	21.1
Day laborer in formal non-agricultural (such as road repairing and construction, including government programs for the poor)	13.1
Day laborer in informal non-agricultural (such as restaurants, shops, informal workshops, sweeper)	8.5
Housemaid	7.0
Formal service (such as orderly that does not require formal education)	0.7
Self-employment	
Livestock and poultry rearing (such as cows, goats, chickens, ducks)	30.2
Farming (vegetables)	4.2
Farming (crops)	3.3
Petty trade (such as fish, vegetables, fruits, spices, betel leaf, bamboo products, eggs, logs, honey)	4.3
Begging	3.1
Feriwalla (mobile trader selling door to door items, such as pots, used utensils, biscuits, puffed rice, sweetmeats, bangles, lace, oil)	1.5
Semi-skilled (such as tailoring, repairing bicycles and watches, locksmith, blacksmith, hair dressing)	1.1
Faria (middlemen in small trade)	0.5
Others	0.4
Total	100

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