Essays in Development Economics

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Essays in Development Economics

A thesis submitted to the Geneva School of Economics and Management, University of Geneva, Switzerland, in fulfilment of the requirements for a PhD in Economics

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Introduction

The thesis contains three self-contained chapters. The first chapter of the thesis studies the interaction between informal risk sharing and network size, and its impact on decision to migrate. I study the importance of informal network size, and network income with a focus on disadvantaged communities in India. In the next chapter, I analyse how reducing credit market imperfection for the migrant household effect their well-being. I focus on gender of the loan applicant in the migrant households at the place of origin. The third chapter studies the unintended consequence of large scale education programs on the age at marriage of women.[1]. Age at marriage plays a significant role in the well being of the women. We provide causal evidence in this chapter to estimate the impact of women's education. We also study the differential impact on age at marriage due to outside option (wages).

In the first paper, I study the impact of network size on temporary migration. Network size reflects the extent of the informal risk-sharing options available to a rural household. Temporary migration is another form of self-insurance in the rural economy. I particularly focus on how the impact of network size varies depending on the endowment of the network, and show that the channel is via credit constraints for the low endowed network. I use the Indian Human Development Survey 2011-12 data to construct a measure of network size based on the caste of the households. To establish causality, I use historical caste-wise population shares from the 1961 census as an instrument of network size and low permanent migration regions. I find that an increase in network size leads to a

[1]This paper is co-authored with Madhuri Agarwal and Sayli Javadekar

decrease in temporary migration in highly-endowed upper-caste networks and an increase in temporary migration for the low-endowed lower caste networks. Further, I investigate the economic mechanisms using exogenous variation in network income due to negative rainfall shock. I show that an increase in the network size reduces the credit constraints of the low-endowment lower caste households via the income of the network.

In the second paper, I measure the impact of reducing credit market imperfections at the place of origin by providing loans to female members of the migrant household. I use a unique dataset provided by Shram Sarathi, a credit organisation in Rajasthan, India. Using past positive rainfall shock as an instrumental variable for migration, this paper finds a positive impact of loans to female members of migrant household on the household well being indicators such as consumption, livestock holding, asset holding and savings. There exists heterogeneous effects depending on the household asset holding and migrant duration type. The positive impact of the loan is larger for the households with lower asset holding and long duration migrants.

In the third paper, we study how an exogenous increase in female education, a preferred attribute in the marriage market, affects her age at marriage. The District Primary Education Program (DPEP) launched in India in 1994, provides a regression discontinuity set-up to estimate the causal impact of education. Using Demographic Health Survey (DHS) 2015-16 data, we find that the program leads to an increase in women's education by 0.8-1.5 years. Next, to see the impact of education on age at marriage, we use the program cut-off as an instrument for education. In contrast to the literature, we find one year increase in education leads to decrease in age at marriage by 0.44 years. Using a simple transferable utility model, we provide a framework for a negative relationship between education and the age at marriage. As educated and young brides are more desirable in the marriage market, educated women are cleared from the marriage market before less educated women. Further, we find that an increase in education leads to a stable match. Finally, we check if the effect of education on age at marriage varies by the availability of an outside option in the labor market. Our results indicate that educated women in high- wage districts on average marry later than the low-wage districts. A 100 rupee increase in women's wages (25 percent of weekly income) leads to a delay in the age at marriage for educated women by 0.1 years.

Chapter 1

Network Size and Temporary Migration[1]

1.1 Introduction

Rural households in developing countries face credit market imperfections because they lack access to formal banking and insurance. These households depend on informal networks, such as kinship and castes, to cover their risks. These networks can also help households to find jobs, access credit and secure other forms of support (Angelucci et al., 2017; Fafchamps, 2011; Townsend, 1994). Informal risk sharing provides only partial insurance against idiosyncratic household shocks (Udry, 1994). Also, households can also send a temporary migrant to get insurance against bad economic shock. Recent evidence from India points to a rising trend of temporary migration. At least 20 percent of the rural households have one temporary migrant, with migration income contributing more than 50 percent of the total household income. Thus, both informal networks and temporary migration play an important role in overcoming household risks, in the absence of credit

[1] I am extremely grateful to my advisers, Giacomo De Giorgi and Christian Ghiglino, for their guidance and support. I would like to thank Seema Jayachandran, Jean-Louis Arcand, Alessandro Tarozzi, Dilip Mookherjee, Michele Pellizzari, Tuan Nguyen, Avichal Mahajan, Sayli Javadekar, and Aakriti Mathur for their valuable inputs. I would also like to thank all the participants of SSDEV 2019-20, SSES 2019 and GSEM (University of Geneva) brown bag seminar, for their valuable inputs.

and insurance markets (Morten, 2019).

I focus on network size, an important characteristic of informal networks. Within an informal network, the size of the network affects the extent of risk sharing. An individual in the network benefits from an increase in the number of people in the network (Bramoulle and Kranton, 2007). Munshi and M. Rosenzweig (2016) use a mean-variance framework to show that an increase in network size reduces the variance in consumption. Therefore, larger networks potentially increase payoffs from the network. Temporary migration is another form of self insurance, and the interplay between temporary migration and risk sharing is studied in the literature (Morten, 2019). However, to my knowledge there is no literature on the impact of network-specific characteristics on other forms of insurance. Here I identify how an increase in network size might alter the probability that a household will send a temporary migrant.

To identify the effect of network size on temporary migration I use the Indian Human Development Survey (IHDS) 2011-12. It is a nationally representative survey of 42152 households in 1420 villages and 1042 urban neighbourhoods. The survey tracks work-related temporary migration for each household. Temporary migration is defined in terms of the duration that the household sends a migrant for. If the migrant returns to the village in less than a year, the episode is described as a temporary migration. I use caste as the risk-sharing unit, as discussed in the literature. Castes are broadly defined as upper caste (UC), other backward classes (OBC) and scheduled caste and scheduled tribes (SCST).[2] Network size is defined as the number of households of the same caste in the village. In the analysis, I use a linear model with triple interaction to estimate the impact of network size on temporary migration. I interact the network size variable with the caste indicator and permanent income of the household. To study the heterogeneous impact, I estimate the average marginal effect of network size depending on the caste network. Further, while testing the plausible mechanism I use negative rainfall shock as a network income

[2]Upper caste includes Brahmins, Rajputs, Marwaris etc. Scheduled caste and scheduled tribes are historically disadvantaged communities. The rest of the communities belong to other backward classes.

shock. This exogenous shock tests the causal credit constraint channel through network income.

The ideal setting for identification would require an exogenous shock on the network size to measure its impact on temporary migration. However, it is difficult to find an exogenous shock which only affects network size and not migration. Given the complexity, I try to address each issue that can lead to endogeneity in the empirical specification to make a causal claim.

First, households might self-select into a particular network, which could bias the estimate of network size. They might self-select on the basis of land holding, education, occupation or other socio-economic characteristics. However, in India the household network is determined by caste. I use caste as the unit of informal network: self selection is not an issue as the assignment of caste to the household is by virtue of birth. Caste compositions are centuries old and have not changed substantially over time (Anderson, 2011). Second, migration may have an impact on network size, inducing reverse causality. In this framework, temporary migration does not change the number of households involved in a risk sharing arrangement. Hence, the estimates are not affected by reverse causality.

Third, permanent migration, where the entire household moves away, may still lead to a change in network size and subsequently temporary migration. Munshi (2003) demonstrates how networks at destination that form due to permanent migration can induce more temporary migration. Hence, permanent migration can lead to a change in network size at origin and induce more temporary migration due to network effects at destination. In the data, we do not have a direct measure for permanent migration. This leads to omitted variable bias in the estimation but historically, permanent migration is very low in India. This issue of low permanent migration is extensively discussed in recent literature and is attributed to informal risk sharing arrangements. Households do not want to leave informal risk sharing arrangements in rural areas, especially the landless poor. In the paper, I find that more than 92 percent of the households have stayed in the village for over a century. This reduces concerns about endogeneity of network size due to permanent migration. However, there are regions with relatively high permanent migration. To address this issue I identify regions with very low permanent migration and estimate the impact of network size in these regions.

Fourth, caste level fertility and death rate can differ, and change the network size over the years. Fertility and death rates are not available at the village level. This can lead to omitted variable bias in the specification. Network size could also be correlated with village level development indicators and other unobservables. This could affect network size and the probability of sending a temporary migrant. To deal with this endogeneity, I use historical network size from 1961 census data as an instrument for present network size. The contemporaneous unobservables will not affect the historical network size.

I find a significant impact of network size on the decision to send a temporary migrant. Further, there is a differential impact of network size on temporary migration depending on the caste network. For upper castes, a one standard deviation increase in network size decreases the probability of sending a temporary migrant by 1 percentage point. For lower castes, a one standard deviation increase in network size increases temporary migration by 1.5 percentage points. Upper caste networks are high in endowment and are historically advantaged compared to lower caste networks. Even in this sample, I find that households in lower caste networks have little to no land holdings.

For households in upper caste networks, an increase in network size increases the payoff from the network and so reduces the probability of sending a temporary migrant. A reason for the decline in the probability of migrating could be the capacity of the upper caste network to absorb the individual who would otherwise migrate, by providing opportunities at origin as network size increases. In contrast, the lower caste network is low in endowment. For a network to be able to provide risk sharing requires some level of network endowment and network income. In such a situation, the alternative of sending a temporary migrant becomes more feasible, but there are barriers for the household to overcome to send a temporary migrant: the cost of migrating; cost of staying at destination, and the cost of staying away from village, for example. Bryan et al. (2014) show that very poor households are not able to migrate despite having better opportunities at destination. When provided with credit/cash support the likelihood of these households sending a temporary migrant increases. I find that the lower caste households belong to low endowment networks and are liquidity constrained.[3]

To understand the mechanism behind the positive effect of network size on temporary migration for lower caste networks, I test whether network income matters. Network income, which is calculated as the sum of income of all the households in the network, is interacted with network size to see its effect on temporary migration as network size increases. As expected, I find a larger impact of network size when network income increases. I then introduce a negative rainfall shock to affect network income, to measure the impact on temporary migration. If network income helps support the households to send a temporary migrant, then there should be lower temporary migration in the lower caste network due to the negative rainfall shock. I use heterogeneity in the share of agriculture among the networks to test for the impact of the negative rainfall shock. If the share of agriculture is higher in the network, then the impact on network income should be larger due to the negative rainfall shock. I find that the impact on temporary migration of the negative network income shock when interacted with network size is negative and significant. This implies that the increase in network size provides support to the lower caste households through network income. A shock to network income reduces the temporary migration in the lower caste network.

This article relates to the literature on informal risk sharing and temporary migration. This strand of literature explores the interaction between informal risk sharing network and other self-insurance mechanisms such as migration (Munshi and M. Rosenzweig, 2016). Morten (2019) furthers this literature by studying the endogenous model for risk sharing and temporary migration. She finds improving access to risk sharing de-

[3]There are different lower caste networks at different levels of aggregate income. The impact on temporary migration might be different for each lower caste network depending on their level of network income, if the network supports the household to send a temporary worker.

creases temporary migration by 36 percentage points. Bryan et al. (2014) highlights the importance of reducing the credit constraint to increase gains from temporary migration. Subsequently, credit constraint for each household can vary depending on the size of informal risk sharing network. Therefore, it is important to study the impact of size of the informal risk sharing network on temporary migration.

My research also contributes to the literature on the impact of network size. This literature, mostly theoretical, explores the optimal size for risk sharing networks and the interaction of risk sharing with the size of the network (Fitzsimons et al., 2018; Genicot and Ray, 2003; Murgai et al., 2002; Wang, 2014). Network size also plays an important role in the political economy. Oberholzer-Gee and Waldfogel (2005) find a differential impact on political mobilisation, depending on the size of the group. Chay and Munshi (2012) show the importance of the size of network in network formation among black migrant communities after emancipation. They find a non-linear relationship of network size at destination on migration. I add to this literature by studying the impact of the network size in communities of origin, one of the salient features of the network.

Another important contribution of the paper is to study the causal impact of network size. The inter-dependence of migration and local community network size makes identification difficult. In this paper, I discuss possible sources of endogeneity between network size and temporary migration. It includes self-selection into the network, reverse causality due to permanent migration, fertility and death rate changing the network size, and omitted variable bias due to unobservable socio-economic indicators. I use low permanent migration regions and historical network size to estimate the causal impact of network size. I test the credit constraint mechanism using a negative rainfall shock at the network level. This provides a modest causal estimate for the impact of network size.

The other important contribution of the paper is to differentiate low endowment networks from high endowment networks. Banerjee and Newman (1998) in their two sector model explain that the poorest and the least productive leave the traditional sector and join the modern sector as they have nothing to lose and cannot get a loan in either sector.

However, the option to migrate has some cost attached to it. Recent evidence shows that temporary migration is risky. Despite there being better opportunities from migration, very poor households do not migrate due to cost of migration. After relaxing the credit constraint, Bryan et al. (2014) find that temporary migration increases. Similar to the earlier literature, I find the low-endowed lower caste networks show an increase in temporary migration as the credit constraint is relaxed.

1.2 Historical background

In India, the majority of the population lives in rural areas. According to the Socio Economic and Caste Census 2011 (SECC, 2011), 73 percent of the households are in a rural area.[4] Hindus are the major religious group, comprising 80 percent of India's population (Census 2011). Hindus are divided into a number of castes with strict, long-standing rules and social norms. The historical concept of *varna* divides people into five levels, Brahmin, Kshatriya, Vaishya, Shudra and Untouchable. In the data, I categorize the village population into Upper Castes, Other Backward Class (OBC) and Scheduled Castes and Scheduled Tribes (SC/ST). Upper Castes include Brahmins, who are at the top of the caste hierarchy, along with the forward class[5]. The SC/ST comprises 21.5 percent of the population of rural India. The SC/ST are historically disadvantaged groups. According to the 2011 census, 47 percent of India's rural poor are concentrated in the SC/STs category (Gang et al., 2008).

In rural India, there are informal insurance networks formed along caste lines. The strength of the network can be seen from the imposition of the marriage rule, requiring individuals to marry within the caste or sub caste. This marriage rule is enforced through social customs and norms (Mazzocco and Saini, 2012). According to recent genetic evidence, the marriage rule has existed for 2000 years. Chiplunkar and Weaver (2017) also find that there has been no change in the proportion of inter-caste marriages in rural

[4]179.7 million households in rural areas; 244.9 million total households.

[5]Rajputs, Marwaris, Baniyas etc. belong to the forward class.

areas over the period 1920-2011. This implies that the strength of caste network and social norms has not declined even in recent times.

Caste composition in rural areas has not changed for centuries. Anderson (2011) compares present caste composition with the 1921 census for the villages in northern states such as Uttar Pradesh and Bihar. She finds that the caste composition is similar to the past census[6]. This implies that caste compositions and subsequently network size were determined centuries ago. Permanent mobility would be a concern as I use a similar methodology to overcome endogeneity. I address this concern below.

It is well documented in the literature that permanent mobility has been low in India. There is little caste-based permanent migration in India. Women will migrate between villages after marriage but men mostly stay in their villages. This low permanent mobility is attributed to informal insurance caste networks in the village. The census figure for permanent migration is 24 percent in Bihar, of which 89 percent are female migrants.This shows that male migration which is due to economic reasons is less than 3 percent in these states. I also find low permanent mobility when I look at the sample (IHDS 2011). Table A.1 shows how many years ago a household arrived in the village. In the data 91 percent of the households report that they have stayed in the village forever. In Rajasthan, UP, Bihar, Jharkhand, Madhya Pradesh and Gujarat more than 95 percent of households have always lived in the village. In Chhattisgarh, Andhra Pradesh and Karnataka 93-94 percent of households have always lived in the village. These figures are higher for the most populated states across India. This shows that mobility has been low throughout rural India.

The earlier discussion strongly suggests that village level caste composition in India has been historically determined centuries ago. I use this caste composition and size of the caste network across the villages as exogenous.

[6]This paper measures the caste composition at district level. The district boundaries have changed since then but the caste composition is still similar.

1.3 Empirical strategy

My main aim is to measure how the size of the household's network impacts their decision to send a temporary migrant. I use the rural setting in India to measure the impact of network size. In rural India, Hindu households become part of caste-based network by birth. Individuals are born into the caste network, which is exogenously assigned.

I define network size as number of households from the same caste staying in the village. This provides us with a measure of network size for each household. The rural population in India has very low permanent migration. This strengthens the setting that the network size has not changed for centuries. Temporary migration on the other hand is a widespread phenomenon. The households sends a migrant and if the migrant returns back within a year then it is measured as temporary migration.

In the empirical specification, temporary migration (Y) is the dependent variable. It has network size, education, land holding and permanent income as covariates. The impact of network size may vary with education and the endowment level of the household. For this, I use the interaction of network size with education and permanent income for each network separately. This would give the differential impact of network size on temporary migration depending on education and endowment level.

$$\begin{aligned} Y_h = \alpha + \beta_1 C_h NS_n E_h + \beta_2 C_h NS_n PI_h + \beta_3 C_h NS_n + \beta_4 E_h NS_n + \beta_5 PI_h NS_n \\ + \beta_6 NS_n + ... + \beta_9 X_v + \gamma_s + \varepsilon_h \end{aligned} \tag{1.1}$$

The empirical specification has Y as an temporary migrant indicator (if the household has a temporary migrant then one, otherwise zero), L as land owned by the household, NS as network size, E as education level of the household head, PI as permanent income and C as caste network indicator. The caste network indicator takes value one if the household belongs to the specific caste (Upper caste or lower caste), otherwise it is zero. There are village level indicators such as village population size and village infrastructure variables included in X. The data has household h from network n staying in village v and state s. The coefficient γ_s is a state dummy to control for state fixed effects. I cluster the error term at village level. The caste term in the specification takes a binary value. I run the specification for each caste separately: the upper caste, the OBC and the lower caste (SC/ST). In this specification, interpreting marginal effect is not straightforward given the triple interactions. I estimate average marginal effect for network size to measure its impact.

$$\frac{dY_h}{d(NS_n)} = \beta_6 + \beta_1 C_h E_h + \beta_2 C_h PI_h + \beta_3 C_h + \beta_4 E_h + \beta_5 PI_h \tag{1.2}$$

The linear probability model specification in equation 1.4 will give a list of marginal effects. I want to estimate the average marginal effect (AME) to interpret the impact of each variable on temporary migration. [7] Using the linear probability model, I estimate corresponding $\beta's$ for each regressor in the specification. Equation 1.2 will provide an estimate for the marginal effect (ME). I estimate the value of ME for each household in the data and take the average of the entire distribution to get AME. AME measures the average marginal effect, which estimates the total impact of network size on temporary migration. However, I am interested in estimating the differential impact of network size based on caste. This is given by the interaction of the marginal effect of network size with caste.

Interaction marginal effect of caste with network size can be estimated from equation 1.3. I differentiate equation 1.2 by caste to get the interaction marginal effect of caste and network size. This estimate of the impact of network size on temporary migration can be different for each caste. This is the estimate I will be focusing on in the analysis.

[7] We can also estimate predictive margins for each caste category. To estimate predictive margins, first we estimate the coefficients for each independent variable from equation 1.4. Once we have the coefficient then we fix the value for variable of interest. In this case NS is the variable of interest, which is on the X-axis. After fixing the value of NS, we use every data point from the sample to estimate the probability of temporary migration, and then take the average of the estimated value for the fixed value of NS. This gives the predictive margin for that particular value. We repeat this for each value of NS we are interested in. Similarly, if we want to estimate the predictive margins by varying two variables then we fix the values for both and repeat the above steps.

$$\frac{d^2 Y_h}{d(NS_n)d(C_h)} = \beta_1 E_h + \beta_2 PI_h + \beta_3 \tag{1.3}$$

I claim exogeneity of network size by arguing that the caste networks were formed centuries ago. These networks in rural areas have not changed significantly, due to immobility of rural households. As described in the previous section, caste compositions in villages have remained the same for centuries. From this I argue that the network size is unaffected by recent changes and is exogenous to the empirical setting. But network level unobserved characteristics still may affect the outcome variable. To address this issue, I use historical network size as an instrumental variable to address the endogeneity issue. For robustness, I create a low permanent migration area made up of regions with more than 92 percent of the households having lived in the village forever.

1.4 Data

I use the Indian Human Development survey for the analysis. The Indian Human Development survey II (IHDS II), 2011-12 is a nationally representative survey of 42,152 households in 1,420 villages and 1042 urban neighborhoods. It has detailed information on household socio-economic characteristics and village level attributes.

In the analysis I restrict the data set to rural areas only. The question of the impact of the caste network is relevant to rural India. I also restrict the analysis to Hindu households, as caste-based networks are a feature of Hindu religion. After restricting the data to rural Hindu households, there are 21,472 households[8] for 1,337 village clusters.

In the analysis, I take informal networks as given, a common practice in the literature. Each household belongs to a caste network. The upper caste and lower caste networks (SC/ST) are clearly distinguished according to caste. Using OBC as a caste network may not be correct, as it groups together castes that historically do not form part of the same network. It comprises approximately 55 percent of India's population. Hence, I focus

[8]Including only complete observations.

the analysis on the upper caste and lower caste networks. I have network size as the main independent variable, along with education level of the head of the household, land ownership and wealth of the household.

IHDS is one of the few surveys which has information on temporary migration. The survey categorizes a returning individual who went away from the village for work as a temporary migrant. I define the variable temporary migration as an individual returning within a year as a temporary migrant. [9] Migrants who do not return within a year are not classified as temporary migrants. There are 1,638 households with a temporary migrant in the sample data. Table A.5 shows the caste-wise categorization of households with temporary migrants. Upper castes have lower temporary migration than OBC, SC/STs. Upper castes have the lowest rate of temporary migration at 3.4 percent while the migration rate for OBC is 7.7 percent and for SC/ST it is 11.9. This difference in migration rates signals the importance of caste level dynamics in the determination of temporary migration.

Temporary migrants are not evenly distributed across occupations. For lower castes there is a higher number of migrants involved in manual labor at the origin and at destination. The SC/ST has 49 percent of the migrants who were involved in agricultural labor, as shown in table A.6 while upper caste has only 27 percent in agricultural labor. The non-agricultural labor involves 30 percent of SC/ST migrant and 20 percent from upper caste. In total, 80 percent of lower caste migrants are laborers (agricultural and non-agricultural) while this figure is 50 percent for upper castes. We have similar figures of occupation by caste at destination. Thus, I find that the lower caste network has relatively less occupational heterogeneity than the upper caste network.

The network size (NS) is defined as the number of households of the same caste in the village. The informal insurance risk sharing network is observed at the village level for a rural household. If the household faces an idiosyncratic shock[10] then they may seek

[9]The majority of temporary migrants visit the place of origin within six months.

[10]Idiosyncratic shocks are household level shocks; aggregate shocks like rainfall will impact the entire network.

support from the village network. I calculate the size of the network from IHDS 2005 data set. The value of the network size is the same for all the households in the village that share the same caste.

The average network size in the data is 12.11 households, with a minimum of one and a maximum of 61. The standard deviation is around 7.5 for all caste networks in the sample. In figure A.1, the distribution for upper castes and lower castes is similar, while the distribution of OBC is on the higher side. The sizes of the networks do not differ much from one another.

Land owned by the household is an important variable that determines migration. The land variable has extreme outliers in the higher quantile of the distribution. I trim the land holding variable by 1 percent for large land holdings. Table A.3 summarizes the covariates. The average household land holding is 2.16 acres, with a standard deviation of 3.38 acres. In figure A.1, I show the distribution of land holding for upper caste and lower caste. As one would expect, the upper caste land holding is significantly higher than the lower caste land holding.

In the analysis, the household is the main unit of observation. For household level education I use level of education of the head of the household. There is lot of variation in this variable. In India, primary education is five years of education and upper primary is a total of eight years of education. Secondary education means ten years of education and higher secondary denotes 12 years of education. Graduation is the highest education level category in the data set, at 15 years of education. The distribution clearly shows that the upper caste network is more educated than the lower caste network. The median value for the lower caste network is zero years of education and the median value the education. This clearly sets the two caste networks apart in terms of human capital levels.

Land holding and household income do not capture the permanent income of the household. I use consumption as a proxy for permanent income, as is common in the literature (Deaton and Zaidi, 2002). The distribution in figure A.1 shows the difference in the consumption (permanent income) levels for upper and lower castes.

Caste index (CI_v) is the measure of caste diversity in the village. This will take into account the caste composition of the village. In particular, if we consider a village composed of $K \geq 2$ caste categories and let γ_k indicate the share of caste k in the total population of the village, the resulting value of the CI index is given by:

$$CI_v = 1 - \sum_{k=1}^{K} \gamma_k^2$$

This indicator measures the probability that two randomly drawn households from the village population will belong to different caste groups. A lower value CI_v index represents dominance of one caste in the village. Banerjee and Somanathan (2007) use a similar index at district level to consider caste heterogeneity. I use the caste index as a covariate in the robustness check.

I include village level covariates in the analysis. There is village level population, to control for the village size effect. I also include village level infrastructure variables such as distance from secondary school, distance from nearest bank and distance from the nearest bus stop.

1.5 Estimation results

1.5.1 Main results

In this section, I estimate the regression specification in equation 1.4. I estimate this for each caste separately. The analysis focuses on upper caste and lower caste (SC/ST) results. Table A.9 gives the regression output for each specification. The first column shows the positive impact of network size on temporary migration. The remaining columns show caste-specific regression output.

I find a significant effect of the variable network size on temporary migration. From table A.10, I find that a one standard deviation increase in network size increases the temporary migration by 1 percentage point for upper castes and decreases the temporary migration by 1.5 percentage points for lower castes. The interaction effect and total effect is hard to interpret from the regression table. Table A.10 gives the estimates of the interaction effect of network size with caste for the regression specification, as discussed in equation 1.3.[11] I find a significant negative slope for upper castes and a significant positive slope for lower castes. The temporary migration for upper castes decreases as the network size increases. The increase in network size increases the payoff from the network, which translates into a reduction in temporary migration.

On the other hand, for lower caste networks I find a positive impact of network size on temporary migration. The lower caste networks are is not similar to the upper caste networks in any of the observable characteristics. The lower caste networks have lower endowments in terms of education, land holding and permanent income. Bryan et al. (2014) finds that due to credit constraints, very poor households from rural Bangladesh do not temporarily migrate, but once they are incentivized by relaxing credit constraints temporary migration increases. Similarly, I find a positive impact of network size for the lower castes. If the network is small then the lower caste households, which have around 80 percent of the households members involved in manual labor, are too poor to migrate for work. An increase in the network size helps the households to send a temporary migrant by relieving the credit constraints.

If the network supports its members then network income should play an important role in temporary migration. Figure A.2 shows the comparison of network income density plots. The lower caste network income distribution is to the left of upper caste distribution. This implies that lower caste networks are poorer compared to upper caste networks. I find a positive correlation of network income with the number of temporary migrants in the network for lower caste networks. This correlation suggests a mechanism by which networks reduce the credit constraint, which helps lower caste workers to migrate. The upper caste correlation is negative, which is similar to the impact of network size on

[11]Results for village level covariates included are discussed in the robustness check section. I find similar results for the full specification.

temporary migration.

The occupation structure for the upper castes is very different to that of the lower castes. Table A.8 shows the percentage of the network population involved in different occupations by caste. The upper caste network has 29 percent of its population involved in manual labor. The population farming and doing related activities is 34 percent while the network population involved in high end occupations is around 35 percent. For lower castes, there are 66 percent of households in manual labor (42 percent in agricultural labor). Only 10 percent are involved in agricultural activities and 17 percent in high end occupations. The upper caste network is a high endowment network and as the network size increases it absorbs the manual laborers who are potential migrants. The lower caste network does not have too many opportunities within the network, but as the network size increases the increase in network income eventually increases temporary migration from the network.

Figure A.3 shows the impact at different levels of network size. It shows a downward sloping impact of network size for upper castes and upward sloping impact for lower castes (SC/ST). The differential impact of a low endowment and a high endowment network on temporary migration is the main result of the paper. A one standard deviation increase in the network size decreases temporary migration by 1 percentage point for upper castes while increases temporary migration by 1.5 percentage points for lower castes. These results are robust under different specifications.

The impact of network size on temporary migration does not change for different specifications. I add village level indicators, a state dummy and a CI index. I also check for impact only in areas where households have lived in the same place for many decades. The magnitude of the impact is similar for these low permanent migration regions.

The village level indicators include village size and village infrastructure variables. The village size indicator differentiates the impact of village size from network size. The village infrastructure variable includes distance from nearest bank, secondary school and bus stop. This takes into account the economic development of the village. The CI index includes the heterogeneity of the caste population in the village. This helps to differentiate an upper caste dominated village from equally distributed caste population village. I do not add village level fixed effects as it will remove villages with only one caste. I also control for state level effects by adding a state level dummy in the specification. There are 34 state and union territories in the sample.

After adding all the above variables I still get a significant negative impact for upper castes and significant positive impact for lower castes. Table A.11 column three shows the negative coefficient is significant under the full specification for upper castes. A similar robust result for lower castes is shown in table A.12 column three.

1.5.2 Low permanent migration region

The rural caste composition has not changed for Uttar Pradesh, Bihar, Jharkhand and Uttarakhand, as discussed in the earlier section. There are states where the mobility is very low and the households report that their family has been in the village for more than 90 years. These regions include Rajasthan, Madhya Pradesh, Gujarat, Chhattisgarh, Andhra Pradesh and Karnataka. The low permanent migration region includes all these states. The results for this sub-sample are shown in Table A.11 and Table A.12. Column six in Table A.11 shows the impact of network size on temporary migration for the upper caste network. The results for both the castes are consistent with our earlier findings.

1.5.3 Census 1961: network size

I perform further robustness checks to confirm the impact of temporary migration, using 1961 census data. This census has information about the population of scheduled castes and schedule tribes at district level. This 1961 aggregated data for lower castes can used as an instrument for present network size.

There are some caveats to this data. The number of states and districts has changed since 1971. In 1971, India had 19 states, which were further divided into 29 sub-states.

The number of districts increased from 356 to 593. This reduces the variation in the data set. I use the same value for sub-districts which were part of same district in 1971. As discussed earlier, I have district level data in the census while the IHDS data is at village level. I combine these two data sets at district level, which reduces the variation further. This rich census data set only provides estimates for lower castes and rest. The category SC/ST was introduced pre-independence but the OBC category came into existence later. The Mandal commission report, which introduced the OBC category, was implemented in 1992. This gives us only the lower caste categorisation in the 1961 census data.

Taking these caveats into consideration, I use 1961 network size values at district level as an instrument for village level network size for lower castes. Because there is less variation in the data, I run the following specification with no interaction. I restrict the sample to lower caste households. The F-stat of excluded instruments in the first stage is 97.75. This shows the relevance of the instrument. [12] I find that the impact on temporary migration is similar to earlier findings. Table A.12 in column 4 shows a positive impact on temporary migration that is due to an increase in network size. However, the impact is not significant, which could be due to noise and lower variation in the district level data.

$$Y_{hnvs} = \alpha + \beta_1 N_{nvs} + \beta_2 N_{nvs}^2 + \gamma_s + \varepsilon_{hnvs} \tag{1.4}$$

The specification has household h from network n staying in village v and state s.

1.6 Proposed Mechanism

Upper caste networks have a conventional impact on temporary migration. Larger networks and high-endowed networks offer a higher payoff from the network to poorer households in the network. This higher payoff from the network increases the threshold for

[12] The weak identification test estimate, Kleibergen-Paap Wald rk F statistic, is 30.51. This shows the validity of the instrument.

migrating from the network. There is less migration from upper caste networks as the households benefit more from the high network endowment.

The lower caste networks are low in endowment and human capital and hold less land than upper caste networks. Households in the lower caste networks are very poor and liquidity constrained. More than two-thirds of the households in these networks are involved in unskilled manual labor. An upper caste network can provide opportunities within the network for workers who would otherwise migrate, while reducing the temporary migration with an increase in network size. This is not the case for lower caste households, as a lower proportion of households is involved in high level skilled occupations that could absorb workers who would otherwise migrate. In the early stages, the lower caste households were not able to overcome the threshold to migrate due to high migration cost. A larger network relaxes the credit constraint for poorer households. This informal risk sharing arrangement allows them to borrow, which helps them overcome the threshold and experience the income gain from temporary migration.

I check if the impact of network size in the lower caste networks is different for liquidity constrained households (low income). I interact income with network size and a caste indicator to check if the increase in network size has a differential impact for lower castes. A negative coefficient for lower castes would imply that liquidity constrained lower caste households are those which send a temporary worker as network size increases. I do see a negative coefficient for lower castes in Table A.13. This implies the increase in network size facilitates the poorer households from the lower caste networks to migrate more.

This channel of risk sharing can be further confirmed from the relationship between network income and temporary migration. I estimate the correlation between total migrants sent by the network and network income. The lower caste network has a positive correlation with network income while the upper caste network has a negative correlation. The signs of these coefficients are similar to the impact of network size. This demonstrates the mechanism through which network size impacts temporary migration. To demonstrate this further, I add an interaction of network size with network income (Table A.13).

For the lower castes, we would expect that as the network income increases, temporary migration among members of the network also increases. We find a positive and significant impact of network income. This implies that as the network size increases for the lower caste networks, the households are able to cross the barrier to migrate. For networks with higher income, temporary migration is higher. Bryan et al. (2014) finds that for very poor households, relaxing credit constraints increases temporary migration. In the analysis, the increase in network size relaxes the credit constraint, which further increases temporary migration in the network.

1.6.1 Negative rainfall shock

India is an agrarian economy. Rural economy is highly dependent on agriculture. Majority of the agriculture is dependent on seasonal rainfall. TThis leaves rural households vulnerable to negative rainfall shocks. Due to credit market imperfections, households depend on their network for informal insurance. The network may have heterogeneity in the occupational structure, which would help the households to cope with the rainfall shock. If most households in the network are involved in agriculture and related activities, then the negative rainfall shock will be an aggregate shock to the network. The agriculture share of the network will provide us with different intensities of the shock to the network. Temporary migration in the lower caste increases as network size increases. If most of the members of the network depend on agriculture (as in the case of lower castes) network income and network insurance are more likely to be negatively affected by a negative rainfall shock. This should lead to a decrease in temporary migration for lower caste networks. If the network income supports lower caste households to migrate then we should observe a negative impact on temporary migration of a negative income shock. This can help us to understand the network insurance mechanism better.

The IHDS data used for the study has two waves, 2005 and 2012. I have information on the year of temporary migration for the household. Using this information, I create yearly panel data from 2005 to 2012. The information includes whether the household sends a temporary migrant and the year of migration. I merge this information with yearly rainfall data at district level. The survey does not release village level identifiers. The highest level at which these two data sets can be combined is the district level. This provides us with panel data from 2005 to 2012 with district level measure of rainfall for each network in the village.[13]

I create a high/low rainfall indicator for each region for each year. I use a 20-year historical average of rainfall in the region as the reference. If the yearly rainfall is one standard deviation below the historical average I code the rainfall indicator as one. If the rainfall indicator is one, that represents a negative rainfall shock for the region; otherwise it is zero. This gives us a yearly series for negative rainfall shock, along with re-created panel data.[14]

There are some caveats with the data. The panel data has a recall bias as the question was asked after returning from migration. The migrants may not be able to recall the exact date of migration but recalling year of migration should not be an issue. As mentioned earlier, the rainfall data has measurement error as I use district level rainfall for village level data.

I run the regression to measure the impact of network size on temporary migration. In equation 1.5, I have an interaction for rainfall indicator ($RainI_{hnd}$) and network share working in agriculture ($Sh_A gri_{hnd}$). The empirical specification has household h from network n staying in village v, district d, and state s.

$$\begin{aligned} Y_{hn} = \alpha + \beta_1 NS_{nv} + \beta_2 NS_{nv}^2 + \beta_3 NS_{nv} C_{nv} E_{hnv} + \beta_4 NS_{nv} C_{nv} PI_{hnv} \\ + \beta_5 N_{nv} RainI_{hnd} Sh_A gri_{hnv} C_{nv} + ... + \varepsilon_{hn} \end{aligned} \tag{1.5}$$

In Table A.14, I show the interaction effect of network size with share of agricultural workers in the network for rainfall affected regions. The rainfall indicator takes value one

[13] I use rainfall data from Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS).

[14] I created this panel data by repeating the values between two surveys (2005 and 2011) and later merged with yearly rainfall for each district.

for a drought region. For lower castes, the rainfall-affected region has a negative impact of an increase in network size as the share of workers in agriculture increases. The network with a high share of workers in agriculture will experience a larger impact of a rainfall shock compared to a network with a lower share of workers in agriculture. The rainfall shock will reduce the network income if the share of agriculture is higher. This will impact the payoff from the network via reduced risk sharing. The entire network will be liquidity constrained. With no means to relax credit constraints, the household from a lower caste network with a high share of workers in agriculture will not be able to overcome barriers to migration.

1.7 Robustness check

1.7.1 Network size vs. village size

It is important to differentiate the effect of network size from village size. It is highly likely to find larger networks in larger villages. Larger villages may have better infrastructure in terms of roads, electricity and market. This may lead to bias estimate towards larger villages.

The empirical specification takes into account village level variables. The impact of network size is significant even after adding village size in the covariates. In the specification, I find the impact of village size is not significant. In Table A.11 and A.12, even after adding controls there is a significant impact of network size.

To check for robustness of the effect of village size, I check for interaction effect with education and permanent income. In table A.15, I find impact of network size on temporary migration even after interacting village size with household education and permanent income. The initial specification without interaction does not show any significant impact of village size after adding network size in the specification. Even after adding interaction terms with village size, the impact of village size is still not significant, however, network size has significant impact. From the above results I conclude that the village size do not have any impact on temporary migration.

1.7.2 Occupational heterogeneity

The upper and lower caste networks have different occupational structures. The lower castes have more households with agricultural and non-agricultural laborers. The lower castes have 67 percent of the households as laborers (agriculture and non-agriculture), as shown in Table A.8, while for upper castes the corresponding figure is 27 percent. The occupational heterogeneity may have a differential impact on temporary migration. I measure occupational heterogeneity at network level using the Hirschman Herfindahl index[15]. It measures the concentration of one occupation in the network or the heterogeneity of occupation in the network. A higher value of the index indicates lower heterogeneity.

Table A.17 shows the average marginal effect of network size when interacted with HH index. The direction of the impact is similar as compared to earlier results. The occupational heterogeneity does not change the direction of the impact for lower and upper caste networks.[16]

1.8 Discussion

Informal risk sharing and temporary migration are prominent features of a developing economy in the absence of formal credit and insurance markets. I study the interplay between one of the most important characteristics of informal risk sharing networks, network size, and temporary migration, which is a self-insurance mechanism. I look at the impact of network size on households' decisions to send a temporary migrant. Larger networks can provide better risk sharing and may impact the decision of the household to send a temporary migrant. I also study the differential impact of network size according

[15]It is the sum of squares of the share of each occupation (percent) in the network. The index has a minimum value of 0 and a maximum value of 10000.

[16]But the standard errors are larger which reduces significance level.

to the network's endowment.

I use the India Human Development Survey (2011) data for the analysis. I use caste as a network for rural Hindu households. I focus on upper caste and lower caste networks. Upper caste networks are high-endowed networks compared to lower caste networks. The caste compositions in rural India were determined centuries ago. I try to address the endoegeneity of network size with other variables that might also affect temporary migration. The size of caste network could be affected by permanent migration, different fertility rates across castes and self-selection into the network. In India, permanent migration is very low. However, to overcome the endogeniety which arises due to permanent migration, I create low permanent migration regions for my analysis. I also use 1961 census data to create network size and use this as an instrument for present network size.

I find a differential impact of network size on temporary migration, depending on the type of network the household belongs to. The upper caste network is a high endowment network, which is able to absorb the potential temporary migrant by providing opportunities at origin. For risk sharing to operate, the network requires some level of endowment. This makes the alternative of sending a temporary migrant more attractive for low-endowed lower caste networks. However, they need to overcome the barrier to migration. Larger networks help the households to cross the barriers to migration and increase temporary migration. We find an increase in temporary migration for lower caste households as network size increases. I propose that network size relaxes the credit constraint for the liquidity constrained households and promotes temporary migration. I test the mechanism using negative rainfall shocks at the network level and find that for lower castes, network size helps to overcome their credit constraint.

Policy makers can focus on improving the livelihoods of households belonging to smaller networks. Imperfect credit and insurance markets create inefficiencies in the labour market, especially for these households. Formal credit and insurance markets may provide better ways to cover their risk. Financial inclusion through efficient remittance processes and financial products to create income-generating assets can improve the livelihoods of migrant-sending households. Better working conditions at destination and local development at origin may also improve outcomes for these households. For future research, financial inclusion intervention along these lines can be explored.

Chapter 2

Micro-credit to woman and temporary migration[1]

2.1 Introduction

Temporary migration is widespread in developing economies and increasing over the years. More than 20 percent of the rural households in India have at least one temporary migrant and migration income represent more than 50 percent of their total income (Morten, 2019). Recent field experiments in Bangladesh show that there are substantial gains from temporary migration Bryan et al. (2014). Temporary migration reduces credit constraint and spatial misallocation for the rural households, however, the household left behind are still vulnerable to shocks and need credit market to cover their risks.

This paper explores credit channels at migrant's place of origin. The migrant household left behind especially woman are vulnerable due to imperfect credit market in rural areas. Reducing credit constraint at origin and targeting woman members can increase gains for the migrant household. In this paper, we test the impact of credit to women

[1]I am extremely grateful to my advisors, Giacomo De Giorgi and Christian Ghiglino, for their guidance and support. I am grateful to Shram Sarathi and Dvara Trust for providing me the fellowship. I would like to thank Shram Sarathi again for giving me access to the migrant credit database. I thank, Rupal Kulkarni, Rajiv Khandelwal, Monami Dasgupta, Misha Sharma, Indradeep Ghosh and other team members for their valuable comments and suggestions. I want to thank Kishan ji and other team members of Shram Sarathi for helping me during the fieldwork.

on migrant household consumption as compared to credit to men. I use data provided by Shram Sarathi (SS), a micro-credit organisation in India, which focuses exclusively on migrant households.

The paper finds large positive impact using instrumental variable approach. The household consumption increases by 22 percent if the credit is provided to woman in the migrant household. It also reduces the share of food consumption by 10.1 percentage points which is normally observed with increase in income levels. The credit at origin act as insurance mechanism in bad times for the households left behind. I find that the impact is heterogeneous depending on the migrant type and household characteristics. The migrant household with lower asset holding has larger impact of the loan to female members of the household. The impact is larger for long duration migrant where the migrant is not present for longer duration at the place of origin.

The paper uses loan application data provided by SS. The loans to men and women are not allocated randomly by the organisation. The female loan applicant households can be different as compared to male applicant households. For instance, the female applicant households may have better risk coping strategies to overcome negative shocks. The households most likely differ on the basis of ability and risk behaviour. Due to lack of relevant information the estimate in the ordinary least square (OLS) would be biased and may not measure the actual impact of credit to woman. I use the instrumental variable approach to overcome the endogeneity issue in our specification. I use past heavy rainfall shock at the origin as an instrument for the gender of the loan applicant. Internal migration as a response to shock is a risk coping mechanism in the rural areas (Gröger and Zylberberg, 2016; Munshi and M. Rosenzweig, 2016). Rainfall shock at the place of origin would encourage the household to send a member in search of work to the long distant areas. In India, temporary migration is mostly male dominated. As a result, at origin we would find mostly female borrowers due to absence of the male members in the household. I use this exogenous change to identify the impact of gender of the applicant on the household consumption.

In India, there are very few surveys which capture seasonal migration. National Sample Survey Organisation (NSSO) 64^{th} round (2011), Indian Human Development Survey (IHDS) 2011-12 and International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) are surveys which capture detailed information on temporary migration. NSSO and IHDS are nationally representative survey but they exclude short duration and commuter migrants. NSSO also exclude long duration which spend more than 6 months away from the village. Both these surveys do not have information on destination of the migrant. ICRISAT has detailed information of the migrant duration and destination. However, it has small sample size of 459 households from six villages. These datasets capture past migration patterns. NSSO was collected in 2007-08, IHDS has information of migration for the years 2005-2010 and ICRISAT is also a decade old survey[2]. There is lack of detailed micro-data on temporary migration. The SS provides unbalanced panel for 8611 households. It is geo-coded data of the migrants along with information on destination, occupation, duration and loan information. This paper adds to the literature by studying the recent and detailed data on temporary migration.

This paper contributes to the literature in three ways. First, we show how access to credit affects the returns to migration. Experimental evidence shows that there are substantial returns to migration i.e. around 30-35 percentage points gain in household consumption (Beegle et al., 2011; Bryan et al., 2014). Reducing migration cost is an recommended policy option. Imbert and Papp (2020) claim that migration cost are large but majority of the cost is non-monetary. Using detailed survey by Coffey et al. (2015), the authors in their structural estimates find fixed cost is small part of total migration cost. However, even after accessing these gains from migration after overcoming the migration cost the households at the place of origin are still vulnerable to shocks. I add to this literature by exploring a channel of targeting credit at origin especially to the woman which further increases the household well being.

[2] Coffey et al. (2015) also have a dedicated survey on migration on the borders of Rajasthan, Gujarat and Madhya Pradesh in India. However, it does not important information on household consumption and is not a representative sample.

Second, the paper highlights the gender impact of credit to woman in the migrant household. There are number of studies examining the impact of micro-credit on the socio-economic well being of the household. Khandker (2005) and Pitt and Khandker (1998) show positive impact on income and reduction in poverty. Recent evidence shows significant impact on business expansion, profits and self-employment activities (Banerjee, Duflo, Glennerster, et al., 2015; Crépon et al., 2015). I add to this literature by studying the impact of micro-credit to woman.

Third, we present a new causal evidence on the effect of credit to woman and returns to migration. The existing evidence on the impact of credit to woman is mixed. There is also mixed evidence on returns to migration. Lagakos et al. (2019) show that observational returns (observed data) are close to zero while the experimental returns are positive. Using a model, they claim that in equilibrium the household which are left behind are those with high potential benefits from migration. I provide an instrumental variable approach to show a causal impact of credit to woman and further increase in gains from migration. These are estimates are a step forward in causality, however, there are still some concerns about the channels of instrumental variable. Past rainfall shock might affect other household indicators as well. We try to address some of the issues in the paper.

2.2 Data

I use primary data from Shram Sarathi (SS), a micro-credit organisation which focuses exclusively on migrant households. SS is based in the district of Udaipur, Rajasthan, India and operates in the rural parts of Udaipur. It provides credit to the migrant households of the region since 2009. SS collects the household level data during the loan application process before providing credit. It collects detailed information on the household expenditure, migration (source and destination) and loan characteristics. I use this household level loan application data in our analysis.

2.2.1 Measuring temporary migration

Internal migration broadly consists two types of migration streams, permanent and temporary. Permanent migration are the households who leave the place of origin/village along with the other members of the household. Temporary migrant are the household who send a member of the household outside the village for work. Permanent migration has been low in India and temporary migration is increasing over the years (Morten, 2019; Munshi and M. Rosenzweig, 2016). In this paper we focus on the temporary/short term/circular migration.

The Round 64 of National Sample Survey (NSS) Employment Survey, India, has a special schedule on seasonal migration. It classifies short term labour migrants as household members who spend between 30 and 180 days outside the place of origin. This definition is restrictive and does not incorporate short duration migrants who travel for work and return to the village every month. The data does not have information on the destination of the migrant workers. Another nationally representative survey, Indian Human Development Survey (IHDS) defines short term migration as household member who spend more than one month outside the village. This measure also excludes short duration and daily migrant. It also does not have information on the destination of the migrant worker.

The SS data has detailed information on the duration and destination of temporary migrant. It includes daily and short duration migrant as well. I define migrants into three categories depending on the duration of migration. First, the daily migrants or commuter migrants (CM) who travel for work outside the village however return back to the place of origin on a daily basis. Second, the short duration migrant (SDM) who travel for work and visit the place of origin at least once a month. Third, long duration migrants (LDM) who travel for work and visit the place of origin with a gap of more than a month but less than a year.

2.2.2 Loan process

SS provides credit exclusively to migrant household. Table B.1 shows the targeting matrix used to provide credit to the migrant households. The aim of the targeting matrix is to focus on the vulnerable section. The matrix focuses on six main migrant characteristics. First, the duration of the migration which is the time spent away from the place of origin. Second, skill level of the migrant worker. Third, the flow of income stream which is classified as daily, contractual, monthly or self employed. Fourth, the proportion of total income is represented by migration income. Fifth, whether the household belongs to a scheduled caste or scheduled tribe. And sixth, whether the loan applicant is the migrant his spouse or other member of the household.

Using these six characteristics SS assigns a score to each household. The matrix in table B.1 explains how these scores are created. The column represents the six categories mentioned earlier and the rows represent the features of each of these categories. These features are arranged in ascending order of scores allotted according to SS. For instance in category *migration type*, a long duration migrant gets the score 1, short duration a score of 2 and so on. Similarly, for *skill*, Unskilled migrant gets the lowest score 1 while high skilled gets the maximum score of 4. Thus, for each category a score is given and the total score of these six categories is used to decide whether the applicant is eligible for loan or not. A person who falls in the first row of the matrix gets the lowest score of six while the one in the last row gets the maximum score of 24. As mentioned earlier SS focuses on vulnerable groups of society, accordingly a person with low total score is preferred for loan over a person with high score.

2.2.3 Descriptive statistics

In this section, we discuss descriptive statistics of the data provided by SS. SS has primary data for 8611 households which includes 17,475 loan observations. Households can have single or multiple loans from SS. I include only households with more than one loan to create a household panel. This reduces our sample to 3,700 household with 8,253 pooled loan observations over time. Further, we sub sample the data to households having same loan applicant over time. Finally, there are 3,060 household-loan in the baseline. Table B.2 shows the segregation by total number of loans. There are 1791 households with two loans, 769 households with three loans and 488 households with four loans. These households represent 96 percent of the total sample.

Table B.3 shows summary statistics of the main variables. The variable *Gender/Female* which represents the gender of the loan applicant is the main variable of interest. In this dataset 46 percent of loan applicants are female. I use this variable to understand the differential impact of loan to women as compared to men. In the sample, 40 percent of the households have *Pakka* house structure[3]. The education level of the applicant is extremely low with a mean of 1.44 years of education. The average household size is 5.5 members per household. On an average, each household has 1.3 migrants in the sample. I also create a female labour force participation (FLFP) variable which is defined as number of female members participating in the labour market. In the dataset there are 0.53 female members working per household. The data also has information on consumption expenditure of the household. I use per capita consumption of the household in log form in our analysis. It has a mean of 6.78, around 996 INR per month[4]. The data in the sample is for a period of seven years starting from 2012. Table B.16 shows the segregation across the year by gender of the applicant.

SS provides credit irrespective of the purpose of loan. Table B.14 shows the segregation of credit by purpose of loan and the gender of the applicant. The purpose of loan is similar across gender of the loan applicant. However, most of the households borrow for home construction, repayment of old debt or agriculture and allied activities. There are also few business and social expense loans in the sample.

The distribution of the sample can vary by gender of loan applicant. The gap between

[3]solid and permanent dwelling.
[4]Consumption is log normal.

two loans provided by SS.[5] Majority of the loans have gap of one year followed by loans with two year gap. The gap between loans does not vary by gender of loan applicant. The year-wise loan rollouts by the SS are show in the Appendix B. In the initial years male applicants have received more loans and in later years female applicants were provided more loans.

A salient feature of this dataset is that it does not restrict the migrant definition by duration of migrant. Table B.4 shows the classification of migrants depending on the duration of migrant. According to the sample, most of the migrants are either commuter migrant who travel for work outside the village and come back on a daily basis or the long duration migrant who travel for work and return with a gap of more than 30 days.

Migrant workers mostly work in the labour intensive sectors such as construction. The dominant sector is construction sector for the migrant workers in the sample followed by Food/restaurant sector. Table B.5 shows the classification of the migrant workers according to the major sectors. In our sample, there are 61 percent of the migrant workers in the construction sector. The next popular sector among migrant workers is food sector with 20 percent of the migrant working in the sector. The migrants worker mostly work at restaurant as chefs, waiters or helpers. These two sectors cover 80 percent of the migrant workers. The remaining migrant work in the sectors such as travel, manufacturing and supply chain logistics.

These migrant workers leave their place of origin in search of better livelihoods and income. They migrate within state and even to other states for work. Table B.6 shows the popular destinations for the migrants from rural parts of Udaipur. Udaipur is a southern district of Rajasthan which shares the boundary with state of Gujarat. Rajasthan is an high out migration region especially on the borders of Rajasthan, Gujarat and Madhya Pradesh (Coffey et al., 2015). Approximately 40 percent of the migration is inter-state in our sample while rest is within state. The popular destinations for migration are Ahmedabad, Surat, Rajkot, Mumbai and Unjha for inter-state migrants. For within state

[5]Refer to tables in the Appendix B

migrants the popular destinations are geographically nearby location of Udaipur. These destination include Udaipur city, Gogunda town, Sadadi, Sayra and Nathdwara. There are around 80 unique destination locations in the sample.

Household indicators can provide a better comparison of the differences in the household by loan applicant. We perform a mean test on household consumption, food consumption, female labour force participation and house structure as shown in table B.7. These indicators broadly defines the permanent income and household well being. The female loan applicant households have higher level of consumption and labour force participation as compared to male households. The female loan applicant households are significantly different on observable characteristics as compared to male loan applicant households. The female on an average have lower education in India as compared to men which is observed in the sample as well. But, the female applicant households are better off in the baseline on household consumption and FLFP. This may lead to selection bias in the sample.

2.3 Empirical strategy

The impact of credit to woman on consumption is biased in ordinary least square (OLS) due to self-selection. The female/male member of the household is not randomly assigned to get a loan. The households with female loan applicant are different as compared to households with male loan applicants. Table B.7 shows the difference in the household characteristics across gender of the loan applicant. I am using an instrumental variable framework to overcome this issue of endogeneity.

The standard instrumental variable specification has equation 2.1 as the first stage and equation 2.2 which estimates the impact of gender of loan applicant. Here I use past rainfall shock as an instrument for gender of loan applicant. The first stage estimates the probability of gender of loan applicant. Further, the predicted probability of gender of loan applicant is used to measure the impact on household consumption and other relevant household well being outcome variables. The empirical specification is mentioned below:

$$F_{hv(t-1)} = \delta_0 + \delta_1 RF_{t-5} + \delta_2 X_{hvt_0} + \epsilon_{hvt} \tag{2.1}$$

$$Y_{hvt} = \alpha + \beta_1 \hat{F}_{hv(t-1)} + \beta_2 Y_{hvt_0} + \beta_3 X_{hvt_0} + \varepsilon_{hvt} \tag{2.2}$$

where Y_{hvt} is consumption of the household h in the village v and in time period t, Y_{hvt_0} is initial period household consumption before taking the loan at time t_0, F_{hvt-1} is the gender of the applicant within the household (it takes value 1 if female member takes loan else 0), $\hat{F}_{hv(t-1)}$ is the predicted value from the equation 2.1, RF_{t-5} is the past rainfall shock, X_{hvt_0} is a set of household level characteristics, and ε_{hvt} and ϵ_{hvt} are household and village level shock. Household level characteristics include loan amount, education of the applicant and roof of the household which represents permanent income. We report results for β_1 in the results section. It measures the impact of loan provided to female on outcome variables.

2.3.1 Rainfall shock

I use rainfall shock in the empirical strategy identification process. The rainfall raster files are downloaded from Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS). These raster files include monthly rainfall for India. Using exact migrant destination geo-locations we extract the rainfall data.

I estimate yearly rainfall by summing the rainfall for monsoon season. In India, the monsoon season starts from the month of June and ends in September. I create a standardised annual rainfall measure using the historical rainfall data before 2009. The mean and standard deviation of the rainfall are estimated using the historical values. The rainfall shock is defined if the standardised measure is above 1.25 or below -1.25. This implies one standard deviation away from the historical mean. In the analysis, the positive rainfall shock i.e. above 1.25 standard deviation or heavy rainfall is an important variable in the instrumental variable specification.

2.3.2 Instrumental variable

To address the selection in the sample we need an exogenous variation in the gender of loan applicant. The objective is to find a variable which induces borrowing exogenously from female members without directly affecting the household consumption. Tumbe (2018) in his book, *India Moving: a history of migration*, has a fascinating story of migrants from Udupi. In the 1920's, the region of Udupi faced devastating floods which led to mass migration, especially men, from Udupi to different parts of the country. These migrants set up the famous Udupi restaurant and expanded through community networks. Interestingly, even the recent 2011 census shows sex ratio of 1090 per 1000 males. I use similar idea to find the instrumental variable using past rainfall shock.[6]

A recent study by Gröger and Zylberberg (2016), shows that the floods in Vietnam

[6] I use heavy rainfall shock in this chapter as opposed to negative rainfall shock in the first chapter. Considering the small region of Udaipur, heavy rainfall shocks have been a common occurrence in this region which affects migration decision. In the first chapter, I study shock on agriculture so negative rainfall shock is relevant in the analysis for the entire country.

induce internal migration as a risk coping mechanism. Households in response to local shock send a migrant at a distant location. Another study by Munshi (2003) found that the past rainfall shock at origin increases migration from Mexico to the US. Excessive rainfall at the place of origin can be a good indicator to predict temporary migration. Temporary migration in India is male dominated (Morten, 2019). In the absence of male member, the borrowing at origin will be skewed towards female member of the household. Thus, the rainfall shock at origin can be used as an instrument for gender of loan applicant.

The contemporaneous rainfall shock at the time of borrowing can be used as an instrument, however, the current rainfall shock at origin and destination can directly affect the livelihoods of the households. It damages the house conditions given that most of the migrant do not have a pakka house structure. This might push the male migrant to spend more time at the place of origin. In our context, the past rainfall shock can be a better instrument as it will predict the gender of loan applicant and it will not affect the contemporaneous consumption pattern. Munshi (2003) uses lagged $t-4$ rainfall as an instrument for migration. Similarly, we use lag four heavy rainfall shock as an indicator for gender of loan applicant.

Table B.8 shows the correlation between heavy rainfall shock and gender of loan applicant. The past rainfall shock induces long distant migration as a coping mechanism to recover from the local shock. I find positive correlation between past rainfall shock (i.e. lag four and five) and gender of the loan applicant. This implies lagged rainfall shock predicts increase in borrowing from female members of the household. As predicted, the recent/current rainfall shock at origin have negative correlation with gender of loan applicant. I find in the data that the borrowing pattern (i.e. gender of loan applicant) switches after two-three years of rainfall shock at origin. However, using current rainfall shock does not overcome the exclusion restriction for a valid instrument. Therefore, we use lag five rainfall as an instrument in our analysis. Using lag rainfall is good idea to overcome the contemporaneous variation, but the consumption might still be correlated with rainfall overtime. We address this issue by controlling for rainfall in the specification.

It is important to keep these caveats in mind while interpreting the results.

2.4 Results

I use an instrumental variable two stage least square (IV-2SLS) method of estimation to estimate the impact of loan to female applicants. The main variable in the specification is $Female$ which indicates if the loan is given to the female household member. Table B.9 reports the IV-2SLS estimates using the equation 2.2. Column one reports the change in the total consumption, columns 2-4 show the change in the share of consumption under different categories, columns 5-7 show the change in the levels of different types of asset holding and the last column shows the effect on marginal propensity to save.

I find a positive impact of credit to female as compared to credit to male in the sample. There is a 22 percent gain in household total consumption due to credit to woman (column 1). The next columns report how the share of consumption under different heads changed due to the loan. There is a reduction in the share of food consumption by 10.1 percentage points which is normally observed with increase in income levels. I also find that there was a significant increase in the share of consumption under social category. Further, there is significant increase in the levels of livestock holding and savings. Along with savings we also see increase in marginal propensity to save.

These results have an important implication for the growing body of evidence on gains from migration (Bryan et al., 2014). The findings suggest that the gains from internal migration can be increased by reducing the risk faced by the household at the origin. Credit provided by micro-credit organizations acts as an insurance for the households. They cover their risk by borrowing from formal sources instead of informal source such as moneylenders and network (relatives etc.). I argue that the gains for a migrant household can be increased further by targeting woman members at the origin.

Next, I explore the heterogeneity in the impact of loan to female applicants. First, the initial level of savings or asset holding can have differential impact. The loan may have a larger impact on the households with lower level of endowment or in other words those household whose credit constraints are binding. Second, there can be differential gains from the loan depending on the duration of migration.

2.4.1 Initial asset holding

Credit constraints can significantly affect household well being especially for those with low level of endowment. Here, I check the impact of loan for a subset of the total sample. The subset includes households with low asset holding. Those from bottom 50 percentile of asset holding constitute low assest households. Using the same IV specification for the low asset households I estimate the impact of loan to female applicant.

Table B.10 shows the impact on the household with low level of asset holding. I see a larger positive impact on household consumption and livestock holding as compared to the full sample. Providing a loan to female applicant increases the household savings, however, the increase is larger for households with initial lower asset holding.

2.4.2 Migrant duration

The gains from migration can vary depending on the nature of migration (commuter, short duration and long duration). There is a trade-off between working in nearby places as commuter migrant and working in far off destination as long duration migrant. The commuter migrant spends more time in the household with a direct influence on household decision making. While, the long duration migrant spends more time at work destination increasing monetary gains from the migration but with less involvement in the day to day activities at home.

Here, I check if the impact of the loan to the female applicant varies depending on the duration of migration. Similar IV specification for each migrant category is used to estimate the impact. Table B.11, B.12 and B.13 show the estimates for a subset of commuter migrants, short duration migrant and long duration migrants respectively. In all the specifications I find a positive impact on household consumption but the impact is not significant any more. Next, I find that the marginal propensity to save increases irrespective of the duration of the migrant in the household. Although, the long duration migrant household experience a larger increase in total savings. The long duration migrant household has significant increase in the livestock holding as well. This may be due to increase in gains from migration at work destination.

Overall, there is a positive impact irrespective of the duration of the migrant. The impact of loan to female applicant for the long duration migrant household has larger gains with increase in livestock holding and total savings.

2.5 Discussion

This paper highlights the important role of reducing credit constraint at the origin for the migrant household. We find that targeting credit to the woman at the origin improves the livelihood for the migrant household. Due to access to credit at the origin which acts as an insurance for the households, the migrant is able to increase gains from migration. The gains are also reflected in the increase in livestock holding especially for long duration migrant. There is significant increase in the total savings and marginal propensity to save for the household. Apart from loan disbursement, SS also provides financial literacy to the applicants. The positive change in the savings pattern could be an outcome of the financial literacy.

The impact of loan varies depending on the initial endowment of the household. Households with lower asset holding have larger gains from the loan to female applicant. These households have higher savings and invest in livestock holdings. Targeting households with lower level of asset holding can have higher marginal returns for the loan to the female applicant. The returns to migration can be raised further through proper targeting of credit in the migrant household.

Chapter 3

Marrying Young: The Surprising Effect Education[1]

3.1 Introduction

Early marriage is still a common practice in many developing countries. In 2015, nearly 27% of Indian women aged 20-24 were married before the legal age of 18 (DHS, 2017). Child marriage can have negative consequences on women's health and economic outcomes. (Chari et al., 2017; Corno et al., 2020; Field and Ambrus, 2008; Jensen and Thornton, 2003). Studies have shown that education can increase women's age at marriage through increased labour market prospects (Chiappori, Iyigun, et al., 2009; Heath and Mobarak, 2015; Jensen, 2012). However, the positive association between education and age at marriage is not obvious when (a) perceived labor market returns to women's education are low or (b) preferences and beliefs in the marriage market are gender-biased (Buchmann et al., 2021; Jayachandran, 2021). Hence, more evidence is required to understand the relationship between female education and age at marriage.

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In this paper, we estimate how an increase in women's education affects their age at marriage in the context of India. In theory, female education can affect their age at marriage through the matching on local marriage markets and the preferences of men and women (Chiappori, Dias, et al., 2018). In India, majority of marriages are arranged by parents where preferences and beliefs play a significant role in finding a match in the marriage market. For instance, women's family prefer a groom with high income. According to Adams and Andrew (2019), parents believe that the chance of a poorly educated daughter receiving a marriage offer from a "high quality" groom with a government job is very low. Therefore, one of the main reasons parents invest in their daughter's education is to increase her gains from marriage. Men's family, on the other hand prefer a younger bride due to lesser autonomy and perceived high quality (Anukriti and Dasgupta, 2017). Also, education of women is a desirable attribute in the marriage market due to the inter-generational transmission of health and education (Chen and Li, 2009; M. R. Rosenzweig and Wolpin, 1994; Thomas et al., 1991). In such a setting, we investigate how an exogenous increase in education, a preferred attribute of women in the marriage market, affects her age at marriage.

To causally estimate the relationship between women's education and their timing of marriage, we exploit the quasi-random variation in schooling induced by a large-scale education program in India, District Primary Education Program (DPEP). The policy aimed to increase access to primary schooling and reduce the gender gaps in education. DPEP targeted low literacy districts by building schools, hiring teachers, and upgrading infrastructure (Jalan and Glinskaya, 2002). Districts, where the average female literacy rate was below the national average of 39.3 (Census 1991), were eligible for program benefits. We exploit this discontinuity around the cut-off using regression discontinuity framework similar to Khanna (2015).

We find that the program leads to an increase in women's education of around 1.48 years. Our estimates are comparable to Sunder (2020), who also finds that the program increased women's education by around 0.8 years. Another study by Akresh et al. (2018)

on the long-term effect of the school construction program in Indonesia, finds an average effect of 0.46 years of education for women in the treated district. We are estimating a local average treatment effect (LATE) for those districts around the cut-off who were induced into taking the program as opposed to the average treatment effect. This could explain the large effect in our study.

Next, to causally estimate the impact of an increase in education on age at marriage we use the DPEP cut-off indicator as an instrument for education. We find that one year increase in women's education leads to a fall in their age at marriage by 0.44 years.[2] The average age at marriage in the comparable districts is 19.2. This suggests that one year increase in women's education reduces the average age at marriage to 18.75 years which is just above the legal age of 18. Our results are contrary to the existing evidence that finds a positive association between education and age at marriage (Breierova and Duflo, 2004; Brien and Lillard, 1994; Ikamari, 2005; Kirdar et al., 2009). From a policy perspective, increasing education alone might not help in delaying age at marriage for women. At times policies can have unintended consequences for certain groups depending on the economic and social environment (Ashraf et al., 2020; Bau et al., 2020).

We explore probable mechanisms and provide a conceptual framework for the negative association between education and age at marriage in our context. First, we find that the negative results are more pronounced for women who live in districts with low wage rates (a proxy for opportunity cost of marriage) compared to those with high wage rates. We interact district wise average female wages with women's education using DPEP cut-off indicator as an instrument. We find that a 100 rupee increase in women's wages leads to an increase in age at marriage for educated women by 0.1 years compared to less educated women.

Second, the negative association between education is larger at median and higher levels of education. We perform IV quantile regression to study the distributional impact

[2]The identification assumption holds around the cut-off. There are 98 districts within the cut-off range of plus-minus 4.7 percent. Out of these 54 are below and 44 are above the cut-off.

of education on age at marriage using the framework of Kaplan and Sun (2017). We find that the there is fall in age at marriage for mean and median level of education (8 years). At higher education quantiles there is further decrease in age at marriage.

To explain the empirical findings, we use a transferable utility framework in a unitary household model (Chiappori, 2020; Low, 2014). Under transferable utility framework a stable match can be established by maximising the sum of utilities of the partners. In our framework, men have one dimension of income and woman have two dimensions education and age. We assume men's utility to be decreasing in the age of the women due to their preference for a younger bride. Men value the quality of their children which is increasing in their wife's human capital. In such a context, a stable match at equilibrium implies a negative association between women's education and age at marriage. Given that more educated and younger brides are more desirable on the marriage market, women who have more education improve their returns on the marriage market as they are cleared from the market before less educated women.

Our theoretical framework shows that utility received by the spouses should be jointly higher than the surplus and that all the individuals receive positive benefit from marriage. A stable match would therefore require an increase in the surplus for women. To check empirically if education leads to an increase in women's surplus in the marriage, we use DPEP cut-off indicator as an instrument for women's education. We then analyse if education leads to an improvement in women's post marriage well-being indicators such as domestic violence, household wealth, health-care access and decision making power in the household.

In the literature, divorce is used to indicate an unstable match. India has the lowest divorce rates in the world, (Jacob and Chattopadhyay, 2016), therefore, we cannot use it as an indicator of stability. Instead, we use post marriage domestic violence and health indicators to signal stability. We find a drop in the domestic violence experienced by women due to an increase in education. Next, we check how education affects wealth and healthcare access post marriage. In the matching framework there exits assortative matching on men's income and women education. We also find that educated women are more likely to be matched in the high wealth percentile households. Further, there is improvement in their health care access. Education leads to an increase in hospital deliveries, access to antenatal care and contraceptive use by 7 percent, 5 percent and 14 percent respectively. However, there is no change in decisions making power regarding spending their earnings and big household purchases. Overall, these indicators suggest an improvement in the well being of the educated women. This suggests that the match is stable as educated women have higher post marriage surplus as compared to uneducated women.

We perform several robustness checks for validity of our main estimate of age at marriage. First, we test whether the younger cohorts in the sample who are not yet married influence our estimate of age at marriage. In our main specification we use data on women in the age group of 15-40. In India, by the age of 25 more than 96 percent of the women are married. Thus, we restrict the sample to the age group of 25-40 to include only women who have completed their marriage cycle. Table C.5 shows the result using this restricted sample. We find the age at marriage falls in this sample as well.

Second, the DPEP program affected both men and women (Khanna, 2015). We want to check how the increase in men's education affected their age at marriage. Using similar IV specifications, we estimate the impact of an increase in education on partner's age at marriage. We find that the partner's age at marriage does not change due to an increase in education (table C.10). This indicates that the impact is not a common trend for both men and women but it is specifically for women. Next, we restrict our sample to couples where only women were affected and men were not affected by the program. This allows us to isolate the effect of the program only through increases in women's education and not of men. These are men who were too old to change their schooling decision when the program was launched. On average, there is a 4-year difference between husband and wife's age in the sample. Thus, the restricted sample is not too different from an average couple in the full sample. Even in this sample, we observe a fall in the age at marriage for women.

Third, the IV method uses a fixed bandwidth from the first stage (table C.5). To check the robustness of the estimate, we use various bandwidths. We find the impact of age at marriage is still negative and significant and does not vary with change in bandwidth size. Fourth, we also estimate the model using a difference-in-difference strategy. This estimation would allow us to capture the intention to treat the effect. Districts received the program at different years between 1994 to 2002. For each of the treatment years, we compare districts that received DPEP to districts that did not receive DPEP. The treated cohort is women who were 6-19 years of age when DPEP was implemented in their districts and the control cohort is women who were too old to change their schooling decisions, hence, ages 20-30. We find that for every year of DPEP implementation, the age at marriage in DPEP districts decreases significantly for the treated cohort of women (shown in figure C.6).

This study adds to the literature on early marriage. It investigates the schooling consequences on early marriage in developing country context where labour market opportunities for women are low and education is a valued attribute in the marriage market. It also provides insights on the policy channel to delay age at marriage in such a setting. This paper also adds to the literature of investment in schooling for women. There is puzzling phenomenon that labour market returns for women are low but the schooling attainment for women has been increasing and stagnant for men. Browning et al. (2014) add the channel of marriage market return to explain the increase in schooling attainment for women. We add to this literature by providing empirical evidence on increase in marriage market returns for women due to increase in education. We show there is substantial increase in post marriage surplus for women due to increase in education in terms of improvement in health care access, wealth indicator and reduction in domestic violence.

There exists mixed evidence on the causal effect of female education on age at marriage. On one hand Breierova and Duflo (2004), Brien and Lillard (1994), Ikamari (2005), and

Kirdar et al. (2009), find a positive association between education and age at marriage, while recent evidence from countries with stricter gender norms find no effect of increase in education on women's age at marriage (Khan, 2021; Lavy and Zablotsky, 2011). Our paper adds to this literature by highlighting the role of preferences in the marriage market and low female employment rates due to gender biased norms (Buchmann et al., 2021; Dhar, 2021; Jayachandran, 2021). This paper is closely related to the literature on (a) factors that affect age at marriage (Corno et al., 2020; Goldin and Katz, 2002) and (b) marriage markets in developing countries (Anukriti and Dasgupta, 2017; Banerjee, Duflo, Ghatak, et al., 2013; Beauchamp et al., 2017; Chiplunkar and Weaver, 2021).

The rest of the paper proceeds as follows. Section 2 provides background information of the DPEP. Section 3 describes the data. In section 4 we present the conceptual framework. Section 5 and 6 provides the estimation strategy and results respectively. Section 7 concludes the paper by discussing the key findings and steps ahead.

3.2 District Primary Education Program (DPEP)

The District Primary Education Program (DPEP) is one of the largest donor assisted programs launched by the Government of India in the year 1994. The scheme was run in partnership with the central government, the state governments and external donor agencies. The main objectives of the program were to increase access and quality of primary education and reducing gender and socio-economic inequality. Financing of the program was based on a 85:15 ratio with 85 percent given as a grant to the states by the central government (in partnership with international development agencies, World Bank, ECU, DFID, UNICEF) and 15 percent contributed by the state governments. In order to avoid crowding out of government investment in elementary education, the state governments had to maintain at least their existing levels of expenditure on elementary education. Overall, the project lead to an increase in the total allocation by the government for elementary education by about 17.5 to 20 percent.

Apart from civil works the program interventions ranged from enrollment drives, community mobilization campaigns, establishing academic resource centers, to in service teacher training, textbook and curriculum renewal (Sipahimalani-Eao and Clarke, 2003). The program also focused on decentralised management of elementary education with districts as the main administrative unit. To ensure that a large part of the funds were spent directly on quality improvements, strict guidelines were laid regarding the proportions spent on civil works (24 percent) and management costs (6 percent) (Pandey, 2000). According to the 16th Joint Review mission (MHRD, 2002), DPEP covered around 51.3 million children and 1.1 million teachers in the school system. By the year 2002 around 86,850 new schools and 83,500 alternative school centers were set up.

An important feature of the program was that it was targeted to districts with poor educational outcomes. There were two main criteria which were used to select districts under the DPEP. First, the districts with female literacy rate below the national average of 39.3 were selected, and second, districts where the total literacy campaigns were successful. However, by 1994, the total literacy campaign had been implemented in almost all districts in India. Hence, the main selection criterion into DPEP was the national average female literacy rate. The program was introduced in four phases across the country. The total number of districts covered by all DPEP phases (1994-2002) was 242 (273 with bifurcated districts) covering 18 states of India.

Initial evidence showed that the program helped in improving access to primary education and progression into higher levels of education beyond primary (Jalan and Glinskaya, 2002). More recent studies provide evidence of the policy on education levels after the completion of the program. Azam and Saing (2017) use difference-in-difference method to estimate the impact of the policy on the probability of completed primary education and years of schooling. While, Khanna (2015) uses an Regression Discontinuity Design to estimate the general equilibrium (GE) effect of the policy on education and labor market outcomes. Both studies find a positive effect of the program on the years of schooling.

3.3 Data

For our analysis, we combine National Family and Health Survey (NFHS-4, 2015-16), the NSS employment and unemployment survey (2005), the District Information on Systems in Education (DISE 2005) and Primary Census Abstracts 1991 (Adukia et al., 2020; Jayachandran, 2017). The NFHS is a nationally representative survey carried out under the aegis of he Ministry of Health and Family Welfare (MoHFW), Government of India. The survey includes data on fertility, health, and family welfare for the country at individual level. The sample is generated using the stratified two-stage sampling method with the 2011 census as the sampling frame. Primary Sampling Units consists of villages in rural areas and Census Enumeration Blocks (CEBs) in urban areas (DHS, 2017). For our analysis we use the Women's Questionnaire with detailed information on women's background characteristics (age, literacy, schooling, religion, caste/tribes), marriage and fertility decisions. A total of 723,875 eligible women age 15-49 were identified for individual women's interviews. Interviews were completed with 699,686 women, for a response rate of 97 percent.

To get information on schools District Information on Systems in Education (DISE 2005) is used. We use aggregate district level data available from the DISE website for the years 2005. We also use primary census abstracts for the year 1991 to get information on district level literacy rates and sex ratios. Finally information on DPEP status was collated manually using various GOI review reports published by NEUPA to map the progress of DPEP over the years.

The target group of the program consists of women, below the age of 19 in 1994. In 2015, this corresponds to women below the age of 40. Thus, for our analysis we focus only on women below the age of 40. This provides us with a sample of 543,023 eligible women. Out of these, 358,303 women are married in the sample (69 percent) and 316,728 women have given birth to at least one child (60 percent). The average age of women in the sample is 26 years. The mean years of education is 7.5. In the sample, almost half of the women marry by the age 18 (average age at marriage for women is 18.5 years) and have their first child by age 20-21. Table C.1 has detailed descriptive statistics for all variables including marriage, fertility, household indicators and surplus variables (women health access, domestic violence etc.). Table C.2 has definitions of each variable used in the analysis.

3.4 Estimation Strategy

The decision of an individual to invest in education is correlated with various unobserved family, social and individual characteristics which might also effect their marriage and fertility outcomes. This makes it difficult to casually estimate the effect of education on marriage market outcomes. The District Primary Education Program (DPEP) provides a quasi-random variation in access to education that can be used to overcome the endogeneity of education. DPEP was targeted to districts with low educational outcomes. Districts with an average female literacy rate below the national average of 39.3 (Census 1991) were eligible to get funding under the program. We first estimate the effect of the program on years of education using regression discontinuity framework similar to Khanna (2015). The identification of the causal effects of DPEP program comes from the assumption that all other factors determining the outcomes are continuous with respect to female literacy (Lee and Lemieux, 2010; Van der Klaauw, 2008).

There is imperfect compliance to DPEP on female literacy rates. It was found that not all districts below the cut-off got the treatment while some districts that were not eligible (i.e above the cut-off) received the treatment. In a setting of imperfect compliance a fuzzy regression discontinuity design can be applied to estimate treatment effects. We estimate the first stage relationship between the running variable and treatment status in the close neighbourhood of the centered female literacy rate using equation 3.1 below.

$$T_{id} = \alpha + \gamma \mathbb{1}[X_d \leq c] + f(X_d) + \epsilon_{id}, \qquad c - h \leq X_d \leq c + h \tag{3.1}$$

where X_d is the centered assignment variable (39.3 - district female literacy rate). T_{id} is a dummy which takes value 1 if the individual belongs to a district which got DPEP. $\mathbb{1}[X_d \leq c]$ is a deterministic and discontinuous function of female literacy rate that equals 1 if the centered female literacy rate of district d is below 0 (below 39.3 district female literacy rate) and 0 otherwise; $f(X_d)$ is a function used to flexibly model X_d and allowing for different slopes on different sides of the cutoff; h is selected using mean square error (MSE-RD) optimal bandwidth (Calonico et al., 2017).

In the second stage we estimate equation 3.2,

$$Y_{id} = \beta + \tau_{FRD}\hat{T}_{id} + g(X_d) + \varepsilon_{id}, \quad c - h \leq X_d \leq c + h \tag{3.2}$$

where Y_{id} is either age at marriage of the women or other marriage market outcomes; $\hat{T}_{id}$ is the estimated probability of treatment from the first stage; τ_{FRD} is the main coefficient of interest which gives us the impact of DPEP on the outcome variable; $g(X_d)$ is a polynomial controlling for smooth functions of female literacy rate in district d and allowing for different slopes on different sides of the cutoff to account for the conditional expectation of the outcome.

The regression discontinuity specification in equation 3.2 measures the effect of the DPEP program on education and age at marriage. However, our main question is to estimate the effect of education on the age at marriage and not the DPEP program. The DPEP assignment rule can be used as an instrument to identify the causal effect of education. We create an indicator variable which takes value 1 if the district is below the average literacy cut-off and 0 otherwise.

The 2-SLS approach is shown in the equations 3.3 and 3.4 below:

$$Educ_{id} = \delta + \theta\mathbb{1}[X_d \leq c] + f(X_d) + \epsilon_{id}, \quad c - h \leq X_d \leq c + h \tag{3.3}$$

$$Y_{id} = \zeta + \tau_{IV}\hat{Educ}_{id} + g(X_d) + \varepsilon_d, \quad c - h \leq X_d \leq c + h \tag{3.4}$$

In equation 3.3, the instrument $\mathbb{1}[X_d \leq c]$ captures the discontinuity in the relationship between education $Educ_{id}$, and district female literacy rate $f(X_d)$. Since this discontinuity is the source of exogenous variation in education, the analysis is carried out only for districts in the close neighbourhood of the cut-off. In equation 3.4, $\hat{Educ}_{id}$ is the estimated exogenous change in education. τ_{IV} is the main coefficient of interest which gives us the impact of education on the outcome variable.

3.4.1 Validity checks

In figure C.1, we first show a discontinuity in receiving the treatment on the centered female literacy rate at the cut-off. The districts lying in the close neighbourhood around the cut-off show a significant difference in the probability of receiving the treatment. The probability of treatment assignment jumps by nearly 20 percentage points for districts just below the literacy cut-off.

The validity of RD design requires that there is no manipulation of the assignment variable around the cutoff. The DPEP program was introduced for the first time in the year 1994. As the eligibility criteria for DPEP funding was based on a predetermined variable (female literacy rate as per 1991 census) individuals do not have precise control to select themselves into the program. We further provide a formal test to check whether the density of the assignment variable is continuous or not around the cut-off. In figure C.5, we can see that there is no discontinuity in the assignment variable. Further, to the best of our knowledge no other government program used female literacy rate for program eligibility.

Finally, we provide balance test on predetermined variables that would otherwise bias the estimated parameters (table C.3). We use the district level data of DHS 1991-92 to estimate the difference in the pre-determined variables using the RDD method discussed above. The RDD coefficients are not significantly different from zero.

3.5 Results

Our main results examine the effect of education on women's age at marriage and other marriage market and fertility outcomes. Table C.4 reports the estimate for increase in women's education using non parametric inference procedure as shown in equation 3.2. In the table we show the impact of the program using different bandwidth specification such as mean square error (MSE), coverage error rate (CER) and using different bandwidth on both sides of the cut-off (MSE-2 and CER-2). We find that the program lead to an increase in women's education of around 0.8 to 1.48 years. The MSE optimal bandwidth estimate shows that on average women in the treated district completed 1.48 more years of education. CER-2 have an impact of 0.8 more years of education. Our estimates are comparable to Sunder (2020) who also find that the program increased women's education by around 0.8 years. Another study by Akresh et al. (2018) on the long term effect of school construction program in Indonesia, report an average effect of 0.46 years of education for women in treated district. One of the reasons for the large effect in our study could be because we are estimating a local average treatment effect (LATE) for those districts around the cut-off who were induced into taking the program as opposed to average treatment affect.

The main question of the paper is to estimate the impact on age at marriage due to increase in education. To check if the age at marriage is falling due to increase in woman's education, we use the 2SLS approach as shown in section 3.4. We present the reduced form estimates using 2SLS in table C.5. In the first stage we use DPEP cut-off indicator as an instrument for education around the female literacy cut-off. We use bandwidth from previous RDD specification where we estimate the impact of DPEP program on education (section 3.4). It is estimated using MSE-optimal bandwidth framework i.e 4.7. It is used in all IV specification.

Table C.5 shows the second stage results of the impact of education on age at marriage using the IV estimation. The IV estimates show that an increase in education is associated with a fall in the age at marriage by nearly 5 months. The results suggest that on average educated women in the treated districts are married just after reaching legal age of marriage, 18. We do not find any impact on the age at which women give birth to their first child. The fertility outcomes show that the educated women are more likely to have fewer children than the less educated women. Further, we strengthen our results using various robustness checks which are discussed in the section 3.9.

3.6 Impact of education on marriage surplus

At equilibrium, a stable match is formed when there is an increase in the individual's utility from the match or if they do not find a better match than the current one. Hence, we check if there is increase in the surplus within marriage for the educated woman. An increase in education should be followed with an increase in the surplus, if education of women is a preferred attribute on the marriage market. We use a similar IV framework as discussed in the section 3.4 to identify the impact of women's education on their post marriage well being indicators. We focus on three important indicators - experience of domestic violence their health status post marriage and their decision making power.

3.6.1 Domestic violence

The stability of marriage is usually measured by the divorce rates. In India, since the divorce rates are very low. Hence, it does not provide a good measure of stability of the match. Instead, we use domestic violence post marriage as an indicator of conflict or an unstable match. We use two variables to measure the extent of domestic violence. First, *Any Violence*, is the ratio of women who reported in the survey that they faced any form of physical, sexual, emotional violence or control behaviour by partner. It can be used as a direct measure of the conflict within marriage. We find that the probability of *Any Violence* decreases due to increase in education. As shown in table C.8, the drop in *Any Violence* is around 22 percent and significant. The control mean of 0.27 shows the impact of education on *Any Violence* is substantial.[3] Second, *Justifies Violence* records if the woman justifies violence under any circumstance i.e. if the wife thinks that her husband can beat her if she was unfaithful, disrespectful or in any other circumstance. The negative coefficient in this specification suggests that due to education fewer women justify violence within marriage. The reduction both in the experience and justification of domestic violence indicates that with increase in education a more stable match is achieved.

3.6.2 Wealth and Health

We use other measures to test whether more educated woman benefit from the match. We check if women marry in a wealthier household or avail health care benefits post marriage. In this section, we check the impact of increase in education on wealth and health care access.

First, *Household wealth* is used as an indicator of husband's wealth percentile category. We create a binary variable indicating if the household is above or below median on the wealth distribution. Using our IV specification (as in section 3.4), we find that the educated woman in the treated districts are more likely to get married in wealthy households as compared to uneducated women (see column 1 table **??**). This indicates assortative matching on women's education and men's wealth.

Second, health care access is measured using hospital delivery, antenatal care and use of contraception. We present these results in columns 2-4 of table **??** .We find there is 7 percent increase in the hospital delivery post marriage due to education. There is 5 percent increase in the antenatal care access for educated women post marriage. The use of contraception also increases by 14 percent for the educated women. These measures indicate improved health care access for the women post marriage.

[3]In DHS, a random sub-sample was used for the domestic violence module

3.6.3 Decision making power

Lastly, we also check if there is any change in the decision making power of the women post marriage. Given there is less autonomy for women in the decision making (Misra, 2006). A stable match would expect an increase in the decision making power for the educated women.

We use following purchasing decision making indicators, person who decides on spending the women's own earning, person who decides on the women's healthcare spending, and person who decides on major household purchases. We create a binary variable with value one if the women is involved in the decision making else zero as shown in table C.9. Using the similar IV specification (as in section 3.4), we find education does not change the decision making power for the women significantly in own earnings, household purchases and health care spending. Most of the indicators show the stability of the match post marriage for the educated women.

3.7 Theoretical Framework

The economic analysis of marriage market is usually analyzed using either frictionless matching framework or search models. In search model, frictions are important. It involves search cost and discounting the risk of never finding a partner. Matching models assumes frictionless environment. It assumes each woman has access to pool of all potential men with perfect knowledge of the characteristics of each of them. In the context of India, marriage migration for the women is the norm. Usually, women leaves her place of origin to join her husband's family. However, 73% of the women stay within their birth district after marriage (Beauchamp et al., 2017). These marriages are predominantly within same caste community. Chiplunkar and Weaver (2021) report that 94% of the marriages occur within same caste or jati. The links within the community are very strong. So there will be full information available to the family about the match especially within a district. Given the low marriage migration outside the district and full information available about the match, the use of frictionless matching framework is appropriate for our setting (Chiappori, 2020; Chiappori, Dias, et al., 2018; Low, 2014).

In this paper, we use an ad-hoc model that creates a conceptual framework to understand our empirical findings on age at marriage. We use a transferable utility (TU) framework in a unitary household model.[4] For women, we have two dimensions: education (H_w) and age (a_w). For men, we have one dimension, income (y). Men prefer to marry younger women due to longer fertility cycle, lesser autonomy and perceived high quality. Also, education of women is a desirable attribute in the marriage market due to the inter-generational transmission of health and education. For women's parents, daughter's education increases the chances of her securing a better match.

Individuals care about children (Q) and private consumption (q). The post-marriage surplus, $s(y, H_w, a_w)$, produced from the consumption can be estimated by maximising the sum of utilities of men and women. Let the surplus exhibit following properties:

1. Supermodularity in income and education: $\frac{\partial s^2}{\partial y \partial H_w} > 0$
2. Women's preference for high income: $\frac{\partial s}{\partial y} > 0$
3. Men's preference for educated brides: $\frac{\partial s}{\partial H_w} > 0$
4. Men's preference for younger brides: $\frac{\partial s}{\partial a_w} < 0$

The household surplus is supermodular in income and women's education. Given the preferences, the surplus is increasing in education of women and decreasing in the age of women. This will create a negative association between the two traits in the matching function. To see this trade-off mathematically, we derive the marginal rate of substitution between these two traits along the surplus function. In the appendix C, we show the surplus maximisation and marginal rate of substitution for a specific functional form.

$$MRS = \frac{\frac{\partial s}{\partial H_w}}{\frac{\partial s}{\partial a_w}} = \frac{\partial a_w}{\partial H_w} < 0$$

[4]In a unitary household model one maximises the total surplus of the household and not the share within the household

3.8 Labour market returns and age at marriage

Education for women is valued in the marriage market and labour market. The outside option for the women can play a significant role in the decision of marriage. In the paper, we find that the educated women has lower age at marriage as compared to uneducated women. But this may change if the educated women has a better outside option. Here, we investigate the impact of increase in the labour market returns on the age at marriage for the educated women.

The labour market returns can be measured by women's wage levels in the district, an intensive margin measure, and female labour force participation at the district level, an extensive margin measure. The wage variable is constructed using National Sample Survey (2005) weekly wage variable for women. Using the same database we create female labour force participation at the district level.

Here, the objective is to understand the impact of education due to an increase in the wage level on the age at marriage. We use similar IV specification as discussed in the section 3.4, where DPEP is used as an instrument for education. To measure the impact we interact the DPEP variable with wage level. In table C.12, see a positive coefficient for the interaction between education and district level women's wage. It implies there is delay in the age at marriage by 0.1 years as the weekly wage increases by 100 INR for the women i.e. equivalent to 25 percent of the average weekly wage. The outside option for the women plays an important role in the decision of the marriage. With increase in the labour market returns there can be delay in the age of marriage.

3.9 Robustness checks

The DPEP cut-off provides with a good instrument to estimate the impact of education on age at marriage. Although, the identifying assumption is valid only in the close neighbourhood of the cut-off. Thus, it is important to see how sensitive the estimates are to choice of bandwidths. In all our IV specifications, we use the bandwidth from the first stage of RDD regression (equation 3.1). We follow the method for optimal bandwidth selection using mean square error as in Calonico et al. (2017). This gives us a bandwidth of 4.7. We check the impact on age at marriage for different bandwidth sizes. In table C.5, we show the impact for bandwidth 4, 6 and 7 percent. We find that the impact on age at marriage is still negative and significant.

The target group of the DPEP program consists of individuals, below the age of 19 in 1994. In 2015, this corresponds to women below the age of 40. Thus, for our analysis we focus on women in the 15-40 age group in the year 2015. This provides us with a sample of 543,023 eligible women. Out of these, 358,303 women are married in the sample (69 percent). In our sample there can be some individuals who have not yet finished their marriage cycle. For instance, an individual who is 21 years old now could get married at age of 23, but is accounted for as we are only looking at those who are currently married. This leads to censoring bias in the sample. We might underestimate the average age at marriage by censoring individuals who marry later. To deal with this we create another sample where we look at women in the age group 25-40. Since most women in our sample get married by the age of 25, we can say more confidently that the age group 25-40 includes individuals who have completed their marriage cycle.[5] Table C.6 compares the impact on age at marriage for various age-group samples. Column 2 shows the impact of age group 25-40. The age at marriage decreases by around 1 year due to increase in education. As expected, the fall in age at marriage is smaller for this age group as it accounts for the negative censoring bias by looking only at those who have completed their marriage cycle.

The DPEP program lead to an increase in education for both men and women. This makes it difficult to disentangle the effect on increase in women's from increase in men's education on age at marriage. To understand more clearly the mechanisms for the fall in age at marriage for women we carry out two separate analysis. First, we check the impact of increase in education on husband's age at marriage. DHS has information on husband's characteristics. This sample survey was conducted on randomly drawn men from the full

[5] 96 percent in the sample get married by the age of 25.

women sample. Using similar IV specification, we find that there is no impact of education on husband's age at marriage as shown in table C.10. This implies that due to increase in education only women's age at marriage has changed and not men's. Next, we also check the impact for a specific cohort where only women were exposed to the program and men were not exposed to the program. This would suggest during the implementation of program men were too old to change their decision and women were exposed to the program. On average there is 4-5 years difference in age of husband and wife, so this sample is similar to the full sample. Column 4 in table C.5 shows the impact on this specific cohort. The impact on age at marriage is negative. Due to small sample size we lose significance of our estimate.

An increase in the women's education can have heterogeneous impact on age at marriage depending on the level of education attained. Here, we check for the distributional impact on age at marriage at different quantiles of education attained. We perform IV quantile regression to study the distributional impact of education on age at marriage using the framework of Kaplan and Sun (2017). Table C.11 shows the impact of depending the level of women's education.[6] We find that the there is fall in age at marriage for mean and median level of education (8 years). At higher education quantiles there is further decrease in age at marriage. Hence, we find the fall in age at marriage is not just around the mean but it is also prominent along the distribution.

Next, we estimate the model with difference-in-difference strategy. This estimation would allow us to capture the intention to treat effect. Districts received the program at different years between 1994 to 2002. For each of the treatment years, we compare districts that received DPEP to districts that did not receive DPEP. The treated cohort is women who were 9-19 years of age when DPEP was implemented in their districts and the control cohort is women who were too old to change their schooling decisions, hence, ages 20-30.

[6] The education quantiles follow the categorisation as mentioned: Q25 has 5 years of education; Q50 has 8 years of education; Q75 has 14 years of education.

$$Y_{id} = \beta_0 + \beta_1 Cohort_i + \sum_{t=1994}^{2002} \zeta_t DPEP_{td} + \sum_{j=1994}^{2002} \beta_j Cohort_i \times DPEP_{jd} + \alpha_d + \epsilon_{id} \quad (3.5)$$

From figure C.6, we find that for every year of DPEP implementation, the age at marriage in DPEP districts decreases significantly for the treated cohort of women.

3.10 Conclusion

In this paper we study the relationship between women's education and the age at marriage. We estimate this by exploiting the quasi-random variation created by a large scale education intervention called DPEP that targeted districts with low female education.

Our empirical findings show that with an increase in female education due to DPEP, the age at marriage decreased by 0.44 years or by 5 months. This implies that the in the treated districts women who completed primary schooling are more likely to be married just after reaching legal age. These women have fewer children than women who do not complete primary school. Our results indicate that surplus obtained from marriage for educated women is higher than uneducated women when labour market prospects are scarce. However, we also see that as women's labour market returns increase, they delay marriage. Contrary to existing evidence that shows a positive relation between female education and delay in marriage, our findings have important implications for policy. In countries where women traditionally have early marriages and do not work outside home, education would lead to a delay in marriage when labour market opportunities for women increase. It highlights the importance of complementarity of policies to achieve the policy goal of delay in women's age at marriage. Education as a policy tool needs to be combined with other policy that will provide better economic opportunities to women to delay the age at marriage.

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Appendix A

Appendices

A.1 Figures

Figure A.1: Caste comparison

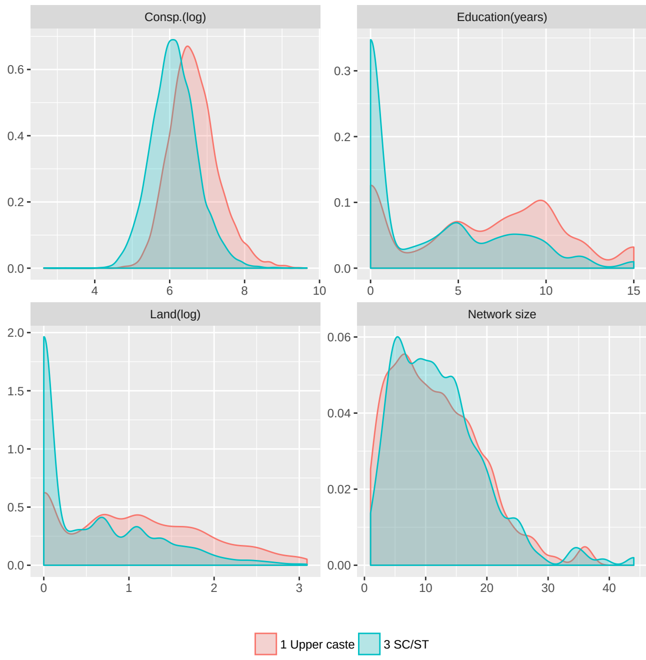


Figure A.2: Density plot: network income by caste

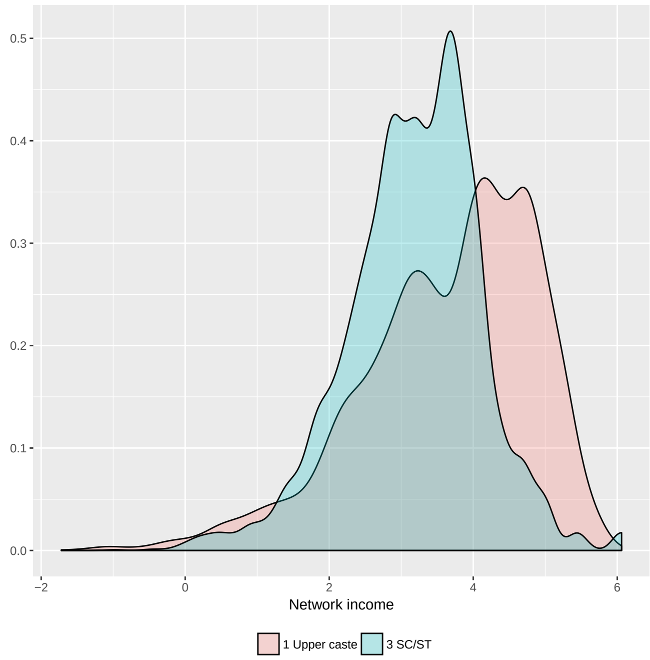
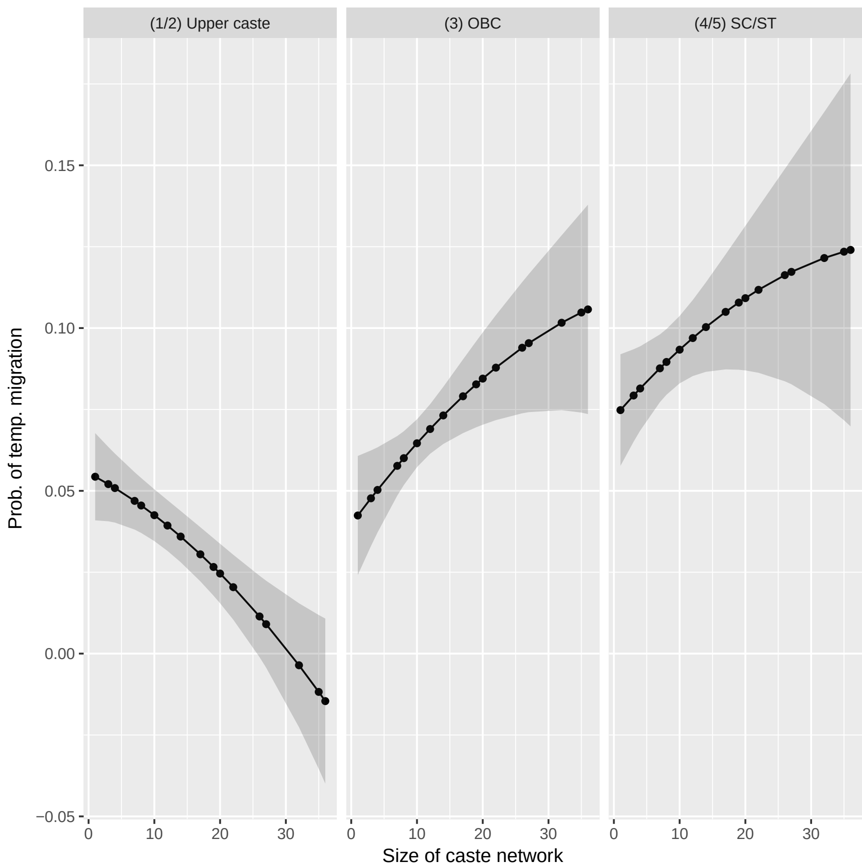


Figure A.3: Predictive margins: size vs. caste



A.2 Tables

Table A.1: How many years ago did your family first come to this village?

Years ago	Percent
<20	2.10
20-50	4.11
50-85	2.35
Forever	91.34

Table A.2: Percent of household staying in rural villages for more than century

State	Percent staying forever
Jharkhand	99
Bihar	98
Haryana	97
Uttar Pradesh	97
Rajasthan	97
Gujarat	96
Sikkim	95
Madhya Pradesh	95
Himachal Pradesh	95
Chhattisgarh	94
Karnataka	93
Andhra Pradesh	93
Assam	92
Uttarakhand	90
Pondicherry	90
Orissa	88
Punjab	88
Daman & Diu	86
Maharashtra	86
West Bengal	85
Tamil Nadu	78
Kerala	74
Arunachal	67
Jammu & Kashmir	51
Goa	46
Nagaland	38
Meghalaya	17

Table A.3: Summary

Statistic	N	Mean	St. Dev.	Min	Max
Temporary migration	21,572	0.08	0.26	0	1
Network Size	21,572	12.89	7.56	1	61
Education	21,487	4.46	4.45	0	15
Land	21,572	2.16	3.38	0.00	21.00
Consumption	21,556	711.10	668.60	4	15,773

Table A.4: Summary of village variables

Statistic	N	Mean	St. Dev.	Min	Max
Dist: bank	1,310	4.6	5.3	0	50
Dist: sec. school	1,237	3.5	4.6	0	60
Dist: bus stop	1,310	1.8	3.2	0	40
Village size	1,338	19.2	8.5	1	83
Caste index	1,338	0.5	0.2	0.0	1.0

Table A.5: Migration caste-wise

Caste	Not migrating (0)	Migrating (1)
Upper caste	4457	150
OBC	8433	652
SC/ST	7044	836

Table A.6: Prior occupation of temporary migrants by caste

	Upper caste	OBC	Lower caste
Professionals	2	0	1
Adm., executive and managerial workers	2	2	2
Clerical and related workers	3	1	1
Sales workers	7	3	2
Service workers	9	8	5
Farmers, Fishermen, hunters etc.	24	16	6
Producition	4	2	2
Transport equipment and operators	1	2	1
Labourers	20	22	31
Agr. labourers	28	42	49
Total	100	100	100

Table A.7: Caste wise mean for covariates

	Upper caste	OBC	Lower caste
Network size	11.7	14.1	12.2
Education (years)	6.3	4.6	3.2
Land (acres)	3.2	2.4	1.3
PI	971.1	704.8	566.3

Table A.8: Occupation by caste

	Upper caste	OBC	Lower caste
Professionals	6	2	2
Adm., executive and managerial workers	4	5	2
Clerical and related workers	8	3	3
Sales workers	8	7	3
Service workers	7	7	7
Farmers, Fishermen, hunters etc.	34	25	10
Producition	2	3	2
Transport equipment and operators	2	3	3
Labourers	12	14	25
Agr. labourers	17	31	43
Total	100	100	100

Table A.9: OLS (HH variables)

	Temporary migration			
	(1)	(2)	(3)	(4)
Network size (N)	0.0016***	0.0029**	0.0025*	0.0022*
	(0.0006)	(0.0012)	(0.0014)	(0.0012)
NS^2	-0.0000	-0.0000	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Upper caste		-0.0098		
		(0.0149)		
OBC			-0.0254	
			(0.0192)	
Lower caste				0.0313
				(0.0200)
PI		-0.0029***	-0.0016**	-0.0019***
		(0.0007)	(0.0007)	(0.0004)
Education		-0.0032***	-0.0039***	-0.0022**
		(0.0009)	(0.0010)	(0.0009)
R^2	0.001	0.021	0.016	0.020
No. of Obs.	21572	21472	21472	21472

Notes: Here I estimate the impact on temporary migration. The dependent variable is binary indicator which takes value 1 if the household sends a temporary migrant and 0 other wise. The variable caste (lower or upper) takes value 1 if the household belongs to that particular caste and 0 otherwise. I include double interactions and triple interactions of network size variable with education, and caste. I use cluster robust standard errors at village level. There are 1337 clusters. This table is estimated for basic regression with caste interaction with no village level variables and state dummy.

Mean: Size (12.9); Educ. (4.46); Land (2.16) Consp. (711)

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table A.10: Avg. marginal effect of network size vs. caste

	Temporary migration		
	(1)	(2)	(3)
NS*Upper caste	-0.0013***		
	(0.0004)		
NS*OBC		0.0018***	
		(0.0007)	
NS*Lower caste			0.0019*
			(0.0011)
No. of Obs.	21472	21472	21472

Notes: *p<0.1; **p<0.05;***p<0.01
Here, I estimate the value of marginal effect for each household in the data and take the average of the entire distribution to get average marginal effect (AME). Refer to the equation 1.4. The variable caste (lower or upper) takes value 1 if the household belongs to that particular caste and 0 otherwise. We use cluster robust standard errors at village level. There are 1337 clusters. This table is estimated for basic regression with caste interaction with no village level variables and state dummy.
Mean: Size (12.9); Educ. (4.46); Land (2.16) Consp. (711)

Table A.11: Average marginal effect of network size: Upper caste

	Temporary migration				
	Full data			Low migration regions	
	(1)	(2)	(3)	(1)	(2)
NS*Upper caste	-0.0013***	-0.0004	-0.0008	-0.0005	-0.0017***
	(0.0004)	(0.0004)	(0.0005)	(0.0007)	(0.0007)
Household variables	Yes	Yes	Yes	Yes	Yes
State dummy	No	Yes	Yes	No	Yes
Village variables	No	No	Yes	No	Yes
Observations	21472	21472	19902	12329	11556
R2	0.0207	0.0476	0.0474	0.0193	0.0407

Notes: *p<0.1; **p<0.05;***p<0.01

Here, I estimate the impact on temporary migration. I estimate the value of marginal effect for each household in the data and take the average of the entire distribution to get average marginal effect (AME). The dependent variable is binary indicator which takes value 1 if the household sends a temporary migrant and 0 other wise. The variable caste (lower or upper) takes value 1 if the household belongs to that particular caste and 0 otherwise. I use cluster robust standard errors at village level. There are 1337 clusters. N is network size. Low permanent migration area include (UP, Bihar, UK (Anderson, 2011) and states with 92 percent households staying in the village forever: RJ, MP, GJ, CH, AP, KA, JH etc. HP is hilly Himalayan region with high migration cost and low migration compared to rest of India. I remove HP from the analysis.)

Mean: Size (12.11); Educ. (4.46); Land (2.16) Consp. (711)

Table A.12: Average marginal effect of network size: Lower caste

	Temporary migration					
		Full data		Census 1961	Low migration regions	
	(1)	(2)	(3)	(4)	(1)	(2)
NS*Lower caste	0.0019*	0.0024**	0.0016*	0.0041’	0.0057***	0.0046**
	(0.0010)	(0.0010)	(0.0010)	(0.0056)	(0.0018)	(0.0017)
Household variables	Yes	Yes	Yes	Yes	Yes	Yes
State dummy	No	Yes	Yes	No	No	Yes
Village variables	No	No	Yes	No	No	Yes
Observations	21472	21472	19902	20191	12329	11556
R2	0.0198	0.0496	0.0487	-	0.0291	0.0479

Notes: ′p<0.2; *p<0.1; **p<0.05;***p<0.01
Here I estimate the impact on temporary migration. I estimate the value of marginal effect for each household in the data and take the average of the entire distribution to get average marginal effect (AME). The dependent variable is binary indicator which takes value 1 if the household sends a temporary migrant and 0 other wise. The variable caste (lower or upper) takes value 1 if the household belongs to that particular caste and 0 otherwise. I use cluster robust standard errors at village level. There are 1337 clusters. N is network size. In column 4 census IV specification, the F-stat of excluded instrument is 97.75 and KP F-stat is 30.51. Low permanent migration area (UP, Bihar, UK (Anderson, 2011) and states with 93-95 percent households staying in the village forever: RJ,MP,GJ,CH,AP,KA,JH etc. HP is hilly Himalayan region with high migration cost and low migration compared to rest of India. I remove HP from the analysis.)
Mean: Size (12.11); Educ. (4.46); Land (2.16) Consp. (711)

Table A.13: Does AME of network size depend on network income (liquidity constraint)?

	Household		Network	
	(1)	(2)	(3)	(4)
NS*Income	-0.0009**	-0.0007***		
	(0.0004)	(0.0003)		
NS*Income*Upper Caste	0.0006			
	(0.0005)			
NS*Income*Lower Caste		-0.0008		
		(0.0008)		
NS*Income network			0.0000	-0.0002**
			(0.0001)	(0.0001)
NS*Income network*Upper Caste			0.0000	
			(0.0001)	
NS*Income network*Lower Caste				0.0003***
				(0.0001)
No. of Obs.	21471	21471	21472	21472

Notes: *p<0.1; **p<0.05;***p<0.01

Here, I estimate the impact on temporary migration. I estimate the value of marginal effect for each household in the data and take the average of the entire distribution to get average marginal effect (AME). The dependent variable is binary indicator which takes value 1 if the household sends a temporary migrant and 0 other wise. The variable caste (lower or upper) takes value 1 if the household belongs to that particular caste and 0 otherwise. We use triple interaction between network size, network income and caste indicator.

Table A.14: AME of network size: negative rainfall shock and network share in agriculture?

	(1)	(2)	(3)
NS*RainI*Sh.Agri*Upper Caste	-0.0000		
	(0.0007)		
NS*RainI*Sh.Agri*OBC		0.0020*	
		(0.0011)	
NS*RainI*Sh.Agri*Lower Caste			-0.0023**
			(0.0011)
No. of Obs.	133539	133539	133539

Notes: *p<0.1; **p<0.05;***p<0.01

Here, I estimate the impact on temporary migration varies depending on the shock to the network income. I use negative rainfall shock at the place of migrant origin and share of network in agriculture as intensity variable. The dependent variable is binary indicator which takes value 1 if the household sends a temporary migrant and 0 other wise. The variable caste (lower or upper) takes value 1 if the household belongs to that particular caste and 0 otherwise. This specification has quadruple interaction which includes network size, negative rainfall shock, share of agriculture (intensity variable) and caste indicator. I add rainfall data and create negative rainfall shock using a standardise past average measure for every district. If the rainfall is lower than 1 std. dev. in historical average we term it as negative rainfall shock. This is the rainfall indicator indicating if it is a shock or not.

Table A.15: AME: interaction of village size and HH variables

	(1) Upper caste	(2) OBC	(3) SC/ST
NS*Upper caste	-0.0010-**		
	(0.0005)		
NS*OBC		0.0008	
		(0.0007)	
NS*Lower caste			0.0015
			(0.0010)
No. of Obs.	21472	19902	19902

Notes: *p<0.1; **p<0.05;***p<0.01

Here I estimate the impact on temporary migration. The dependent variable is binary indicator which takes value 1 if the household sends a temporary migrant and 0 other wise. The variable caste (lower or upper) takes value 1 if the household belongs to that particular caste and 0 otherwise.

Table A.16: AME of network size: Low permanent migration region

	(1) Upper caste	(2) OBC	(3) SC/ST
NS*Upper caste	-0.0021***		
	(0.0007)		
NS*OBC		0.0007	
		(0.0008)	
NS*Lower caste			0.0045**
			(0.0017)
No. of Obs.	11814	11814	11814

Notes: Here I estimate the impact of network size on temporary migration for regions with low permanent migration. I refer to low permanent migration regions as exogenous area. The dependent variable is binary indicator which takes value 1 if the household sends a temporary migrant and 0 other wise. The variable caste (lower or upper) takes value 1 if the household belongs to that particular caste and 0 otherwise. I use cluster robust standard errors at village level. There are 1337 clusters. I also have state dummy (30 states) to remove state level effects in the analysis. Caste index takes into account the dominance of caste in a village, higher the value more dominance by one caste in the village. I include village infrastructure variables like distance bank, secondary school and bus stop. Exogenous area is defined as states with more than 92 percent (average) of HH staying in the village forever. It includes UP,BH,JH,RJ,GJ,MP,CH,AP and KA. Mean: Size (12.9); Educ. (4.46); Land (2.16) Consp. (711)

*p<0.1; **p<0.05;***p<0.01

Table A.17: AME of network size: Occupational heterogeneity

	(1)	(2)	(3)
NS*HH index	0.0052	0.0089	-0.0009
	(0.0048)	(0.0058)	(0.0029)
NS*Upper caste	-0.0032		
	(0.0053)		
NS*OBC		-0.0098	
		(0.0076)	
NS*Lower caste			0.0102
			(0.0083)
No. of Obs.	21472	21472	21472

Notes: Here I estimate the impact on temporary migration. The dependent variable is binary indicator which takes value 1 if the household sends a temporary migrant and 0 other wise. The variable caste (lower or upper) takes value 1 if the household belongs to that particular caste and 0 otherwise. I measure occupational heterogeneity at network level using Hirschman Herfindahl (HH) index. It measures the concentration of one occupation in the network or heterogeneity of occupation in the network. A higher value of the index indicates lower heterogeneity.

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table A.18: AME: Occupational heterogeneity (double interaction)

	(1)	(2)	(3)
	Upper caste	OBC	SC/ST
NS*Upper caste	-0.0011***		
	(0.0004)		
NS*OBC		0.0017**	
		(0.0007)	
NS*Lower caste			0.0010
			(0.0012)
No. of Obs.	21472	21472	21472

Notes: *p<0.1; **p<0.05;***p<0.01
Here I estimate the impact on temporary migration. The dependent variable is binary indicator which takes value 1 if the household sends a temporary migrant and 0 other wise. The variable caste (lower or upper) takes value 1 if the household belongs to that particular caste and 0 otherwise. I measure occupational heterogeneity at network level using Hirschman Herfindahl (HH) index. It measures the concentration of one occupation in the network or heterogeneity of occupation in the network. A higher value of the index indicates lower heterogeneity.

A.3 Model

There exists a payoff to stay in the network which reduces the probability of migration. We define the payoff W as a function of three factors, size of the network (N), human capital (H) and permanent income (P). The household will choose to send a temporary migrant when the payoff from migration is higher than the payoff of staying in the network. The payoff of the migration destination depends on the migration income (m), cost of migration (d) and proportion of network payoff (α) which the household receives even when the household sends a migrant away from the village. The household can receive this payoff from the network in the form of social capital support (non-monetary payoff).

$$W(N, P, H) < (m - d) + \alpha W(N, P, H)$$

leading to

$$W(N, P, H) < \frac{m - d}{1 - \alpha} = K(constant)$$

Where W, payoff from the network, is the latent variable for temporary migration. For household i, y_i is temporary migration variable:

$$y_i = \begin{cases} 1 & \text{for} \quad W(N, H, P) < K \\ 0 & \text{for} \quad W(N, H, P) > K \end{cases}$$

Let x_i be covariates matrix, β be coefficient matrix and ϵ_i be i.i.d error term.

$$W_i = x_i'\beta + \epsilon$$

then:

$$\begin{aligned} P(y_i = 1|x_i) &= P(W_i < K|x_i) \\ &= P(x_i'\beta + \epsilon < K|x_i) \\ &= P(\epsilon < K - x_i'\beta|x_i) \end{aligned}$$

if $\epsilon \sim N(0, 1)$ then $P(y_i = 1|x_i) = \Phi(K - x_i'\beta)$.

where Φ is cumulative distribution function.

If I assume CES functional form for the payoff from the network, then I get positive impact of size of network on the payoff.

A.3.1 CES functional form for payoff from the network

In the model, this payoff depends on size of the network (N), permanent income of the household (P) and household human capital (H). We assume a constant elasticity of substitution (CES) payoff function (W).

$$W_i(N, P, H) = A[\mu_1 N_i^\rho + \mu_2 P_i^\rho + \mu_3 H_i^\rho]^{\frac{v}{\rho}}$$

Parameter $A \in [0, \infty)$ determines the productivity, $\sum_i \mu_i = 1$ determines the optimal distribution of the inputs, $\rho \in (-\infty, 1]$ determines the constant elasticity of substitution and $v \in [0, \infty)$ is the elasticity of scale.

$$\begin{aligned}\frac{\partial W_i}{\partial N} &= Av\mu_1 N_i^{\rho-1}[\mu_1 N_i^\rho + \mu_2 P_i^\rho + \mu_3 H_i^\rho]^{\frac{v}{\rho}-1} \\ \frac{\partial^2 W_i}{\partial N \partial H} &= Av(v-\rho)\mu_1\mu_3 N_i^{\rho-1} H_i^{\rho-1}[\mu_1 N_i^\rho + \mu_2 P_i^\rho + \mu_3 H_i^\rho]^{\frac{v}{\rho}-2}\end{aligned}$$

The first equation is the marginal effect of network size on the payoff from the network. As the parameters A, v and μ_1 are positive, we get a positive impact of network size on the payoff from the network. This implies that as the size of the network increases the payoff to stay in the network also increases. We assume that the impact of the payoff from the network has an negative impact on temporary migration. Hence, we get an negative impact of network size on temporary migration.

The second equation is the interaction effect of size of the network and human capital on payoff from the network. The interaction of size of network with human capital also has an negative impact on temporary migration if $v > \rho$. The maximum value for ρ is 1. $v > 1$ implies increasing returns to scale from human capital. If we have increasing returns to scale from input factors then the interaction effect of size of the network and human capital is positive on the payoff from the network. Further, negative impact on temporary migration.

Appendix B

Appendices

Table B.1: Loan Targeting matrix

Score	Mig. Type	Skill	Wage	Mig. inc.	Caste	Mig. reln
1	Long	Unskilled	Daily	75-100	ST	Self
2	Short	Semi	Contract	50-74	SC	Wife
3	Commuter	Skilled	Monthly	25-49	OBC	Mother
4	Returnee	High	Self empl.	0-24	General	Others

B.1 Tables

Table B.2: Total loans

Total loans	Freq
2	1791
3	769
4	488
5	102
6	7

Table B.3: Summary

Statistic	N	Mean	St. Dev.	Min	Max
Gender	3,060	0.56	0.50	0	1
Pakka house	3,060	0.36	0.48	0	1
Education	3,060	1.31	2.35	0.00	15.00
HH size	3,055	5.57	1.84	1	16
Total migrants	3,026	1.31	0.60	0	5
Share Food Consp.	3,060	0.53	0.14	0.00	1.00
Consumption (log)	3,060	6.85	0.51	0.00	9.75
Consumption	3,060	1,054.29	711.54	0.00	17,165.50
Female LFP	3,060	0.53	0.57	0	5

Table B.4: Migrant type (HH) by applicant's gender

Mig. type	Female	Male
Commuter	633	689
Long duration	955	474
Short Duration	125	184

Table B.5: Sector of the migrant work

Sector	Obs.
Construction	1799
Food	549
Other	409
Travel	163
Manufacturing	87
Logistics	53

Table B.8: First stage: 1.25 SD Rainfall shock

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7
Rain	-0.071	-0.254***	-0.429***	0.010	0.288***	0.468***	0.556***	0.164**
	(0.062)	(0.054)	(0.056)	(0.055)	(0.055)	(0.060)	(0.067)	(0.078)
KP F-stat	119	119	130	156	119	127	164	168
No. of Obs.	3635	3635	3635	3635	3635	3635	3635	3635

Notes: *p<0.1;**p<0.05;***p<0.01

Table B.6: Prominent Destination of the migrant workers

Destination	State	Obs.
Ahmedabad	Gujarat	622
Udaipur	Rajasthan	470
Gogunda	Rajasthan	212
Mumbai	Maharashtra	145
Surat	Gujarat	134
Sadadi	Gujarat	103
Aaspura	Rajasthan	78
Rajkot	Gujarat	76
Sayra	Rajasthan	48

Table B.7: t-test by gender of applicant

	Female	Male	t-test
Consp. (log)	6.87	6.73	9.4
Food consp. (share)	0.53	0.53	-1.5
Female LFP	0.59	0.47	7.4
Pakka house	0.35	0.37	-1.4

Table B.9: Impact of loan to woman 1.25 SD

	Share of consumption				Levels			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Consp.	Food	Health	Social	Livestock	Total Asset	Saving	MPS
Female	0.228***	-0.109***	0.009	0.046***	0.224**	0.128	0.482***	0.231***
	(0.075)	(0.021)	(0.012)	(0.016)	(0.095)	(0.088)	(0.078)	(0.070)
KP F-stat	171	170	168	171	150	138	173	174
No. of Obs.	3635	3635	3635	3635	3419	3302	3628	3628

Notes: *p<0.1;**p<0.05;***p<0.01

The instrumental variable approach in this table uses past postive (heavy) rainfall shock (5 year lag) as an instrument for female applicant in the migrant household. The rainfall indicator is measured using deviation from historical average for the village/region. In this specification, I use 1.25 standard deviation from the average historical rainfall. The estimates in the table show the percentage change due to loan given to the female applicant.

Table B.10: Impact of loan to woman 1.25 SD: Lower Asset Holding

	Share of consumption				Levels			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Consp.	Food	Health	Social	Livestock	Total Asset	Saving	MPS
Female	0.263**	-0.139***	0.021	0.068*	0.333*	0.100	0.721***	0.189***
	(0.121)	(0.035)	(0.028)	(0.036)	(0.174)	(0.170)	(0.145)	(0.068)
KP F-stat	58	58	57	57	46	45	54	123
No. of Obs.	1683	1683	1683	1683	1562	1531	1717	3325

Notes: *p<0.1;**p<0.05;***p<0.01

The instrumental variable approach in this table uses past postive (heavy) rainfall shock (5 year lag) as an instrument for female applicant in the migrant household. The rainfall indicator is measured using deviation from historical average for the village/region. In this specification, I use 1.25 standard deviation from the average historical rainfall. The estimates in the table show the percentage change due to loan given to the female applicant.

Table B.11: Impact of loan to woman 1.25 SD: Commuter migrant

	Share of consumption				Levels			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Consp.	Food	Health	Social	Livestock	Total Asset	Saving	MPS
Female	0.161	-0.145***	0.064***	0.063**	0.120	0.076	0.569***	0.270***
	(0.099)	(0.029)	(0.020)	(0.030)	(0.147)	(0.126)	(0.115)	(0.081)
KP F-stat	77	77	73	78	68	59	83	94
No. of Obs.	1580	1580	1580	1580	1465	1402	1650	3187

Notes: *p<0.1;**p<0.05;***p<0.01

The instrumental variable approach in this table uses past postive (heavy) rainfall shock (5 year lag) as an instrument for female applicant in the migrant household. The rainfall indicator is measured using deviation from historical average for the village/region. In this specification, I use 1.25 standard deviation from the average historical rainfall. The estimates in the table show the percentage change due to loan given to the female applicant.

Table B.12: Impact of loan to woman 1.25 SD: Short Duration Migrant

	Share of consumption				Levels			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Consp.	Food	Health	Social	Livestock	Total Asset	Saving	MPS
Female	0.384*	-0.049	-0.008	0.026	0.029	-0.251	0.034	0.212***
	(0.202)	(0.051)	(0.018)	(0.020)	(0.265)	(0.194)	(0.172)	(0.077)
KP F-stat	13	13	13	12	13	13	14	50
No. of Obs.	364	364	364	364	349	337	438	2703

Notes: *p<0.1;**p<0.05;***p<0.01

The instrumental variable approach in this table uses past postive (heavy) rainfall shock (5 year lag) as an instrument for female applicant in the migrant household. The rainfall indicator is measured using deviation from historical average for the village/region. In this specification, I use 1.25 standard deviation from the average historical rainfall. The estimates in the table show the percentage change due to loan given to the female applicant.

Table B.13: Impact of loan to woman 1.25 SD: Long Duration Migrant

	Share of consumption				Levels			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Consp.	Food	Health	Social	Livestock	Total Asset	Saving	MPS
Female	0.226	-0.101**	-0.019	0.042	0.492**	-0.091	0.935***	0.118*
	(0.166)	(0.049)	(0.034)	(0.045)	(0.241)	(0.287)	(0.232)	(0.062)
KP F-stat	28	28	28	28	27	25	23	110
No. of Obs.	1265	1265	1265	1265	1189	1155	1333	3164

Notes: *p<0.1;**p<0.05;***p<0.01

The instrumental variable approach in this table uses past postive (heavy) rainfall shock (5 year lag) as an instrument for female applicant in the migrant household. The rainfall indicator is measured using deviation from historical average for the village/region. In this specification, I use 1.25 standard deviation from the average historical rainfall. The estimates in the table show the percentage change due to loan given to the female applicant.

Table B.14: Purpose of loan by applicant's gender

Purpose	Female	Male
Home	777	688
Old Debt	495	257
Agri.	174	132
Social	46	45
Livestock	92	65
Business	89	125
Others	35	30

Table B.15: Year gap between loans by applicant's gender

Gap	Male	Female
1	1464	1738
2	675	594
3	125	63
4	45	16
5	21	4
6	8	3
7	0	1

Table B.16: Yearwise loan by applicant's gender

Year	Female	Male
2012	90	292
2013	108	250
2014	233	309
2015	255	245
2016	378	115
2017	512	87
2018	137	48

Appendix C

Appendices

C.1 Figures

Figure C.1: Probability of receiving DPEP

Figure Notes: This figure plots the discontinuity in the probability of receiving DPEP for districts around the female literacy cutoff. The districts to the left of zero receive the program and the districts to the right do not.

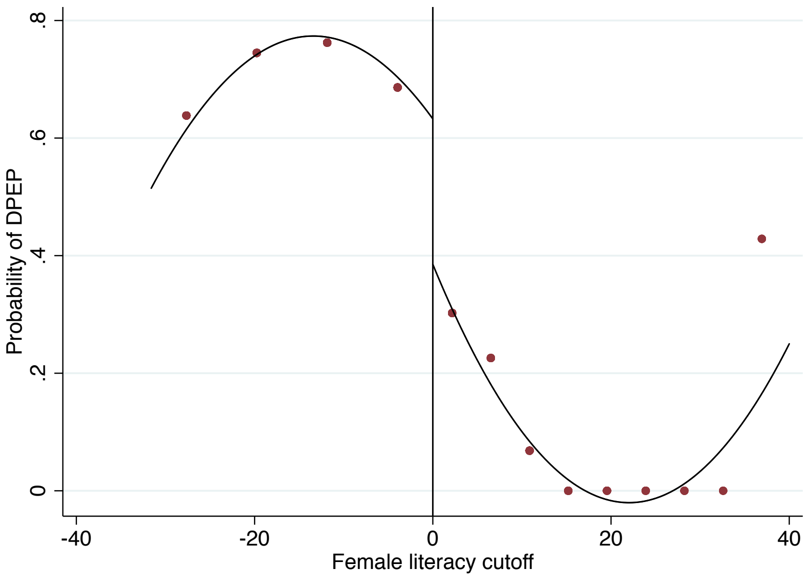


Figure C.2: Mccrary Test

Figure Notes: This figure plots the continuous density of the assignment variable around the cutoff.

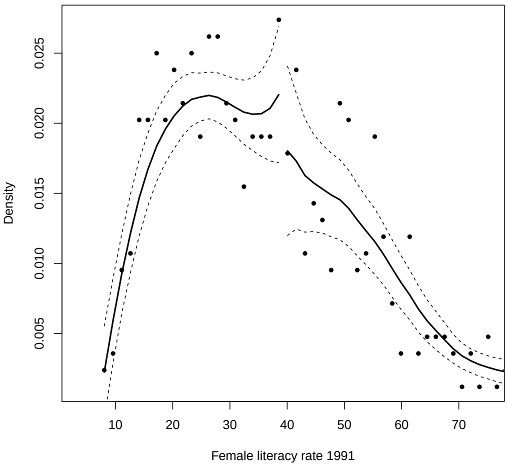


Figure C.3: Balance test: Schools built before 1995

Figure Notes: This figure plots the continuity in the district wise total schools before 1995 around the female literacy cutoff. The districts to the left of zero receive the program and the districts to the right do not.

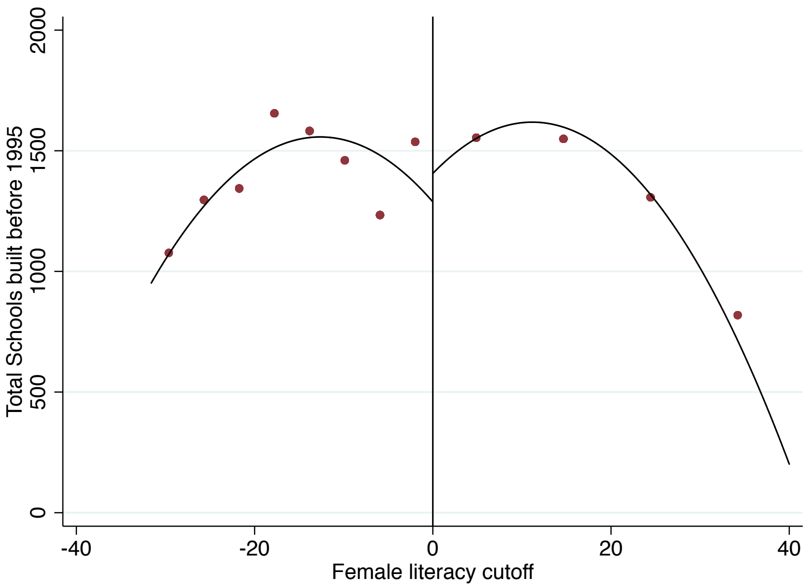


Figure C.4: Balance test: Education

Figure Notes: This figure plots the continuity in the district wise female years of education around the female literacy cutoff. The districts to the left of zero receive the program and the districts to the right do not.

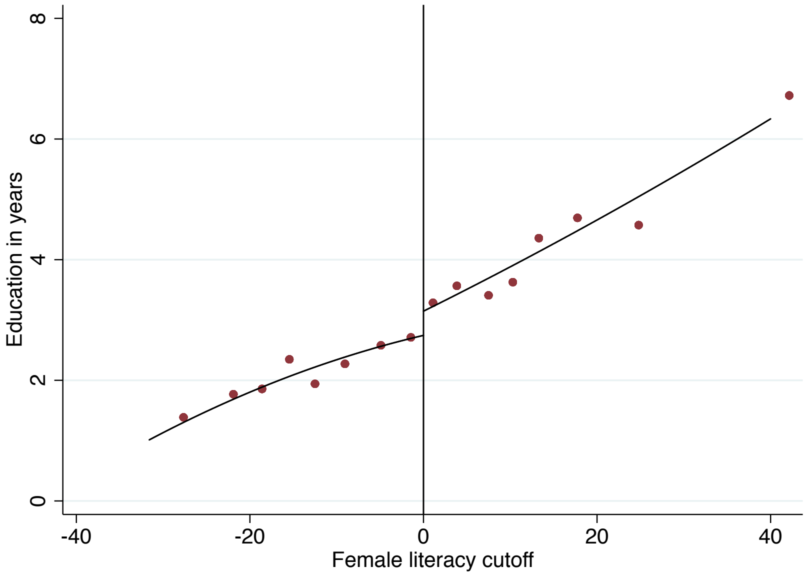


Figure C.5: Balance test: Age at marriage

Figure Notes: This figure plots the continuity in the district wise women's age at marriage around the female literacy cutoff. The districts to the left of zero receive the program and the districts to the right do not.

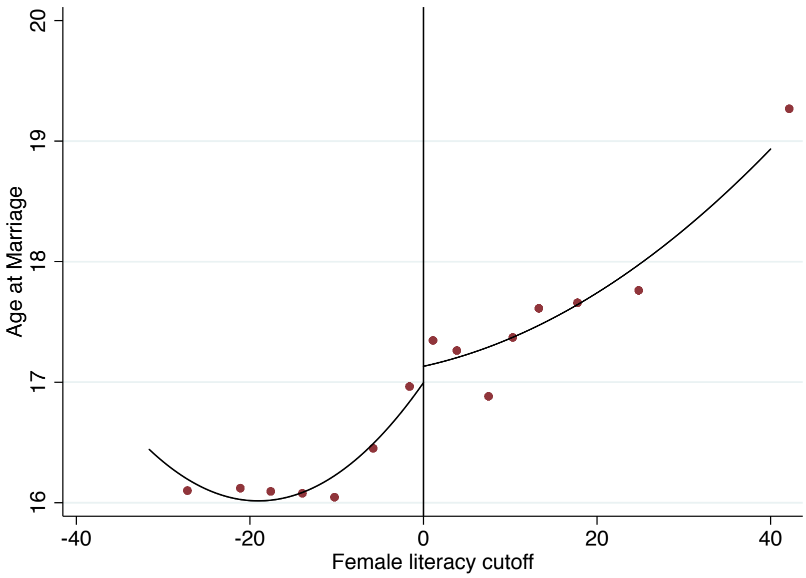
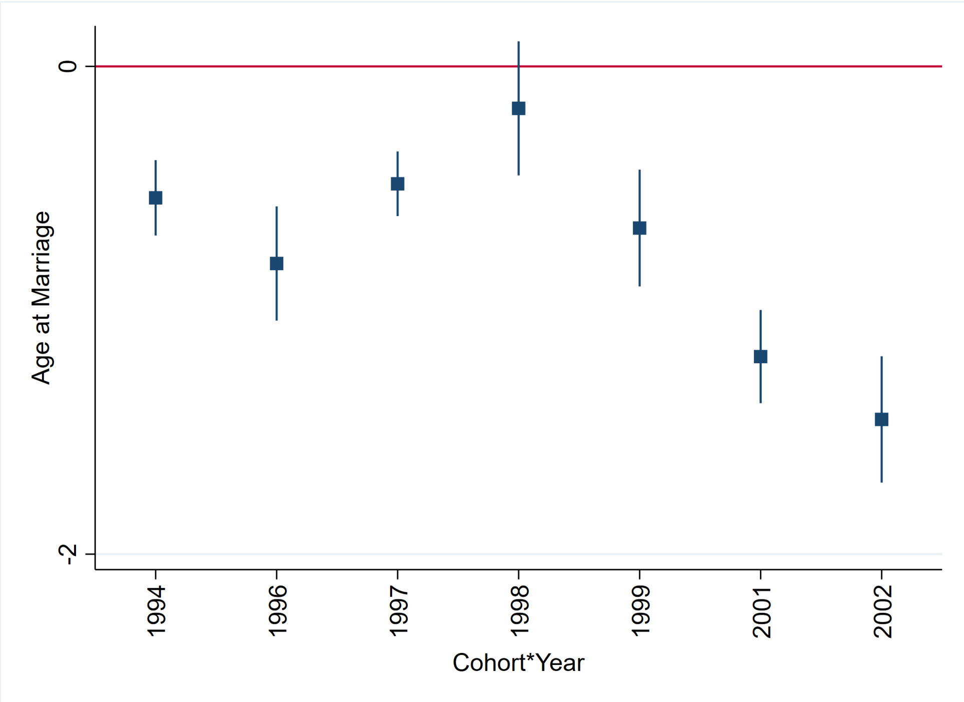


Figure C.6: Difference in Difference

Figure Notes: This figure plots the staggered difference in difference estimates for treatment years 1994 to 2002. The treated cohort is women who were 6-19 years of age and the control is women who were 20-30 at the time of program implementation. We include cohort, DPEP and district level fixed effect.



C.2 Tables

Table C.1: Descriptive statistics

	N	Mean	SD	Min	Max
DHS, 2015-16					
Marriage and fertility					
Age at marriage	358,303	18.65	3.73	10	40
Age at first birth	316,728	20.63	3.41	15	40
Total children	543,023	1.46	1.56	0	15
Background variables					
Woman age	543,023	26.03	7.14	15	40
Education in years	543,023	7.49	5.01	0	20
HH. size	543,023	5.94	2.69	1	41
Ever married	543,023	0.69	0.46	0	1
Ever gave birth	543,023	0.60	0.49	0	1
Partner Age	63,040	33.77	7.28	15	70
Partner Education	65,241	8.00	4.86	0	20
Partner Age at marriage	62,576	23.37	4.75	10	40
Surplus variables					
Own earning decision	13,289	0.82	0.39	0	1
Health decision	543,023	0.09	0.28	0	1
Purchase decision	543,023	0.08	0.28	0	1
Faced any violence	48,623	0.32	0.46	0	1
Justifies violence	93,289	0.39	0.49	0	1
HH. Wealth	543,023	0.38	0.49	0	1
Hospital deliveries	181,160	0.78	0.41	0	1
Antenatal care received	179,729	0.83	0.38	0	1
Use contraception	381,378	0.56	0.50	0	1
NSSO, 2005					
Median District wage (Women)	488,379	414.30	445.45	90.00	3,000.00
Median District LFPR (Women)	493,474	0.36	0.16	0.00	0.79
Marriage squeeze	493,474	140.78	72.61	24.32	700.00
DISE, 2005					

Table C.2: Description of variables

DHS, 2015-16	
Marriage market variables	
Age at marriage	Age at start of first marriage or union.
Age at first birth	Age of the respondent at first birth.
Total children	Total number of children ever born.
Background variables	
Woman age	The present age of the woman.
Education in years	Education in single years.
HH. size	Total members of the household.
Ever married	Dummy for woman who ever got married.
Ever gave birth	Dummy for woman who ever gave birth.
Partner Age	Age of the respondent's husband or partner.
Partner Education	The current husband or partner's education in single years.
Partner Age at marriage	The age at marriage of the current husband.
Surplus variables	
Own earning decision	Person who decides how to spend the woman's own earnings
Health decision	Person who decides on the respondent's health care
Purchase decision	Person who usually decides on large household purchases
Faced any violence	If the woman faced physical, sexual, emotional violence or control behaviour by partner.
Justifies violence	If the woman justifies physical, sexual, emotional violence or control behaviour under any circumstances.
HH. Wealth	Wealth category post marriage
Hospital deliveries	Delivery in a health institution
Antenatal care received	Access to antenatal care during pregnancy
Use contraception	Access to any type of contraceptive methods
NSSO, 2005	
Median District wage (Women)	The median of individuals weekly wages at district level.
Mean District LFPR (Women)	The average LFPR at district level using the current weekly activity status.(Total women age 15-65 working or looking for work/Total women age 15-65)
Marriage squeeze	Ratio of unmarried women age 15-19 to unmarried men age 20-24.

Table C.3: Balance test covariates

	(1) Education	(2) Age at marriage	(3) Schools built	(4) Sex ratio	(5) Total children
DPEP	-1.471	-1.254	720.203	9.333	-0.113
	[1.526]	[1.396]	[445.564]	[39.820]	[0.387]
Sample Mean	3.04	16.90	584.68	942.58	2.64
BW districts	209	135	117	174	189
Bandwidth	14	10	8	12	12
VCE method	NN	NN	NN	NN	NN
BW type	mserd	mserd	mserd	mserd	mserd

Notes: The balance test checks the difference between DPEP and non-DPEP districts before the program was implemented. We use fuzzy RDD design to estimate the impact on the predetermined variables (Calonico et al., 2017). The bandwidth selection is done using data driven mean square error (MSE-RD) optimal bandwidth methodology. The estimation is done at district level. We use nearest neighbour (NN) cluster robust standard errors at district-age level.

$^{**}p<0.05$; $^{***}p<0.01$

Table C.4: Impact of District Primary Education Program (DPEP) on women's education

	(1) MSE	(2) MSE-2	(3) CER	(4) CER-2
DPEP	1.48**	0.33	0.40	0.83*
	[0.72]	[0.35]	[0.81]	[0.46]
Sample Mean	7.49	7.49	7.49	7.49
Obs.	467687	467687	467687	467687
BW-left	4.71	3.06	2.93	1.90
BW-right	4.71	7.71	2.93	4.79
BW type	mserd	msetwo	cerrd	certwo

Notes: Here we estimate the impact of the DPEP program on women's education using non-parametric estimation using different optimal bandwidth selection methods such as MSE, MSE-2, MSE-sum, CER, CER-2 and CER-sum. MSE represents Mean Square Error; MSE-2 represents different bandwidths for both sides of the cut-off; CER represents Coverage Error Rate. We use NN cluster robust standard errors at district age level. **$p<0.05$;***$p<0.01$

Table C.5: Impact of education on age at marriage

		Old Cohort	Bandwidth		
	Main	26-40	4	6	7
Educ.	-0.44***	-1.06**	-1.17***	-0.76***	-0.48***
	[0.17]	[0.41]	[0.40]	[0.28]	[0.16]
Obs.	58140	39385	51364	72784	83379
Control Mean	18.78	19.07	18.76	18.77	18.67
CD Fstat	37.63	14.43	16.52	20.84	43.69

Notes: Here we show results for robustness checks on the impact of education on age at marriage. In column 2 we use old cohort in the age group of 25-40. In the last three columns we use different bandwidth specification. **p<0.05;***p<0.01

Table C.6: Impact of education on age at marriage: Age Cohort

	Main	15-25	26-40	27-35
Education	-0.44***	0.26**	-1.06**	-0.60*
	[0.17]	[0.10]	[0.41]	[0.33]
Observations	58140	18755	39385	26699
Control Mean	18.78	18.17	19.07	19.07
CD Fstat	37.63	30.44	14.43	12.96

Notes: Here we show results for robustness checks on the impact of education on age at marriage. In column 2 and 3 we use old cohort in the age group of 25-40 and 30-40 respectively. In column 4 we use cohort where only women were treated in the program and men were too old to change their schooling decision. **$p<0.05$;***$p<0.01$

Table C.7: Impact of education on marriage market outcomes: Age at first birth and Fertility

	(1)	(2)
	Age at First Birth	Total Child
Education	-0.22	-0.06**
	[0.16]	[0.03]
Observations	51502	87991
Control Mean	20.63	1.46
CD Fstat	26.04	97.05

Notes Here we show the robust estimate for the impact of education on marriage market outcomes. We use DPEP cut-off as an instrumental variable for education. We use the first stage bandwidth of 4.7 around the cut-off. This includes 54 districts below the cut-off and 44 districts above the cut-off. We use nearest neighbour (NN) cluster robust standard errors at district age level. **p<0.05;***p<0.01

Table C.8: Impact of education on domestic violence

	(1) Any Violence	(2) Justifies Violence
Education	-0.22***	-0.14***
	[0.08]	[0.03]
Observations	7688	14485
Control Mean	0.27	0.38
CD Fstat	7.57	33.38

Notes This table shows the IV estimates for the impact of education on domestic violence variables. The first column records if the woman has experienced any sort of physical, sexual violence or has faced control issues. The second column records if the woman justifies violence if the wife was unfaithful or disrespectful. The variable *Fem. Lit.* is the districtwise female literacy in 1991. **p<0.05;***p<0.01

	(1) Household Wealth	(2) Hospital Delivery	(3) Antenatal care	(4) Contraception use	(5) Fertility
Education	0.15***	0.07***	0.05***	0.14***	-0.06**
	[0.01]	[0.01]	[0.01]	[0.03]	[0.03]
Observations	87991	28210	27897	61702	87991
Control Mean	0.48	0.82	0.87	0.57	1.40
CD Fstat	97.05	65.09	63.93	35.45	97.05

Notes: **p<0.05;***p<0.01

Table C.9: Impact of education on spending decisions within household

	(1) Own Earnings	(2) Health care	(3) Purchases
Education	-0.19	-0.01*	-0.01
	[0.56]	[0.01]	[0.01]
Observations	2358	87991	87991
Control Mean	0.85	0.09	0.09
CD Fstat	0.14	97.05	97.05

Notes: This table shows the IV estimates for the impact of education on decision making within household. The dependent variables in columns 1 to 3 are *person who decides on spending the woman's own earning, person who decides on the woman's healthcare, person who decides on major household purchases* respectively. The reference for all columns is that the husband or someone else in the household takes decisions vs the woman taking the decisions alone or jointly with the husband. The variable *Fem. Lit.* is the districtwise female literacy in 1991. **p<0.05;***p<0.01

Table C.10: Impact of education on husband's characteristics

	(1) Husband's AM	(2) Husband's Education
Men's Education	0.27	–
	[0.32]	
Women's Education	–	0.07*
		[0.04]
Obs.	9729	10224
Control Mean	23.37	18.78
CD Fstat	8.98	17.43

Notes: Here we estimate the impact of education on husband's age at marriage. This data is randomly selected sample from the women questionnaire. Hence, there are lower number of observations in the analysis. The second column estiamtes the difference in age at marriage between husband and wife due to increase in wife's education. The column 3 estimates impact of increase in men's education on difference in age at marriage. **p<0.05;***p<0.01

Table C.11: Impact of education on age at marriage: Quantile effects

	(1) Q25	(2) Q50	(3) Q75	(4) Q90
Education	0.26***	-0.08***	-0.24***	-0.49***
	[0.05]	[0.03]	[0.03]	[0.08]
Observations	309607	309607	309607	309607

Notes: Here we estimate the distributional impact of the education on age at marriage using IV quantile treatment effect at different levels of education using Kaplan and Sun (2017) methodology. The education quantiles follow the categorisation as mentioned: Q25 has 5 years of education; Q50 has 8 years of education; Q75 has 14 years of education. **p<0.05;***p<0.01

Table C.12: Impact of education on age of marriage: wage levels

	(1)
Education	-0.7872**
	[0.4011]
Education × Wage	0.0009***
	[0.0003]
Wage	-0.0056**
	[0.0022]
Observations	57648
Control Mean	19.51
CD Fstat	7.00

Notes Here we estimate the heterogeneity depending on outside option available in terms of district wage for women. The dependent variable is age at marriage. Wage means district level wage of women. We use similar IV specification with DPEP cut-off as an instrument for education. The CD Fstat 7 is significant at 10 percent level. With two instruments Craig Donald Fstat is a better statistics to check the validity of the instrument. Stock Yogo (SY) provides the critical values. For this specification the SY critical value is 7 at 10 percent level. **p<0.05;***p<0.01

C.3 Conceptual framework: household problem

The utility for men and women is represented by subscript m and w respectively. Individuals value the private consumption, q, and children and household management as a public good, Q. The household production function follows Cobb-Douglas utility (qQ). The men's family has a preference for young brides. We add cost in the utility function which increases with age of the woman at marriage. $c(a_w)$ is an increasing function of age. Below is the utility for men and women both:

$$u_m = q_m Q - c(a_w)$$
$$u_w = q_w Q$$

We assume the investment in children depends on the parental human capital. The public good, Q, domestically produced from parental human capital is given by Cobb-Douglas utility function.

$$Q = H_m^{\alpha/2} H_w^{\alpha/2}$$

The budget constraint of the household will account for private consumption q and public good consumption i.e. child care. The sum of the consumptions will be equal to household income. We have husband's income, y, bride's income, z, and dowry payment, d. Dowry payment is one time usually around annual income of the husband. But we can consider it as small monthly payment over the life-cycle. Below is the budget constraint for the household. Here we assume the share of private consumption and public consumption is defined by β.

$$q_m + q_w + \beta Q = y + d + z$$

Dowry is an important part of Indian marriage market. It can exceed annual household income (Chiplunkar and Weaver, 2021). We introduce dowry in the model through budget constraint as an perpetuity monthly payment. For simplification, we assume dowry to be a constant amount.

In India, female labour force participation has stagnated around 30 percent and it has decreased in recent years. So the main investment is in the marriage market (Fletcher et al., 2017). Labour market returns are low for woman but they do increase with education. We assume similar logarithmic functional form for women's income. The labour market returns can be assumed to be low which means a low value of δ or z'_{H_w}.

$$z = \delta ln(H_w)$$

Here, we maximise the total household utility under the budget constraint. More specifically, we maximise the sum of utilities for men and women in the household, $u = u_m + u_w$. Below is the maximisation problem:

$$\max_{q,Q}.\ (q_m + q_w)(Q) - c(a_w)$$

$$s.t.\ q_m + q_w + \beta Q = y + d + z$$

We get equilibrium private consumptions and public good consumption. The equilibrium values for private and public good consumption are:

$$Q^* = \frac{(y + z + d + R)}{\beta + 1}$$

$$q^* = \frac{(y + z + d - R)}{\beta + 1}$$

where $R = \frac{2\delta}{\alpha}$.

C.3.1 Surplus function

From the optimal values we can get the joint utility for the household. Joint utility of the household, T, is the sum of utilities of men and woman as shown below:

$$T = q^*Q^* - c(a_w)$$
$$T = \frac{1}{(\beta+1)^2}((y+z+d)^2 - R^2) - c(a_w)$$

Using joint utility we can define the surplus of the household. Surplus function is defined as joint utility minus the utility when the individuals are single. When they are single consume their own income. Using optimal values for private and public good consumption we get surplus function:

$$S(y, z, H_w, a_w) = \frac{1}{(\beta+1)^2}((y+z+d)^2 - R^2) - c(a_w) - y - z$$

The surplus function depends on labour market income for men and women. It reduces with age of woman at marriage. As men's family prefer younger brides surplus decreasing in the age of woman. We also have surplus increasing in men's income.

C.3.2 Marginal rate of substitution

Using the surplus function, we estimate the rate of change of surplus with respect to age at marriage and education of the woman. Further, we comment on the marginal rate of substitution between age of marriage and education of the woman.

$$\frac{\partial S}{\partial H_w} = (\frac{2(y+z+d)}{(\beta+1)^2} - 1)z'_{H_w}$$

Given that we have the numerator positive we have surplus increasing in education of women. For that we need $2(y+z+d) > (\beta+1)^2$.

$$\frac{\partial S}{\partial H_w} > 0$$

Next, we estimate the rate of change of surplus with respect to age of marriage. Surplus of the household decreases as the age of woman increases.

$$\frac{\partial S}{\partial a_w} = -c'(a_w)$$

Further, we estimate the marginal rate of substitution ($MRS_{a_{H_w}}$) between age of marriage and education of woman. We estimate the MRS by taking a ratio between marginal surplus of education of woman and age of woman at marriage. If the labour market returns are low for woman then we get the MRS to be negative. The model predicts a negative association between education of woman and the age of marriage. There is demand for young and educated brides. Educated woman are able to find a match earlier after entering the marriage market.

$$MRS = \frac{\partial a_w}{\partial H_w} < 0$$

C.3.3 Household problem: quasi-linear utility

Here, we use similar set-up as the earlier problem. We use quasi-linear utility functional form where the private consumption does not depend on change in household income. We assume following functional forms:

$$u_m = q_m + ln(Q) - c(a_w)$$
$$u_w = q_w + ln(Q)$$

Another deviation from the above model is we assume dowry increases with education of women. There is evidence of positive correlation between dowry and education of woman (Anukriti, Kwon, et al., 2020). We assume dowry is an increasing function of education of woman. We take a specific logarithmic functional form in our specification. Dowry, d, depends on the woman's human capital, H_w, as shown below:

$$d = \gamma ln(H_w)$$

Keeping rest of the assumption similar to above household problem, we maximise the sum of utilities under the budget constraint. We get following equilibrium values:

$$Q^* = 2\frac{\alpha + \delta}{\alpha\beta}$$
$$q^* = (y + z + d) - 2\frac{\alpha + \delta}{\alpha\beta}$$

This provides us with the following surplus function which is independent of the income (y and z).

$$S(H_w, a_w) = \gamma ln(H_w) - 2\frac{\alpha + \delta}{\alpha\beta} + ln(2\frac{\alpha + \delta}{\alpha\beta}) - c(a_w)$$

The marginal rate of substitution between education of women and age of marriage has a negative relationship using this functional form as well.

$$\frac{\partial S}{\partial H_w} = \frac{\gamma}{H_w}$$
$$\frac{\partial S}{\partial a_w} = -c'(a_w)$$
$$MRS = -\frac{\gamma}{H_w c'(a_w)}$$