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ABSTRACT

The Determinants of Trust: Evidence from Rural South India*

Trust and participation in social networks are inherently interrelated. We make use of India's demonetization policy, an unexpected and unforeseeable exogenous variation, to causally identify the effect of social networks in determining trust. We use first-hand quantitative and qualitative data from rural South India and control for individual characteristics (personality traits, cognitive ability) that could influence network formation and trust, finding that social interactions have a significant effect on trust among men, as well as across castes. Among lower castes, who live in homogeneous neighborhoods and relied on neighbors and employers to cope, extending one's network lowers trust in neighbors. Among middle castes, who live in more heterogeneous neighborhoods and relied predominantly on other caste members, a larger network size leads to greater trust placed in kin among employees but lesser in neighbors. This paper thus shows that social interactions can foster trust and highlights the importance of clearly defining in- and out-groups in trust measures within highly segregated societies.

JEL Classification: O12, D85, D91
Keywords: India, trust, social networks

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1 Introduction

Many transactions in developing countries, from obtaining personal credit to workplace interactions and business transactions, involve personal, informal relationships, relying on so-called social capital instead of formal institutions. Social capital refers to the "actual and potential resources which are linked to the possession of a durable network of more or less institutionalized relationships of mutual acquaintance and recognition" (Bourdieu, 1980, p.2). Trust in those around one is thus an essential ingredient of social capital, enforcing transactions in the absence of formal markets (Fukuyama, 1995; Putnam, 2001). Trust can be understood as an "optimistic expectation or belief regarding other agents' behavior" (Fafchamps, 2006, p.1183) arising from a variety of sources, such as repeated social interactions or a general knowledge about the share of trustworthy and cheating agents in a given population and their incentives. It has been shown to play an important role in economic performance (Knack and Keefer, 1997; Slemrod and Katuščák, 2005).

Despite the importance of trust for facilitating informal interactions, our understanding of the origins and determinants of trust remains limited. Fehr (2009) notes that informal institutions, such as social networks, are likely to shape trust. However, a causal relationship is difficult to establish due to the inherent endogeneity; individuals' beliefs about the trustworthiness of others are influenced by experiences of others' trustworthiness, which in turn feeds back into interpersonal interactions and beliefs. Nooteboom (2007, p. 33) phrases the dilemma as follows: "Trust is both an outcome and an antecedent of relationships. It forms a basis for relationships, and thus generates social capital. It may be based on institutions, and it may be built from relationships, and then it arises from social capital."

In attempting to understand the causal relationship between social interactions and trust, the economic literature has resorted to the use of unexpected shocks (conflict, violence) and economic games. Rohner et al. (2013) take the example of civil conflict in Uganda and, exploiting variations in the spatial and ethnic nature of fighting, find that more intensive exposure to fighting decreases generalized trust and increases ethnic identity, attributing their findings to a breakdown of civic and economic cooperation within society. Similarly, Fearon et al. (2009) look at the effect of a positive shock - the arrival of a donor-aided, community-driven reconstruction program - on social cohesion in Liberia, measured by the amount of funding a community raised through public good games, finding that a simple participatory politics program, designed to increase community committee structures and support those structures in meeting community needs, increases the amount of money that a community raised. The role of social interactions thus seems crucial; Rohner et al. (2013) attribute the reduction in trust following conflict to a breakdown of cooperation, whereas Fearon et al. (2009) find that increased social interaction through a community based program leads to increased group cohesion. Indeed, social connections have been found to be an important determinant of trusting others (Glanville et al., 2013).

The aim of this paper is to causally identify the determinants of trust in a setting marked by high levels of informal transactions and strict social hierarchies: rural South India. In this setting, traditional agrarian structures, based on a strict segmentation and hierarchy of occupations according to caste and gender, are increasingly contested and reconfigured, with social networks playing a growing role (Guérin et al., 2015).

This paper contributes to the literature by causally identifying the determinants of trust in this dynamic rural setting using the demonetization policy in India as a source of exogenous variation and relying on first-hand quantitative and qualitative data sources. Demonetization, the ban of the two highest value banknotes in circulation on November 8th, 2016, was unexpected, unforeseeable, and took place overnight and led to severe cash shortages. Households could not have prepared for it and were hit by an exogenous variation in money supply, which is especially relevant in a cash-based economy such as India. Resulting cash shortages led to an increased demand for informal credit, and people were forced to rely on their social networks more than ever to cope with the shock. This external variation thus shifted individuals' reliance on their networks, revealing information about who they could rely on in times of crisis (based on how they judge others' trustworthiness). The shock did not have any direct effect on levels of trust placed into neighbors or kin: we will assume and show that any effect should purely operate through changed patterns of social interaction.

The setting is quite similar to the cash-deprived economy of early modern England, described by Muldrew (1998), where cash shortages led to an increased demand for informal credit and a multiplicity of informal transactions. As formal credit guarantees provided by the state were weak and demand for informal credit high, households found ways to provide informal credit or material exchanges to each other based on trust. In such an economic system, neighbors were encouraged to judge one another's credit and thrift. This mechanism of coping with shocks had already been well-established in South India before the demonetization shock and intensified as a result. The South Indian setting is special, however, due to its dependence on caste as social capital (Munshi and Rosenzweig, 2016), as illustrated by the following example:[1]

> Gomathi (female, 26 years old) is an agricultural coolie (laborer), living with her husband, who migrates part of the year to another state for work. When asked who she would ask for help while her husband was away, she mentioned her family and the 'people around her'. Asked what she meant by the latter, she described a reciprocal system, in which she could always ask her female neighbors, members of the same caste, for small urgent amounts of money. To quote: "This kind of help, they [other women] never ask any interest. But at the same time, they also demand 100 rupees from me whenever they need it. So you are in a position to give 100 rupees whenever they demand as well."

Trust is likely to be determined not only by social interactions but by a variety of

[1] The life stories included in this paper stem from semi-structured interviews that were conducted by the authors in December 2016, approximately one month after demonetization.

individual characteristics, such as gender, age, height (Dohmen et al., 2008) or cognitive ability and personality traits. Jones (2008) surveys the literature on cooperation games (prisoner's dilemma games) and finds that students from schools with higher SAT scores, a standardized test widely used for college admissions in the United States, cooperate more than those from schools with lower scores. In the game's setting, trust arises as one player (the investor) has to decide whether to send her endowment to the other person or keep it. The decision to send money (and how much to send) depends, then, on the investor's beliefs about the other person's trustworthiness (willingness and probability to cooperate) and the investor's willingness to make herself vulnerable to the actions of another person (Hong and Bohnet, 2007). Dohmen et al. (2008) use data from the German Socio-Economic Panel and present evidence that psychometric measures (measured by the Big Five, a personality test thought to capture the broadest level of personality traits) have predictive power for trust and reciprocity. Our paper is special in its ability to include measures of individual cognitive and non-cognitive ability in a rural developing country setting. Assuming consistent measurement of these traits, we can thereby include variables into the regression that are usually part of the unexplained individual heterogeneity captured by the error term. Further, the determinants of trust could well vary between countries and cultural areas. India, for example, has above average values on positive reciprocity on a global level (Falk et al., 2018), justifying the focus on this particular region.

We find that social interactions only had a significant effect on levels of trust among men. Further, we find important differences along the lines of caste membership. Among lower castes, who live in homogeneous neighborhoods and relied on their neighbors and employers to cope with the shock, extending the network leads to lower levels of trust in neighbors. Among middle castes, who live in more heterogeneous neighborhoods and relied predominantly on other caste members to cope, a larger network size leads to higher levels of trust placed in kin among employees but lower levels of trust in neighbors (who tend to be more dissimilar). This paper thus shows that social interactions can foster trust, though this is dependent on the type of interaction occurring. The paper also demonstrates the importance of having clearly defined in- and out-groups in trust measures, given the highly segregated nature of social interactions in rural South India.

The remainder of this paper proceeds as follows: section 2 provides context for the study region and the demonetization policy; section 3 offers a brief theoretical framework that is useful for understanding the presupposed mechanisms; section 4 introduces our data set and the construction of the main variables; section 5 describes the empirical strategy; section 6 depicts our results and robustness checks and section 7 concludes.

2 Background

2.1 Tamil Nadu

The data collected for this paper stem from Tamil Nadu, a state in the extreme South of the Indian Subcontinent. Like India as a whole, it has seen impressive economic growth over the last several decades, but it is also one of India's most developed, urbanized, and industrialized states. The changes in recent years have been accompanied by strong inequalities between urban and rural areas, however. This two-tier development has resulted in a complex society wherein old structures coexist with new forms of relationships in the labor market and in social hierarchies.

Over the last three decades, in the region studied, members of upper castes (oftentimes landholders) have moved away from local villages to nearby towns, selling their land to members of middle castes, thereby initiating a restructuring of land and labor (Guérin et al., 2015). As a result, the protection traditionally provided by landholders has gradually been replaced by a contractualization of labor. Such a land transfer from the traditionally dominant caste to the intermediate and lower castes has reshaped local power structures, and therefore network structures. The fragmentation of land and the associated changed organization of labor supply have then led to the development of non-agricultural employment, while simultaneously increasing the importance of networks and encouraging intra-caste solidarity (for instance, with regard to accessing urban jobs). New occupations in rural non-farm employment have also increased connections between urban and rural areas and promoted social and geographical mobilities (Breman, 1996; Guérin et al., 2013). Local inequalities remain strong: while the situation of the Dalits has been improving due to a combination of temporary migration and government schemes (Guérin et al., 2015), they continue to be disadvantaged on the labor market as the vast majority of employers are from middle and upper castes.

Social policies targeting the poor and lower castes have led to an increased participation of lower castes through new forms of activism (trade unions, farmers' associations, autonomous caste associations), serving to reinforce local community networks (Vijayabaskar and Kalaiyarasan, 2014). It is in this changing economic and social landscape that we aim to investigate the determinants of trust.

2.2 Demonetization

On November 8th, 2016 at 8pm local time, Indian Prime Minister Narendra Modi announced the ban of the 500 and 1,000 rupee notes, the two highest value banknotes in circulation. From midnight onward, these two notes were no longer legal tender and had to be exchanged in banks for new notes, affecting about 86 percent of the entire money supply. The policy was supposed to contribute to the formalization of the economy by fighting corruption, the illegal economy, counterfeit money, and terrorism, in addition to fostering the digitization of banking.

The implementation process faced many technical challenges, leading to severe cash shortages. Due to the importance of cash in the Indian economy (98 percent of transactions are estimated to be in cash), this measure had strong impacts on employment, daily financial practices, and network use for more than three months, as people relied more strongly on their networks to sustain their economic and social activities. During the first two months, cash withdrawals were limited (first to 2,000 and later 4,000 rupees per day per bank card) and lines at ATMs long, making obtaining cash a time consuming experience. The policy shock hit rural households particularly strongly, as 80 percent of ATMs are located in urban and peri-urban areas, making it more difficult for rural households to travel to them. Further, new notes were unequally distributed. In the state of Tamil Nadu, 44 percent of newly delivered notes were distributed to three private banks with only 900 branches, while public banks, with over 9,000 branches (many in rural areas), received the remainder (Ghosh et al., 2017). Further, few rural households had access to a bank account prior to demonetization, and most who did only used it to receive transfers from government schemes. Most rural households were thus hardly ever in touch with the formal banking system.

Informal social networks have been successful in mitigating the impact of this shock in multiple ways (Guérin et al., 2017). Rich individuals in our study region were able to get rid of their old notes through social relations and business tactics such as prematurely paid advances, while poorer ones could rely on their networks for informal loans; all of these relationships rely on the necessary condition of trust. Demonetization led to new markets to exchange old notes at discount rates ranging from 18-40 percent (Ghosh et al., 2017). Still, this mitigation mechanism only holds for those who are integrated into social networks (Guérin et al., 2017), illustrated by the following example from our qualitative fieldwork:

> Sabeema is a female tailor who manufactures clothes for the women in her community, mostly from the same street. She experienced a reduction in customers and is increasingly working for credit. Her husband is employed as a TV-mechanic in a nearby city. He is usually paid weekly, but he had not been paid for a few weeks as his employer did not have any cash available. As a result of the double shortfall of wages, the family had to reduce their food consumption. They were not able to ask their network for help since everybody in their network was in a similar situation.

This reliance on informal credit channels such as friends and family, moneylenders, and black markets to exchange bills hit the poor and marginalized especially hard, as they saw their oftentimes meagre cash holdings losing value or being worthless. As such, social networks can have inequitable consequences when dealing with shocks, potentially widening the gap between those with and without connections (Fafchamps, 2006; Guérin et al., 2017).

3 Conceptual framework

Trust can be defined as one individual voluntarily placing resources (of whatever kind) at the disposal of someone else. In economic terms, the individual expects to be better off after making her resources available, with better off defined according to whatever goal the investor has in mind (Fehr, 2009). Given this definition, we provide a brief conceptual framework to illustrate the hypothesized relationship between social networks and trust at the core of this paper. The conceptual framework relies heavily on Guiso et al. (2008), who formalized Berg et al.'s (1995) trust game.

Assume that an individual lives in an economy consisting of two types of agents: trustworthy agents and non-trustworthy agents. The individual is then embedded in one of two potential social networks: an honest network, in which the share of trustworthy agents predominates, and a cheating network, in which the share of non-trustworthy agents is in the majority. The individual knows that there are both cheating and trustworthy agents in the economy and knows that either one could be present in her network. However, in this stylized framework, the individual is not *a priori* aware of the type of network that she's embedded in, leading to the following distribution (where $q1 > q2$):

Table 1: Distribution of trustworthy agents and cheaters

	Social Network	
	Honest	Cheater
Share of trustworthy agents	q_1	q_2
Share of cheaters	$1-q_1$	$1-q_2$

In the first period, the individual is endowed with her initial endowment x. In the second period, the individual can invest her endowment within her network, without knowing which of the two types of receivers (trustworthy or cheater) will receive her investment. This simplistic framework disregards the role of reputation as an information-sharing mechanism among individuals, which could influence an individual's propensity to engage (or not) with a specific recipient. All the individual knows prior to investing is that there might be both cheaters and honest recipients, without being able to tell who is who.

With a trustworthy receiver, the individual's investment accrues a positive return, $r > 0$, whereas with a cheater receiver, the individual accrues a loss, $l < 0$. In this framework, the individual needs to make the decision of whether or not to invest her endowment under a condition of uncertainty, as the type of receiver (trustworthy or cheater) is only revealed afterwards. It is only through investing, i.e. through interacting with the receiver, that the individual gains knowledge about the type of receiver and the type of network she's embedded in. Thus, reputation building only occurs at the individual level, and an individual will only keep interacting with those who are honest (reputable). The set-up thus implies Bayesian updating of the network in which an individual lives and interacts. Specifically, an individual might think that her network is a trustworthy one. As a result of a shock, for example, the individual might then grant another individual a loan, thereby investing her endowment. Only after this interaction does the individual realize that her network has a high number of cheaters (i.e. she lives in a cheater environment) and that her endowment is lost. The individual then updates her beliefs about the type of network she lives in.

Let $A = q_1 r + (1 - q_1)l$ denote the expected return if the receiver is part of an honest network and $B = q_2 r + (1 - q_2)l$ the expected return if she is drawn from a cheater network. Given an initial endowment of $x = 1$, we assume that $A > 1$ and $B < 1$, so that the expected return is positive if the population is honest and negative if it is not.

Let h and nh represent the true distribution of honest people (h) and cheaters (nh) in one's network. In line with this set-up, we assume that individuals who do not invest (do not interact) do not learn about the true distribution of h and nh people in their network. People choose not to interact in the first period if their prior is that they live in a cheater network. In a two period game, this then means that only people who have interacted in the first period will interact in the second, since they are the only ones who are able to update their beliefs.

Given these assumptions, an individual who interacts in the first period and finds out she lives in an honest network will thus always interact in a potential second period, since the expected value of $A > x$. However, if she finds out in the first period that she lives in an cheater network, she will not interact in a potential second period since $B < x$.

This framework is useful to keep in mind when looking at the present case of social network interaction and demonetization. In line with this framework, the first period in which the individual decides whether or not to interact with her network based on her priors in our case aligns with the time period just after demonetization. Following this shock, individuals decide to interact more only if they believe that they live in an honest network.[2] We thus expect to see that after the demonetization shock, people who have the prior that they live in an honest environment will interact more with their network and thereby in a next step learn about the true distribution of honest people h and cheaters nh in their network. As a result of this interaction, the individual then updates her priors if necessary. If, contrary to her initial beliefs, it turns out that she lives in a cheater network, this will lead to a reduction in measured levels of trust; if her initial belief of living in an honest network is confirmed, her measured levels of trust should increase.

In line with the model, we expect this increase in interaction to stem from those who already used networks before. Further, in our context, these interactions could be heavily defined by the social hierarchy in place. As such, we do not necessarily expect a similar outcome for different castes.

[2]Alternatively, the shock could have lowered the trustworthiness threshold at which an individual is willing to engage. As will be shown later in this paper, this should have led to individuals listing a larger amount of potential ties, which is not the case.

4 Data and descriptive statistics

4.1 Description of the survey

This paper is based on a novel data set from rural Tamil Nadu, entitled Networks, Employment, Debt, Mobilities, and Skills in India Survey (NEEMSIS), which was conducted in 2016/2017.[3] The survey was collected over two periods, from August 2016 to early November 2016 and then from January to March 2017.[4]

The survey was collected in 19 villages in the Cuddalore, Villuppuram, Kancheepuram, and Tiruppur districts of Tamil Nadu in an economy dominated by agriculture[5] but benefiting from the proximity of large industrial towns (Neyveli, Cuddalore, Tiruppur) and a regional business center (Panruti). The survey uses a stratified sample framework according to first agro-ecological considerations (dry/irrigated agriculture in villages), then urban proximity, and lastly social groups (caste representation). The caste representation was based on self-classification of individuals into castes using local terminologies, which were then categorized into three main categories (Dalits, middles castes, upper castes). In each village, the sample was then determined to stem half from the Ur part of the village, in which mostly upper and middle castes live, and half from the Colony part of the village, which contains mostly Dalits. The two largest caste groups in the region are Vanniyars and Paraiyars, the former classified as a middle caste[6] and the latter one of the major Dalit communities[7] in Tamil Nadu. Despite the Vanniyars' traditionally rather low rank, they are land-owners in the region studied, dominating politically. The upper caste group in the studied zone consists of Mudaliyars, Chettiyars, Naidus, Reddiyars, Settus, and Yathavars, who make up only a small proportion of the village populations. In each village, the sample was then determined to stem half from the Ur part of the village, in which mostly upper and middle castes live, and half from the Colony part of the village, which contains mostly Dalits.

The NEEMSIS consists of comprehensive household and individual level modules, completed by the household head, and a randomly chosen younger member of the house-

[3]The survey was collected by a team of researchers, including the authors of this paper. More information can be found on https://neemsis.hypotheses.org and in Nordman et al. (2017). The 2016/2017 survey is based on the structure of the 2010 Rural Employment and Microfinance (RUME) program, creating a household panel (2010-2016/2017). For this paper, we will only make use of the second wave (2016/2017).

[4]The break in the survey was due to technical issues with the tablets (batteries) and not related to environmental factors (demonetization). The principal crop in the region is paddy and the districts in the region have a three season pattern, meaning they harvest three times a year (July, November, and March). Both of our data collections took place during harvest season.

[5]The sowing and transplanting season takes place from September to December and the harvest season is from January to March. This means that our first sample (pre-demonetization) was interviewed during sowing seasons and the second sample (post-demonetization) during harvest season. This is potentially problematic as more work is available during the sowing season since harvesting is done mechanically. However, we do not actually observe any significant differences in employment shares between the pre- and post-demonetization samples.

[6]Additional middle caste groups present in the region of our survey are Padayachis, Gramanis, Navithars, Nattars, Kulalars and Asarai.

[7]A few Arunthathiyars who are part of the Dalit community are also present in the region.

hold (older than 18 and younger than 35). The total sample size of the individual survey is 952 individuals. This individual-level survey provides more detailed information on labor force participation, labor outcomes, and social networks, alongside a cognitive and a non-cognitive skills assessment (Raven's Colored Progressive Matrices, literacy, numeracy, and a Big Five questionnaire). The social networks module includes information about membership in associations (e.g. self-help finance groups, village councils, sports groups) and detailed information on actual and potential interactions with others, as is explained in more detail in the next section.

4.2 Construction of the social network variables

Using the detailed social networks module of our survey, we construct two different social network variables, capturing interactions of individuals in our data set with a variety of actors. Interactions in our data cover formal and informal social capital as well as actual and potential interactions. Formal interactions include membership in associations (such as a farmers' association). Informal interactions include all sorts of social connections that an individual may have made. The data on interactions was collected using a name generator which was included as part of the individual survey. The name generator follows sociological research approaches (McCallister and Fischer, 1978) and invites the respondent to recall and elicit people ('alters') with whom they maintain certain types of direct relationships in order to delineate the core members of the network (Marsden, 2005). These include borrowing from and lending to each other, helping others or seeking help in finding work, relying on connections for help with a business or supply of tools, and so on. As part of this name generating process, we also collected background information on these alters (such as caste, age, gender, education) and on the relationship between the survey respondent and alters. As we only have a single measure of formal social capital (number and types of associations of which an individual is a member), we will not consider differential effects of formal and informal social networks; instead, we combine both into composite measures.

The actual ties refer then to links an individual has explicitly made. This includes having borrowed or lent money to others, recommended somebody for a loan (or received a recommendation from somebody), recommended somebody for a job (or received a recommendation), or received help with a loan. The potential ties consist of all connections that an individual could use if the need occurred. This includes questions regarding whom the individual would ask for help if in need of information, help with the business, help with finding a job, or recruiting workers. It also includes household size, counting family members 15 and older only, as the survey does not allow for family members to be included in the borrowing/lending links mentioned before.[8]

[8]While we already capture quite a number of interactions, this social network data set is by no means a complete representation of reality. We are relying to a large degree on interactions of an economic nature (financial practices and labor interactions), without being able to capture an individual's full network. For example, while we are including loans taken out for marriage as part of the actual ties, the pure growth in one's potential interactions due to the merging of

Lin (2001) defines the structural foundation of social capital as "resources embedded in a social structure that are accessed and/or mobilized in purposive actions" [ibid, p.40]. In this framework, our potential ties variable would refer to something akin to the resources component of social capital, the part that is potentially accessible to an individual through her social network. Our actual ties variable then relates more to concepts of activation, accessibility, and mobilization. These are the resources that an individual can access not only in theory but in practice. We use the network data to construct two different measures of social networks, which will be our main independent variables of interest for this study.

The first measure of social networks that we will look at is *total network size*, which is the sum of the ties that we observe.

$$size_i = a_i + p_i,$$

where a_i are the actual and p_i the potential ties of individual i.

The rationale of this network variable follows from Johny et al. (2017) who consider intra-village social networks in poor rural areas in Kerala, a state in South India, and find that the number of connections a household has is more important than alternative measures of network centrality such as degree or eigenvector.[9]

The second measure of social networks that we consider relates to *network usage* rather than of pure size. We define network density, the share of connections used as follows:

$$density_i = \frac{a_i}{a_i+p_i},$$

where a_i are the actual and p_i the potential ties of individual i.

Thus, either definition captures a different idea within the broader concept of social networks. Given their different definitions, we do not necessarily expect them to influence trust measures in the same way. Based on our conceptual framework described in Section 3, we would expect $size_i$ to influence trust positively: if, after the demonetization shock, an individual still elicits a large number of ties, this means that the individual, who increases interactions as a result of demonetization, was confirmed in their belief to be living in an honest environment, or at least confirmed in their belief of who can be relied on. We would expect $density_i$ to potentially have a negative effect on measured levels of trust. A higher value on the $density_i$ measure means that individuals have to use their networks more intensely; this includes making resort to ties that would not usually be activated. If the individual has to rely on weaker ties, this could suggest that their belief of living in an honest environment was rejected, as closer ties were unwilling (or unable) to help. As a result of higher network usage, we might then expect lower levels of trust.

two families cannot be taken into account given the structure of the data. We only capture the size of the survey unit, the nuclear household.

[9]Eigenvector centrality is a measure of the influence of a node in the network. It takes into account the number of neighbors, but also the importance of those neighbors, i.e. whether those neighbors are themselves central to the network.

4.3 Measuring trust

We use three different measures of trust, which are all related to interpersonal trust, i.e. trust in other people:

1. People in my neighborhood can be trusted.
2. Among employees, kin members are more trustworthy than non-kin members.
3. Are you generally trusting of other people?

Trust in neighborhood

Villages in rural South India are highly segregated by caste: middle and upper castes tend to live in a part of the village called 'Ur', while lower castes, Dalits, tend to live in the 'Colony'. Upper castes tend to live alongside middle castes in 'Ur'. These parts are oftentimes separated physically. In several survey villages, for example, Ur is located on one side of a cross-country road, while Colony is located on the other. Neighborhoods in the study region can thus be highly homogeneous in terms of caste membership (especially 'Colony') and the socio-economic status of their inhabitants. This is a common finding in India, where spatial segregation leads to a high level of local social connectedness within caste networks (Munshi, 2016a), thus leading to closed intra-group and weaker inter-group relations. Caste groups within villages are usually big enough to support a local community, which would then foster ties with other villages through intra-caste marriages. Munshi (2016a) find that there are on average about 30 different castes per village; in our survey, we can distinguish between 3-8 different castes. As a result of the social segregation, one would thus expect a country like India to score highly on questions about trust in neighbors. Using the World Values Survey, Munshi (2016a) show that almost 90 percent of people in India say that they trust their neighbors. In measuring trust with the question 'People in my neighborhood can be trusted' it is thus important to keep in mind the different reference points for the different castes.

Trust in kin vs. non-kin among employees

The second measure of trust refers to an even closer in-group (kin) versus the out-group (non-kin). South India has tight kinship structures, which has been negatively correlated with out-group cooperation in other countries (Herrmann et al., 2008). The question 'Among employees, kin members are more trustworthy than other non-kin members' relates to the distinction of kin vs. non-kin in a very specific environment: the workplace. In South India, labor contractors are an important intermediary ("maistries"); they are the middlemen between, for example, the contractor responsible for painting a house and the oftentimes unskilled laborers who carry out the work. These middlemen are primarily responsible for finding the laborers to work on the project, including making sure the laborers show up to work and assuring that they have done quality work. Because castes are traditionally occupational units, choosing the right laborers is important for the labor contractor, who therefore oftentimes resorts to hiring his own kin due to informal mechanisms of ensuring quality work (Munshi, 2016a).

Generalized trust

The last question with which we measure trust is most closely related to measures typically used in surveys, such as the World Values Survey. The question 'Are you generally trusting of other people?' is not specifically related to the context of rural South India, but it is thought to capture the concept of generalized trust. It is also the most difficult question to answer and use for the analysis, though, as trust is in and of itself dependent on circumstances (Nooteboom, 2007); for instance, one might trust someone in one condition but not in another seen as beyond that person's level of competence. Generalized trust is oftentimes understood as a broader definition of trust, placing more weight on trusting people beyond the local community.

Answers for all three questions were recorded on a Likert answer scale ranging from completely disagree to fully agree. A Likert scale was chosen to elicit answers to prevent problems with ambiguous wording (Miller and Mitamura, 2003).[10] In general, as they refer to survey questions and not results from a trust game, all three measures capture a combination of people's beliefs about others' trustworthiness, betrayal aversion, etc. (Glaeser et al., 2000; Fehr, 2009). They will be standardized for ease of interpretation in the regression analysis.

The three different questions were chosen as they all represent different aspects of trust in others that are important in the context of rural South India.[11] We decided to keep all three measures of trust separately instead of combining them in an index, as the literature notes the importance of distinguishing between trust in different actors (e.g. Haddad and Maluccio, 2003). This is particularly important in India, as it relates to both the specific cultural context structured by high levels of social segregation and the context of the shock that is used for identification. Indeed, one would expect the demonetization shock to primarily foster interactions locally, which might not translate to any effects if measured by a broad question regarding generalized trust in people. Further, all three measures are purely related to trust in people. This is important to keep in mind, as measures of trust that are related to more formal institutions, such as trust in banks or trust in associations, could potentially be directly influenced by the demonetization policy. Indeed, as will be explained in more detail in section 5.2.2, it

[10] Miller and Mitamura (2003) examine trust questions included in the World Values Survey and find that reducing answer possibilities to a simple agree or disagree can lead to conflicting answers and misinterpretations regarding the concept actually measured, which related closer to a measure of caution than levels of trust.

[11] All three measures are related to prosociality. We looked at other correlates of prosociality in our data, i.e. facets of the Big Five traits agreeableness, openness to experience, and extraversion. Conducting factor analysis over the entirety of the Big Five questionnaire and our trust measures to see whether other questions are in fact very closely related to the three questions chosen, we find that all of the three trust measures used in this paper load on the same factor. The only other question loading on that factor is "Do you enjoy being with people?" which reflects strongly on positive behavioral dispositions to others. While this is certainly related to trust, trust refers more clearly to a belief rather than a social preference towards social interaction. We therefore decided to proceed with the three questions described in this section.

seems unlikely demonetization had a direct effect on trust in people directly. Sentiment analysis of demonetization in Tamil Nadu further shows a neutral perception of policy (Singh et al., 2018).

4.4 Descriptive statistics

Table A1 provides descriptive statistics of the main variables used in the analysis. The sample is restricted to those with non-missing cognitive and non-cognitive skills values. The individuals in our sample are on average 42 years old. A little more than half of the sample is male and most people (about 82 percent) are married. The survey uses a stratified sample based on caste, with about half belonging to the lowest castes (Dalits). The other half belongs predominantly to middle castes, with only a few people (10 percent) identifying as belonging to upper castes. Education in the villages covered is still low: 38 percent of villagers did not complete primary education and another 21 percent stopped after completing primary. The education variables hide important generational differences, though, as younger generations have shown fast improvements in educational attainment. Indeed, the vast majority of people with at most primary education is concentrated among those aged 40 and older, while less than 4 percent of the 19-29 years old have completed less than primary education. Similarly, almost all of the educational attainment above a secondary school degree ("10 Standard") is concentrated among the young, of whom 21 percent have obtained a Bachelors degree.

In addition to educational attainment, we included more objective measures of cognitive ability in the survey (the Raven test) as well as measures of functional learned ability such as literacy and numeracy. On average, individuals answered only slightly more than 13 out of 36 questions of the Raven's test correctly. Interestingly, the vast disparities by age group in terms of educational attainment cannot be observed in the Raven test; while younger people (18-29 years old) perform better than older ones, the differences are small and not statistically significant. The numeracy and literacy questions were set up to test basic, primary school-level knowledge. The low means (less than 2 correct answers for each) reflect the oftentimes poor quality of education in rural India. Measures of non-cognitive skills were included to capture the multidimensionality of skills. Individuals in our sample score highest on the trait conscientiousness and lowest on openness to experience.

Our measure of social network density illustrates that individuals use on average only 15 percent of their social network and that, on average, they have a total of 8.22 ties in their social networks. Trust in the sample is high: on average, individuals score about 3.9 out of 5 on the question asking whether neighbors can be trusted and 3.45 out of 5 on the question on whether kin can be trusted more than non-kin. Generalized trust is slightly lower at 3.2. This is in line with other surveys that also find very high levels of trust in neighbors in India (as cited in Munshi, 2016a).

5 Empirical strategy

5.1 OLS

In order to estimate the effect of social networks on trust, we start from a basic OLS regression:

$$Trust_i = \beta_1 SN_i + \beta_2 X_i + \varepsilon_i \tag{1}$$

where $Trust_i$ represents our outcome of interest, different measures of trust, for individual i. SN_i captures the social network of individual i (total network size or network density), X_i is a vector of individual and household control variables that is thought to affect the level of trust, and ε_i is the error term, capturing any remaining individual heterogeneity. X_i includes among other things information on individual i's cognitive ability and personality traits, as personality traits have been shown to affect levels of trust (Dohmen et al., 2008; Freitag and Bauer, 2016). Assuming consistent measurement of these traits, we can thereby include variables into the regression that are usually part of the unexplained individual heterogeneity captured by the error term, particularly in a rural developing country setting. We also add media exposure and access to a savings account as control variables to capture the channels through which demonetization could have directly affected interpersonal trust.

5.2 Instrumental variables

The correlation captured is likely to suffer from endogeneity bias. For example, if we happen to find a positive relationship between social networks and levels of trust, this could be consistent with our hypothesis that social interactions foster trust, but the correlation could also be explained by people who are by nature more trusting forming larger and more extended social networks. Social network could thus be an endogenous variable. In order to estimate the causal effect of networks on trust, we make use of the demonetization shock as a source of exogenous variation that affects social networks but does not affect trust in other people directly.

Using demonetization as a source of exogenous variation for our study is possible because about two-thirds of our sample was interviewed before (November 2016) and the other third about two months after (January - April 2017) demonetization had occurred. The chronological sequence of household data collection was almost random, or at least had no obvious and systematic collection plan across the 19 villages. As such, around two thirds of the first subsample had not experienced the sudden demonetization shock when we interviewed them; the other third experienced the shock and may have used their networks to cope.

The framework is as follows:

$$SN_i = \alpha X_i + \gamma D + \mu_i \tag{2}$$

$$Trust_i = \alpha X_i + \beta \widehat{SN_i} + \varepsilon_i \tag{3}$$

where D is a dummy variable, taking the value of 1 for individuals who have been interviewed after demonetization and 0 otherwise; X_i is a vector of individual and household control variables that is thought to affect the level of trust. This includes information on individual i's cognitive ability and personality traits, $\widehat{SN_i}$ is the predicted value of SN_i, our measures of social networks, recovering an exogenous measure of SN_i.

For any IV strategy to identify the local average treatment effect (LATE) consistently, the instrument must satisfy two conditions: (1) it must be correlated with our measures of social networks, and (2) it must not be correlated with μ_i, thus it must not be correlated with factors directly affecting levels of trust. Failure to satisfy these conditions can lead to inconsistent estimates, asymptotic bias, and large standard errors (Bound et al., 1995; Wooldridge, 2010).

5.2.1 Relevance

Our data show that interaction increased as a result of demonetization. This is in line with our conceptual framework described in Section 3, as we expect to see that after the demonetization shock, people who have the prior that they live in an honest environment will interact more with their network and thereby in a next step learn about the true distribution of honest people h and cheaters nh in their network. Data on lending behavior, for example, show that while only 5 percent of individuals in our sample claim to have lent money to anybody before demonetization, this figure jumps up to 11 percent among those interviewed after demonetization.

Guérin et al. (2017) provide a first overview of how individuals in our study region coped with the sudden shortage in cash, suggesting that individuals had to rely on their networks more than they usually do. This holds for both richer and poorer individuals: the better off made use of their networks to dispense of old and now invalid notes, enabling them to prevent having to endure the long lines at banks and to cash in potentially illegal notes, while poorer individuals relied on their networks for informal loans to cover shortages in wages. Qualitative evidence supports the view that those who are part of a supportive network made use of it to cope with the shock and were able to mitigate its risks, while those who did not have the 'right' networks suffered. The first example below describes the small business of a woman who belongs to a well-connected family and the effect of demonetization on that business.

> Bargath (female, 32 years old) sells chicken from her home in the Ur part of one of the villages. Bargath is part of a dynasty of chicken vendors: both her father and grandfather were involved in the same business. Her brothers are still involved in chicken farming and selling, though neither of them lives in the same village. Bargath sells mostly to customers from the Colony part of the village. Bargath's father taught her never to sell on credit -

> a guiding principle she has employed in her small business. When asked whether she had experienced any change in her business dealings as a result of demonetization, Bargath replied that for her, demonetization did not have any effect whatsoever, as she could rely on her extended family members. She went on to explain that her supply of chicken had not changed as it came directly from her brothers. Further, she was able to accept "old" 500 rupee notes, as her brothers would then take care of exchanging the money for her. She continued not to sell for credit; however, as she was able to accept notes that were officially no longer legal tender, her customers remained able to pay her.

The second example describes a shop owner who was unable to deal with the demonetization shock through networks and instead had to resort to a loan from a moneylender.

> Saleem Basha (male, 41 years old) runs a small local grocery shop. Following demonetization, he had to start selling goods on credit since customers did not have any cash at hand. He further had to take out a loan from a moneylender in order to buy supplies for his shop. In his opinion, if he did not take out a loan in order to continue offering goods, customers would take their business elsewhere and not return.

The examples above illustrate the role that social interactions had in coping with the unexpected demonetization shock. While they describe the mechanisms at hand, they are also not fully representative of the sample population: in general, women in the study area are less able to access resources (for example, in our data set, the majority of loans have been taken out by men).

5.2.2 Exclusion restriction

The exclusion restriction requires that the instrument (demonetization) does not correlate with factors directly affecting the outcome (trust in people) other than through its impact on social network variables and that the instrument should be close to random assignment. The instrument only affects trust through its effect on social networks.

First, conceptually, the component of trust that we think we measure and that could be changed in a rather short period of time (about 2-5 months had passed between the demonetization shocks and the interview) is not necessarily people's preferences, but rather their beliefs about others' trustworthiness (Fehr, 2009). It seems likely that demonetization changed these beliefs only through the fact that demonetization increased the likelihood of *interacting* with others. This is exactly the framework that we have in mind and described in Section 3: only those who invest (interact) learn about the true distribution of h and nh people in their network. Therefore, only those who interact will update their priors about others' trustworthiness, leading to an increase in measured trust if the individual's belief of living in an honest environment is confirmed and a decrease in trust if her initial belief is rejected. We are further only considering short-term effects (evident 2-5 months after the shock). It is conceivable that the shock affected risk attitudes and as a result trust in the medium to long run; however, this seems unlikely to happen in the 2-5 months time period that we are considering in this paper.

Second, individuals themselves did not think that demonetization as such had a direct impact on their levels of trust. A short additional demonetization module was administered to those who were interviewed from January - April 2017 (after demonetization). This module contained questions about whether or not individuals think demonetization influenced their answers. The question was asked after the answers to the other questions had been elicited and should therefore not frame the answers to the trust questions themselves, meaning they remain comparable between the pre- and post-demonetization samples. Table 2 presents answers to these questions. It becomes clear that most individuals did not think demonetization changed their levels of trust. Among those who did experience a change, the share of individuals experiencing a positive or negative change is almost the same for neighborhood and employee trust.

Table 2: Change of trust in:

	Neighborhood	Employees
Increase	10.6	11.8
Decrease	15.0	14.3
No change	74.4	73.9
N	273	272

Source: NEEMSIS (2016-2017); authors' computations.
Note: Question asked to post-demonetization sample only.

Looking closer into changing trust due to demonetization lets us draw out two interesting observations: first, 78 percent of those who claim not to have experienced a change in the trust questions also claim not to have had to ask anybody else for help because they did not need to. No change in trust levels thus correlates with no additional social interactions. Second, those who claim that demonetization affected their levels of trust (either positively or negatively) also reported having interacted more, whether through asking others for help (12 percent), through realizing there was nobody there to help (34.5 percent), or through asking but being refused help (8.6 percent). Again, this suggests that the effect of demonetization on trust only acts through the channel of social networks. In the IV framework, what we are estimating is the LATE: the average effect of X on Y for those whose treatment status has been changed by our instrument. We are thus identifying the effect of a social network on trust - the underlying research question of this paper - among those whose who interacted as a result of the treatment (demonetization).

Third, the proposed instrument should be as good as randomly assigned across the 19 surveyed villages. The chronological sequence of household data collection did not follow any systematic collection plan in the sense that we did not start our data collection in the poorest or richest villages, nor in the ones closest to, or furthest away from, the regional hubs, which could arguably have significantly altered the composition of the pre- and post-demonetization sample. Table A2 depicts descriptive statistics of the individuals interviewed by timing of interview (before or after the demonetization shock). Despite demonetization being *a priori* as good as randomly assigned, Table A2 shows that this does not hold in practice. Indeed, a Hotelling's T-squared generalized means test rejects the hypothesis that both samples are equal. We will therefore use matching based on covariates to balance the pre- and post-demonetization samples.

5.2.3 Balancing the pre- and post-demonetization samples

Despite the demonetization shock falling randomly into our survey collection time schedule, the previous section has shown that there are significant differences in the pre- and post-demonetization sample. We therefore use matching techniques to balance the samples. Given the rich nature of the data collection, we can match based on a number of covariates that could influence the outcome, including individual characteristics such as personality traits or cognitive skills, age, marital status, education, gender, and caste. We further match based on household characteristics that could affect the outcome, most notably consumption (food expenses, health expenses, ceremonial expenses), household income, and characteristics of the household's dwelling (access to electricity, water, sanitation, and type of house).[12] In total, we are matching based on 12 individual characteristics and 8 household characteristics. We use nearest neighbor matching and restrict our sample to those for whom we have common support (see Figure A1). We use full covariate matching instead of matching based on the propensity score for several reasons: matching on covariates is usually better in terms of asymptotic efficiency (Angrist and Pischke, 2009); our data set includes a large set of covariates for matching, including some individual characteristics such as personality traits and cognitive skills that are oftentimes considered to be part of the unobservables; and the process of matching on observables requires the researcher to focus on the covariates determining outcomes (trust in our case) and choosing the appropriate covariates to match on. While this latter reason could be prone to error, we still have a better idea of what could determine trust than what could determine treatment assignment (being interviewed before or after the demonetization shock), since in our case treatment was not based on certain individual characteristics such as age or gender. Instead, and while this is not fully reflected in the unmatched sample, from the point of view of the data collection, treatment was

[12] Matching on personality traits is based on the assumption that differences in personality traits between the pre- and post-demonetization samples are due to us interviewing fundamentally different people and not due to any direct effect of demonetization on personality traits. As individuals interviewed before and after do significantly vary in their non-changeable characteristics such as gender, educational attainment and (to an extent) age (see Table A2) and as personality traits seem rather stable among adults and only slightly related to adverse life events (Cobb-Clark and Schurer, 2012), this assumption is not unreasonable. We also match without the cognitive and non-cognitive skills variables. This reduces our ability to control for individual heterogeneity, which might be important, especially with regards to trust formation. Results hold in coefficient sign and mostly in significance.

essentially distributed randomly. Matching reduces our analysis sample from 885 to 645 individuals for whom we have common support. Importantly, we manage to match almost all of the individuals from the treatment group. Table A3 displays the matched sample and shows that differences between the post- and pre-demonetization samples are no longer statistically significant for the covariates that we matched on. Conditional on matching, we thus conclude that the demonetization shock is as good as randomly distributed.

5.2.4 LATE framework

The previous sections have shown that our instrument is relevant and as good as randomly assigned. This assumption holds conceptually, as the demonetization shock was both unexpected and implemented uniformly across the country instantaneously, as well as empirically, conditional on matching on covariates. Given these necessary conditions, it is important to note that the effect that we are estimating is likely to be a Local Average Treatment Effect (LATE), as we are covering the effect on the compliers, i.e. those who adjusted their interactions as a result of the treatment (demonetization). While everybody interviewed after January 2017 did by definition live through demonetization, not everybody reacted to it in the same way. In the results section, we therefore consider heterogeneous effects by characteristics that we think could influence somebody's chances of being a complier, such as caste category and gender. Given the specificity of the setting, the results obtained in this study are internally valid, but they are unlikely to be applicable to other settings that do not have the same strict social hierarchies, which fundamentally determine the type of social interactions that are possible.

6 Results

6.1 OLS estimates of the determinants of trust

Table A4 depicts our first results, separate OLS regressions with the different measures of trust as the dependent variables (trust in neighbors, trust in kin among employees, and generalized trust). All three trust measures and both measures of social networks (size and density) have been standardized for easier interpretation. The OLS regressions are based on the balanced samples obtained from matching on covariates, as described in the previous section, and are weighted by the matching weights retained. In the regressions, we control for a variety of potential individual and household determinants of trust: age, gender, being married, caste membership, educational attainment, a set of occupational dummies, the standardized score on the Raven's test (a cognitive test), the standardized scores on the numeracy and literacy tests, and standardized and acquiescence corrected personality traits (Big Five and Grit) for individuals; and household expenses on food, health, and ceremonies (to control for a consumption effect as a result of demonetization), a dummy indicating whether any person of the respondent's household (including the respondent) has a savings account in a formal bank, and a dummy for media exposure (owning a TV or satellite dish antenna) to control for the influence of the policy discourse on interpersonal trust (e.g. Prime Minister Modi's announcement on TV explaining the high prevalence of corruption in India). Sentiment analysis demonstrated a neutral perception of demonetization in Tamil Nadu (Singh et al., 2018). Still, we include media exposure and access to formal banking to address channels through which demonetization could have affected trust directly, for example, through changing trust in government. We include village-area fixed effects to capture village specific heterogeneity. Following Abadie et al. (2017), we decide not to cluster standards errors at the village level because i) the sample was not meant to be representative of the village population; ii) the treatment (demonetization) was not assigned at the village level, but nationally; and iii) there was no treatment assignment overtime across villages as the survey implementation did not follow a strict village sequence of data collection. In other words, within village we have treated but also untreated household and individuals.

Table A4 shows that total network size is positively correlated with agreeing that, among employees, kin can be trusted more than non-kin (column (4), significant at the 1 percent level); it is also positively correlated with more trust in people in general though not statistically significantly so. Network density shows the opposite picture: those who have a higher network density (that is, those who use more connections as a share of their total connections) are more likely to trust neighbors and less likely to trust people in general. None of these effects are statistically significant. While these analyses are probably subject to bias due to the endogeneity of the social network measures being both the cause and consequence of trust, it already illustrates that network size and network density are distinct concepts that do not necessarily have the same effects. While many trust measures are not significant in the OLS, this does by no means mean that the hypothesized relationship between network measures and trust does not hold. Instead, the OLS results are likely to be biased precisely due to the endogeneity of our network measures. We therefore make use of the demonetization shock in the next section to overcome issues related to the endogeneity of the network measures.

6.2 First stage results: determinants of network size and density

Columns (1) of Tables 3 and 4 depict the first stage regressions for our network measures network size and density, respectively. Both show that the demonetization shock is a strong predictor of our network measures.[13] The first stage coefficients make sense intuitively (as described below) and reduced form regressions[14] of the outcome variables (trust measures) on the instrument (demonetization) show the same relationship. Further, our IV estimation is identified with only one potential instrument, which makes it median-

[13]The F-statistic for the first stage of network size is 44.4 and 7.6 for network density, which are above or close to the F-statistic of 10 recommended by Stock et al. (2002).

[14]Results not reported, but available upon request.

unbiased and less subject to the weak instrument critique (Angrist and Pischke, 2009). Therefore, we believe that demonetization is a strong instrument with which to proceed.

The experience of demonetization decreases network size by more than half a standard deviation (0.6) on average for an otherwise equal sample (thanks to the matching), and it increases network density by about a third of a standard deviation (0.29). As mentioned earlier, network size is the sum of all actual and potential connections an individual has either made (mostly related to financial and labor market practices) or claims that she can make if necessary (the potential connections). Table A3 shows that both the amount of actual ties that an individual has made and the amount of potential ties changes with demonetization, with the number of actual ties increasing (marginally) and the amount of potential ties decreasing (more strongly). The mechanism at hand thus seems driven by potential ties, which relates back to the conceptual framework described in section 3; the demonetization shock forces individuals to interact with their networks to cope, which reveals information about their network. In a first step, individuals then update their beliefs about their networks. There is some suggestive evidence of this in the data: among both Dalits and middle castes, those who lived through demonetization and answered that they did ask somebody for help as a result of the shock name more potential ties than those who claimed that there was no one to ask. This could suggest that those who were given help updated their beliefs about who they could turn to in times of crisis upward, while others might have realized that there was nobody to help and updated their estimate downward instead. Density increases with demonetization; given the previous results on size, this suggests that instead of expanding their networks, individuals might have tried to use their existing networks more intensely. Given the strict social hierarchies and spatial segregation in rural South India, expanding one's network to new actors might have been simply unfeasible for some, as network size is essentially determined by the size of one's caste community.

Turning to the covariates, being a women is associated with a smaller total network in terms of size and a lower network density. While both women and men are involved in borrowing and lending, men do both much more frequently. In our sample, only about 25 percent of those having taking out a loan are female. Further, men predominantly borrow from other men (about 90 percent); women tend to mostly borrow from men, with only a minority borrowing from other women. Due to the inherent exclusion of women from the financial system, we might thus not capture a woman's coping network fully. Still, we think that our network variable could capture at least some part of a woman's interactions with her social network as a result of demonetization: the main reason given for taking out a loan after demonetization is family expenses (such as food), which is also the main reason women take out loans according to our data. Higher educational attainment correlates positively with network size, as individuals might have made additional connections through educational institutions. It correlates negatively with network density, though: those with a Bachelor's or postgraduate degree might have other forms than social networks to cope with shocks (such as more access to formal banking). Some household characteristics are also significant: household income, for example, is related to having a larger network, but a smaller network density, as richer households are more able to cope based on their own resources.

6.3 Second stage results: the causal determinants of trust

Columns (2) through (4) in Tables 3 and 4 depict the second stage results, estimating the effects of the predicted network measures, $\widehat{SN_i}$, on the three different measures of social trust after correcting for potential endogenous network formation and use. Network size causally increases trust in kin vs. non-kin among employees: a one standard deviation increase in network size, which increases total network size from a full sample average of almost 8 connections to 12 connections, increases trust in kin by 0.3 standard deviations. This is essentially equal to moving from answering somewhere between 'sometimes' to 'quite often' to solidly answering 'quite often' to the question "kin members are more trustworthy than non-kin members among employees". Network size further has a larger, opposite effect on trust in neighbors: those with larger networks are more likely to say that they trust their neighbors less.

In line with previous results, a higher network density increases trust in neighbors. Network density further has a negative effect on trust in kin among employees, however, not significantly so. Results are in line with the OLS regressions in Table A4 in terms of sign of the coefficients. Compared to the OLS coefficients, the second stage IV coefficients for trust in neighbors and trust in kin employees (due to both network size and density) increase quite substantially. This suggests that network size and density can indeed be considered endogenous.[15]

These coefficients suggest that as networks get larger, people seem to place more trust in their kin than non-kin and less trust in their neighbors, while as usage gets denser, people place more trust in their neighbors. These explanations are not necessarily contradictory. Network size, as it is defined in this paper, does not relate to network usage. Instead, as has been illustrated in the first stage discussion, the effect of demonetization on network size is to a large degree driven by changes in the number of potential ties, due to an updating of information about who could help in times of crises. If updating has led someone to re-estimate their number of potential ties downward, they are probably insecure about whom they can really rely on. Kin, given tight social structures in rural India, seem to be a reliable option. Neighbors, though, might not be. Neighborhoods are quite homogeneous in the 'colony' part of the villages, which is predominantly occupied by Dalits. They are less homogeneous in the 'ur' part, in which middle and upper castes live side by side. The effect seems to be the same as for trust in kin: as network size grows, individuals are more weary about those at the weaker ends and tend to trust those more similar to themselves (kin, neighbors in homogeneous environments), which is essentially the homophily principle. Network density, unlike network size, represents

[15] Corresponding Durbin-Wu-Hausman tests confirm this, though the p-values are higher than ideal (around $p = 0.09$).

Table 3: IV estimates of the determinants of trust – Network size

	First stage	Second stages		
	Network size (1)	Neighborhood (2)	Kin employees (3)	Generalized Trust (4)
Network size (std)		-0.537	0.268	0.045
		(0.196)	(0.150)	(0.147)
Age	0.013	0.008	-0.001	-0.003
	(0.004)	(0.006)	(0.004)	(0.004)
Female	-0.446	-0.271	0.175	0.017
	(0.083)	(0.113)	(0.105)	(0.095)
Middle caste	-0.216	-0.024	-0.114	-0.007
	(0.158)	(0.180)	(0.241)	(0.179)
Upper caste	-0.181	-0.088	0.261	0.182
	(0.206)	(0.288)	(0.291)	(0.232)
Married	-0.039	-0.131	-0.015	-0.155
	(0.095)	(0.151)	(0.130)	(0.116)
Primary completed	-0.114	-0.194	-0.082	-0.092
	(0.120)	(0.132)	(0.133)	(0.116)
High schol (8th-10th)	-0.023	0.087	0.171	-0.091
	(0.125)	(0.132)	(0.112)	(0.096)
HSC/Diploma (11th-12th)	0.075	-0.005	0.074	0.094
	(0.158)	(0.205)	(0.176)	(0.164)
Bachelors (13th-15th)	0.186	-0.435	-0.425	-0.163
	(0.202)	(0.293)	(0.218)	(0.194)
Post Grad	0.876	0.436	-0.219	0.059
	(0.274)	(0.496)	(0.335)	(0.330)
Food expenses	0.154	-0.122	-0.344	-0.082
	(0.103)	(0.128)	(0.132)	(0.109)
Health expenses	0.094	-0.030	0.021	-0.022
	(0.038)	(0.046)	(0.041)	(0.040)
Ceremony expenses	-0.035	0.167	0.012	0.016
	(0.065)	(0.090)	(0.070)	(0.066)
HH income	0.094	-0.025	0.044	-0.035
	(0.050)	(0.073)	(0.068)	(0.057)
Demonetization	-0.602			
	(0.090)			
F-stat	44.4			
N	645	645	645	645
R^2	0.429	0.203	0.346	0.592

Source: NEEMSIS (2016-2017); authors' computations. *Notes:* ; Robust standard errors in parentheses; Village-area fixed effects included. Base categories: caste = Dalit, education = no completed primary, sex = male. Household expense variables are in natural logarithm. Additional controls include cognitive and non-cognitive skills, occupation dummies, access to media, and a savings account.

Table 4: IV estimates of the determinants of trust – Network density

	First stage	Second stages		
	Network density	Neighborhood	Kin employees	Generalized Trust
	(1)	(2)	(3)	(4)
Network density (std)		1.110	-0.553	-0.093
		(0.522)	(0.360)	(0.303)
Age	0.024	-0.026	0.016	-0.000
	(0.004)	(0.013)	(0.009)	(0.008)
Female	-0.550	0.580	-0.249	-0.054
	(0.098)	(0.328)	(0.230)	(0.185)
Middle caste	-0.307	0.433	-0.342	-0.045
	(0.240)	(0.328)	(0.305)	(0.195)
Upper caste	-0.227	0.261	0.087	0.152
	(0.291)	(0.401)	(0.359)	(0.258)
Married	-0.342	0.269	-0.214	-0.188
	(0.133)	(0.267)	(0.183)	(0.141)
Primary completed	0.066	-0.206	-0.076	-0.091
	(0.128)	(0.196)	(0.163)	(0.117)
High schol (8th-10th)	0.163	-0.081	0.255	-0.077
	(0.132)	(0.188)	(0.136)	(0.112)
HSC/Diploma (11th-12th)	-0.133	0.103	0.020	0.085
	(0.147)	(0.241)	(0.207)	(0.171)
Bachelors (13th-15th)	-0.114	-0.408	-0.438	-0.165
	(0.184)	(0.361)	(0.246)	(0.201)
Post Grad	-0.454	0.470	-0.236	0.056
	(0.227)	(0.518)	(0.384)	(0.330)
Food expenses	0.057	-0.268	-0.271	-0.070
	(0.102)	(0.154)	(0.140)	(0.103)
Health expenses	0.004	-0.085	0.049	-0.018
	(0.042)	(0.062)	(0.044)	(0.038)
Ceremony expenses	0.054	0.125	0.033	0.019
	(0.062)	(0.093)	(0.082)	(0.067)
HH income	-0.233	0.184	-0.060	-0.053
	(0.071)	(0.156)	(0.101)	(0.082)
Demonetization	0.291			
	(0.106)			
F-stat	7.61			
N	645	645	645	645
R^2	0.412		0.114	0.591

Source: NEEMSIS (2016-2017); authors' computations. *Notes:* Robust standard errors in parentheses; Village-area fixed effects included. Base categories: caste = Dalit, education = no completed primary, sex = male. Household expense variables are in natural logarithm. Additional controls include cognitive and non-cognitive skills, occupation dummies, access to media, and a savings account.

the share of used connections over all connections. The story here seems to be reversed: those who use their networks more intensely are more willing to trust their neighbors. Given the sorting of different caste group into oftentimes homogeneous neighborhoods relying on weaker ties such neighbors could still mean that individuals are relying on those who are very similar to the themselves.

6.4 Heterogeneity analysis

The previous analysis was conducted for the entire matched sample. Still, important differences might exist between subgroups of the sample that are hidden in a general analysis. This is particularly important in the rural Indian context, in which strict social hierarchies along the lines of caste membership and, to a certain extent, gender have been traditionally prevalent. These segregating lines might have become less dominant, but they remain visible. For example, the vast majority of marriages still take place within the same caste, and caste membership can enhance or hinder economic and social mobility (Munshi, 2016b). Men remain the traditional household heads and tend to be the decision-makers in the household. Accordingly, the following section splits our sample into the different caste categories (Dalits, middle castes, upper castes) and along gender lines. We will further look at differential effects by distance from the nearest town, as it affects the ability of individuals to cope with the shock through means other than networks, such as formal banks.

6.4.1 Heterogeneous effects by caste membership

Table 5 presents our IV estimates by caste membership, split into Dalits, middle castes, and upper castes. Demonetization has the same effect for all caste categories in terms of sign: having lived through demonetization decreases network size for all, presumably as people update their beliefs of who they can rely on. Among middle castes, a larger network size decreases trust placed in neighbors and increases trust in kin among employees, and generalized trust. The identification is weaker for network density; among upper castes for whom it most arguably holds, making use of one's network more intensely decreases trust in kin relative to non-kin employees and trust in general.

The differential effects that we find by caste membership relate back to the strict social hierarchies that prevail in rural South India and the importance of taking these into account for any meaningful analysis (Vijayabaskar and Kalaiyarasan, 2014). A caste can provide important economic support to its members and enable effective consumption smoothing (Munshi, 2016b). To enable consumption smoothing within a group, the group must have good information about its members and must be able to punish those that refuse to adhere to their obligations. Part of this mechanism was illustrated in the introductory quote, in which Gomathi, a 26-year-old women who is part of the Dalit community, explains that her female neighbors are there to help her in times of need, but they also expect help from her whenever need arises. While consumption

Table 5: Estimates of determinants of trust by caste membership for both measures of social networks

(a) Lower castes

	First stage	Second stages			First stage	Second stages		
	Density	Neigh	Kin	Gen Trust	Size	Neigh	Kin	Gen Trust
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Density (std)		2.763	0.011	1.185				
		(2.493)	(0.717)	(1.176)				
Size (std)						-1.947	-0.008	-0.835
						(0.987)	(0.505)	(0.483)
Demo	0.198				-0.281			
	(0.181)				(0.140)			
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-stat	1.2				4.0			
N	291	291	291	291	291	291	291	291
R^2	0.417		0.423	0.082	0.376		0.423	0.582

Notes: Table based on NEEMSIS (2016-2017); Robust standard errors in parentheses.

(b) Middle castes

	First stage	Second stages			First stage	Second stages		
	Density	Neigh	Kin	Gen Trust	Size	Neigh	Kin	Gen Trust
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Density (std)		0.613	-1.207	-0.878				
		(0.435)	(0.658)	(0.520)				
Size (std)						-0.306	0.603	0.439
						(0.168)	(0.193)	(0.188)
Demo	0.308				-0.617			
	(0.160)				(0.120)			
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-stat	3.72				26.2			
N	278	278	278	278	278	278	278	278
R^2	0.445	0.330		0.198	0.497	0.515	0.338	0.547

Notes: Table based on NEEMSIS (2016-2017). Robust standard errors in parentheses.

(c) Upper castes

	First stage	Second stages			First stage	Second stages		
	Density	Neigh	Kin	Gen Trust	Size	Neigh	Kin	Gen Trust
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Density (std)		-0.054	-0.799	-1.681				
		(0.489)	(0.415)	(0.547)		0.045	0.672	1.415
Size (std)						(0.405)	(0.299)	(0.488)
Demo	0.913				-1.085			
	(0.384)				(0.500)			
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-stat	5.6				4.7			
N	76	76	76	76	76	76	76	76
R^2	0.851	0.686	0.596	0.499	0.831	0.699	0.673	0.341

Notes: Table based on NEEMSIS (2016-2017). Robust standard errors in parentheses.

smoothing through borrowing and lending thus largely occurs within castes, caste is also a significant determinant of the type of borrowing that is available to individuals. Intuitively, one can only borrow and lend from one's network if the network has the necessary resources. Looking at the study region at hand, Guérin et al. (2013) show that the financial landscape is highly fragmented along caste lines. Lower castes are less likely to borrow from social networks and more likely to borrow from ambulant lenders, though they are also more credit-constrained in general. This is also visible in our data, as descriptive statistics show that lower castes are the most likely to have asked for help but been refused it.

As a result, loans taken out by Dalits after demonetization are more likely to stem from employers and maistries (labor contractors) than prior to demonetization.[16] This does not hold true for middle castes, though: while their share of loans from employers also increases (from about 0 to about 8 percent), it is accompanied by an even larger increase in the share of loans coming from relatives and 'well-known people' (from 63 to 73 percent of all loans).[17]

As a result of demonetization, different castes thus answer the shock with different borrowing patterns: lower castes respond to the shock by shifting their borrowing from borrowing among their own caste prior to demonetization to borrowing also from upper castes after demonetization (generally their employers); middle castes shift from borrowing from their own caste and upper castes prior to demonetization to borrowing almost exclusively from within their own caste (90 percent of loans) after demonetization. This is in line with previous research, showing that transfers from other caste members are the preferred method of consumption smoothing in response to income fluctuations (Munshi and Rosenzweig, 2009).[18]

Further, while middle castes were less likely than lower castes to say that they asked for help and were refused, they are more likely to say that there was no one around to ask for help. Unlike those in lower castes, who are more likely to be employees, members of middle castes could not ask their employers for help to cope. In light of Table 5, this information suggests that middle castes updated their information about their social network, leading to fewer potential ties after demonetization. Those who then still had (updated) larger social networks were able to borrow from their own caste and are more trusting in their kin in comparison to non-kin as a result. Borrowing also took place on similar social levels (friends and 'well-known people') in comparison to lower castes, who borrowed up, by borrowing from employers. Frequent interactions between different

[16] In fact, prior to demonetization, lower castes received the largest share of loans from 'well-known people' and relatives (67 percent), and about 3.6 percent of loans from employers and labor contractors. This changes to 57 percent and 23.75 percent after demonetization, respectively.

[17] Well-known people, "terinjavanga" in Tamil, is a common Tamil term referring to people that have been known to the individual or family for a long time (years or even generations). Most of the time, these people are known through networks, such as friends of relatives or removed relatives, such as a relative of a daughter married to somebody in another village.

[18] Almost all members of the lower caste in our data set are part of the Paraiyar community. Among middle castes, the majority are members of the Vanniyar caste (82 percent).

ethnic groups has been shown to decrease levels of mistrust between them (Stolle et al., 2008). In our case, however, interactions between Dalits and upper castes are probably not frequent enough for this type of mechanism to take place, so any potentially positive effect could not be big enough to observably overcome existing distrust due to pre-existing social hierarchies. Lower caste members who were able to borrow from neighbors (which still happened, though at a lower rate) still borrowed within-caste, as they tend to live in homogeneous neighborhoods. For lower castes, making use of weaker links (higher network density) still means that those links remain within the caste network and can be trusted. Middle castes, by comparison, live in more heterogeneous neighborhoods.

These findings relate back to other studies on social activities in heterogeneous communities such as Alesina and La Ferrara (2000), who find that the degree of heterogeneity in communities influences the amount of participation in groups. In the context of South India, experiments in social psychology show that study participants tended to define their in-group along caste lines; positive previous contact was associated with more inclusive identities and negatitve contact with less (Reimer et al., 2019). It also relates to other surveys, such as the World Values Survey. In addition to a question about neighbors in general, the survey includes questions about trust in neighbors speaking a different language or following a different religion. Trust levels in India significantly decline, from almost 90 percent saying they trust their neighbors to only about 55-60 percent, when asked about dissimilar neighbors (as cited in Munshi, 2016a). In the case at hand, trust in others is thus shaped strongly with relation to closeness to the self, with similar people considered more trustworthy - illustrative of the homophily principle in social networks (McPherson et al., 2001).

6.4.2 Heterogeneous effects by gender

Gender is an important factor in rural South India, with traditional gender roles dominating. It is therefore crucial to consider potentially differential effects by gender. Table 6 presents our IV results of the determinants of trust by gender.

Table 6: Estimates of determinants of trust by gender for both measures of social networks

(a) Men

	First stage	Second stages			First stage	Second stages		
	Density	Neigh	Kin	Gen Trust	Size	Neigh	Kin	Gen Trust
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Density (std)		0.672	-0.476	-0.112				
		(0.300)	(0.230)	(0.201)				
Size (std)						-0.562	0.398	0.094
						(0.245)	(0.180)	(0.169)
Demo	-0.624				0.522			
	(0.121)				(0.137)			
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-stat	14.5				26.7			
N	368	368	368	368	368	368	368	368
R^2	0.454	0.201	0.272	0.579	0.491	0.222	0.371	0.581

Notes: Table based on NEEMSIS (2016-2017). Robust standard errors in parentheses.

(b) Women

	First stage	Second stages			First stage	Second stages		
	Density	Neigh	Kin	Gen Trust	Size	Neigh	Kin	Gen Trust
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Density (std)		-5.106	1.683	0.060				
		(9.839)	(3.141)	(1.922)				
Size (std)						-0.587	0.193	0.007
						(0.255)	(0.222)	(0.222)
Demo	-0.070				-0.607			
	(0.134)				(0.113)			
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-stat	0.27				28.9			
N	277	277	277	277	277	277	277	277
R^2	0.482			0.678	0.520	0.341	0.479	0.680

Notes: Table based on NEEMSIS (2016-2017). Robust standard errors in parentheses.

It becomes clear that our previous results, which showed network size and density affecting levels of trust, was driven by men. In fact, looking at men and women separately shows that the first stage holds strongly for men for both measures. It also holds for women with regard to network size, but only the trust in neighbors coefficient is significant in the second stage. With regard to network size, among men, the coefficient of trust in kin relative to non-kin shows a slightly increased effect, from 0.27 in the combined (female and male) sample in Table 3 to 0.39 for the male only sample, while the coefficient for trust in neighbors remains almost equal. For network density the coefficient for trust in kin among employees gains significance, while the coefficient for trust in neighbors almost halves.

It is likely that our gendered results are driven by the gender roles in South India. In our sample, men are more likely to say that they have asked somebody for help as a result of demonetization, which would lead to information updating, inducing the sort of intensification of network usage that we have in mind (13 percent of men said they asked for help vs. 6 percent of women). In fact, women are more likely to say that they did not need to ask anybody for help (74 percent of women answered this way compared to 67 percent of men). This could suggest several things: that women do not feel like they need to ask for help as this is assumed to be part of a man's role, that informal lending is socially inaccessible for women, or that women were able to overcome this period of cash shortage with the help of, for example, hidden cash reserves. The literature supports all three hypotheses. Indeed, women and members of lower castes in north Tamil Nadu have more difficulties accessing informal lending, paying on average more and borrowing primarily for consumption (Harriss-White and Colatei, 2004). Further, there is abundant evidence that women do not share their entire income with their husband, often putting some of it away. The vast majority of women does not have access to the banking system, and only via joint accounts with their husbands for those that do. Saving some money in private cash hoards thus provides the only way for women to guard it from the males in their households (who might prefer to spend it on demerit goods) or to save money for their children. Indeed, in the survey area, about 70 percent of women claim to secretly save some cash (Guérin, 2008). Women were then doubly hit by the demonetization shock: standing in long queues to exchange the money could be considered inappropriate while, at the same time, the pure revelation of a secret cash hoard to husbands could have negative repercussions, potentially leading some women to lose control of their reserves (Ghosh et al., 2017). A deeper dive into these different channels of a gendered analysis of the demonetization shock could be a rather fruitful avenue for future research.

6.4.3 Heterogeneous effects by distance from nearest town

While our sample is located in rural areas only, the nearest town is not equally easily accessible for all villages. This could affect the impact of the shock: those who are living close to a bigger town are better able to access the required infrastructure (ATMs, bank offices to create a bank account, more varied lending services). The impact of the shock is likely to be more important in remote areas, where a network is the sole coping mechanism. Table 7 depicts our IV results by distance to the nearest town. Villages defined as remote (panel a) are more than a 45 minute car-drive away from the nearest town; close villages require shorter travel times. Indeed, Table 7 shows that our results hold more strongly for individuals living in more remote villages, who were less able to access formal banking institutions, more exposed to cash shortages and therefore more reliant on their connections. This holds true for both measures of social networks.

Table 7: Estimates of determinants of trust by distance to nearest town for both measures of social networks

(a) Far distance to town

	First stage	Second stages			First stage	Second stages		
	Density	Neigh	Kin	Gen Trust	Size	Neigh	Kin	Gen Trust
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Density (std)		0.799	-0.483	-1.008				
		(0.451)	(0.355)	(0.436)				
Size (std)						-0.389	0.235	0.491
						(0.222)	(0.157)	(0.166)
Demo	0.467				-0.958			
	(0.158)				(0.137)			
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-stat	8.7				49.1			
N	232	232	232	232	232	232	232	232
R^2	0.539	0.291	0.329	0.179	0.622	0.342	0.478	0.632

Notes: Table based on NEEMSIS (2016-2017). Robust standard errors in parentheses.

(a) Close distance from town

	First stage	Second stages			First stage	Second stages		
	Density	Neigh	Kin	Gen Trust	Size	Neigh	Kin	Gen Trust
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Density (std)		0.806	-0.824	0.347				
		(0.625)	(0.607)	(0.450)				
Size (std)						-0.539	0.551	-0.232
						(0.297)	(0.309)	(0.272)
Demo	0.250				-0.373			
	(0.140)				(0.117)			
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-stat	3.2				10.2			
N	413	413	413	413	413	413	413	413
R^2	0.378			0.547	0.343	0.330	0.258	0.623

Notes: Table based on NEEMSIS (2016-2017). Robust standard errors in parentheses;

6.5 Robustness checks

6.5.1 Days passed since demonetization

The survey was conducted over two time periods, one prior to and one after demonetization. The post-demonetization survey collection started in January 2017 (about 2 months after the shock) and ended at the end of March 2017, meaning that the last interview was conducted about 5 months after the shock.[19] According to the mechanism at hand - that trust is built through social interactions - time passed since demonetization is likely to have a positive effect on our measures of trust, as people have more time to actually interact. In this section, we explore the time dimension of the survey, looking at the effect of time passed since demonetization. As expected, network density and days passed since demonetization correlate positively, though not particularly strongly ($r = 0.18, p < 0.000$). Similarly, network size and days passed since demonetization correlate negatively ($r = -0.30, p < 0.000$). Figure A2 illustrates those correlations. Table A5 provides the IV specification, using days passed as the instrument instead of the demonetization dummy used in Table 4. Results mirror the results obtained with the demonetization dummy and suggest indeed slightly stronger effects given the passage of time passed between the demonetization shock and the date of interview.

6.5.2 Lowering the trustworthiness threshold

A potential second channel that could affect our results is that instead of changing beliefs about others' trustworthiness, the shock might have lowered the trustworthiness threshold at which individuals are willing to interact. Instead of revealing information about the ties (if one can rely on them or not), the individual might in this scenario simply be willing to interact with anybody who could help, even if those people are not necessarily trustworthy. Rather than information updating, the mechanism would then be driven by a lower trustworthiness threshold that has to be overcome to facilitate interaction. If this channel was at play, we would expect individuals to increase their number of ties after the shock (having a larger network size), as more ties would pass the lowered trustworthiness threshold. We would also expect individuals to increase their network density (using more of their ties), as, again, a larger share of the network surpasses the threshold. Instead of a larger network size, however, we observe a smaller total network size, driven by a lower number of elicited potential ties. Network density is indeed larger after the shock, but this is also driven by a reduction in the number of potential ties (part of the denominator). This leads us to conclude that demonetization did in fact affect people's beliefs about others, as they elicit fewer potential ties after the shock than before.

[19] The survey started in August 2016 and was interrupted a week before the demonetization shock took place due to logistical survey constraints (in particular, the need to update the survey software and replace batteries in some tablets used for data collection).

6.5.3 Estimations without the agreeableness dimension

One potential concern about including the Big Five in our second stage IV regressions is simultaneity bias, which would be problematic if Big Five dimensions determine trust and trust determines Big Five scores. The dimension for which this is most likely is agreeableness, the tendency to act cooperatively. It relates in fact to the facets altruism and trust, as cooperative interactions require trust between interacting parties. We estimate our IV regressions without the agreeableness dimension. Table A6 displays the second stages for both network density and network size.[20] Table A6 shows that our main results hold, even when estimated without the agreeableness dimension. In fact, our coefficients for the effect of network size on trust in neighbors and trust in kin relative to non-kin are barely affected, with the coefficient for trust in neighbors increasing slightly. The changes in coefficients for the effect of network density on trust in neighbors and kin are equally small. The largest difference is seen for the generalized trust measure, though results remain insignificant, as they have been throughout the paper. This leads us to conclude that the estimations are still valid with the agreeableness dimension.

6.5.4 Migrating households

A fourth channel that could affect our results is migration. There has been evidence throughout the country that migrants were forced to return home after the shock, as employers were often unable to continue paying wages (Ghosh et al., 2017). More than half of the households in our sample are migrant households (meaning that at least one member migrates temporarily for work). While survey collection was essentially random and the break in the survey was not related to demonetization, the survey team did decide to interview migrating households later during the survey timeframe to have a better chance of interviewing them.[21] In order to check that our results are not driven by migrating households, we run the IV estimations while also including a dummy variable that takes the value of 1 if somebody in the household is a migrant (even if it's not the person interviewed) and an additional dummy taking the value of 1 if the individual himself is a migrant. Table A7 shows that only the individual migrant dummy is significant at the 10 percent level (column (6), generalized trust). Results of the effect of network size and network density on trust remain similar in sign and size; however, they are no longer statistically significant.

6.5.5 Poverty

One additional potential confounder of our results could be poverty, as poverty could make people less trusting in general. Lack of trust has been linked to low socio-economic status and lack of material wealth (e.g. Knack and Keefer, 1997; Uslaner, 2002; Delhey

[20] First stages are not reported for simplicity. The F-statistic for network density is 7.03 and for network size 45.1.

[21] Migrants tend to travel to their home villages for festivals.

and Newton, 2003), with one possible channel that the risk of trusting may be too great for the most deprived, as they have a greater share of their total wealth to lose if their trust is betrayed (Putnam, 2001).

In the previous estimations, we already control for households expenses and household income, in addition to basing the estimations on a sample matched based on these households' characteristics and characteristics of the dwelling, which should capture part of this aspect. Still, to make sure that our results hold for poorer and richer households, we build an asset index based on items that are likely to change as a result of the shock (household income and expenses) and items that better capture an enduring poverty status (goods owned by the household and participation in government schemes targeted to the poor).[22] We reduce these items to a composite index using principal component analysis and keep the first component. Table A8 displays the results for the poorest and richest households. Individuals in poor households that had to increase their density depicted decreases in trust in kin among employees and in general; if they had to extend their network size (diversify more), this led to increases in these trust categories.

One has to keep in mind that poverty status oftentimes varies with caste membership, with lower castes being poorer. In our sample, poverty according to the asset index, is spread across all caste groups, leading to differential effects in comparison to caste membership only.

6.5.6 Happiness

The last channel for which we consider robustness checks is happiness. People could be unhappy about the demonetization shock and its consequences and therefore less likely to trust others. Table 2 in the exclusion restriction section provides evidence that people did not think that demonetization itself changed their levels of trust in neighbors and kin (about 74 percent of the demonetization sample).[23] Other research provides evidence that demonetization was mostly perceived positively, even among those who suffered (Ghosh et al., 2017). Unfortunately, the survey does not contain questions about life satisfaction, the most common variable with which happiness can be captured.

Given the lack of a life satisfaction variable, we will rely on the Big Five dimension emotional stability, which has been most strongly related to concepts of happiness (Hills and Argyle, 2001). The descriptive statistics for the balanced sample (displayed in Table A3) show that emotional stability is not statistically different between the pre- and post demonetization sample after the matching. We estimate separate IV regressions for those who score in the lowest tertile of the emotional stability dimension and those

[22]The exact list of variables included in the poverty index are: household expenses on food, ceremonies, and health; household income; whether the household owns a fridge, expensive furniture, a car, a cell phone, a landline, or a computer; whether the household benefits from the ration card, free housing, free cow and goats, or free gas government schemes; and characteristics of the dwelling (water access, electricity, toilet facilities, and type of house).

[23]Demonetization led people to put less trust in banks, with 22 percent saying that demonetization made them trust banks less.

who score in the highest.[24] Table A9 shows that the effect for trust in kin relative to non-kin members is significant and positive for both, but slightly stronger for those with stronger emotional stability. Still, to the extent that it can be approximated by emotional stability, our results do not appear to be driven by happiness.

7 Conclusion

Trust in other people, an essential component of social capital, is particularly crucial in developing countries, where a large share of transactions are informal and take place within social networks. But trust is to a large extent endogenous, as it is "an outcome and an antecedent of relationships" (Nooteboom, 2007, p. 33). This paper aims to disentangle this relationship between social networks and trust by exploring an exogenous variation that directly affected people's information about their social network but did not have a direct effect on interpersonal trust. The exogenous shock explored, the 2016 demonetization policy in India, reduced money supply overnight, inducing individuals to rely on their social networks for everyday transactions.

We use novel quantitative and qualitative data from rural Tamil Nadu, collected by the authors, to provide causal estimates of the effects of two measures of social networks (size and density) and three measures of trust (trust within a neighborhood, trust in kin versus non-kin among employees, and generalized trust). We use an IV approach with the shock introduced by the demonetization policy in November 2016 as an instrument that had a significant effect on network measures but did not directly affect trust placed in other people. This presupposed channel is also visible in first-hand qualitative data collected by the authors to understand how demonetization impacted people's lives in rural South India, thereby offering convincing evidence for the exclusion restriction. We control for a large variety of individual characteristics that could affect trust formation, such as cognitive ability and personality traits, which in other cases have been considered unobservable or required panel data to be purged from the estimates. We use network data collected as part of the survey to construct two measures of social networks: network size, the sum of all potential and actual ties, and network density, the share of ties activated. Both measures are mostly reliant on economic interactions (loans and access to labor).

We find that network density causally increases levels of trust placed in neighbors and decreases trust placed in kin among employees, while network size decreases trust in neighbors and increases trust placed in kin employees. Heterogeneity analyses illustrate that these results for the entire sample hide important differences. Most notably, our results hold mostly for men, as strong gender roles both reduce women's ability to interact in the way that we are capturing interactions and might mean that women have different strategies of coping with shocks (such as cash hoarding), not reflected by our data. Further, we find different results by caste membership. Comparing lower

[24] We also tried quartiles and results are similar.

castes (Dalits) and middle castes still reveals important differences regarding the levels and types of interactions that occurred as a result of the shock. Lower castes coped by taking out loans from those around them (in homogeneous neighborhoods) and from their employers. Among Dalits, who are oftentimes employed as salaried agricultural laborers in the study region, we find that extending one's network decreaes trust in neighbors. For middle castes, though, the story is different. Middle castes live in more heterogeneous environments and often work on their own agricultural land, as the exodus of upper castes to urban areas has enabled a reallocation of land to the middle castes. As a result of the shock, they coped by borrowing from other caste members, or 'well-known people'. Among middle castes, a larger number of ties (network size) leads to more trust in kin members in comparison to non-kin members and lower trust in neighbors, who could be more dissimilar to the self. For this group, higher network density, making use of one's network more intensely, leads to lower trust placed in kin-employees. As middle castes have to expand their networks to cope, they then rely on weaker ties of which they are arguably more dubious, driving the reduction in trust levels.

This paper illustrates that a common shock can have differential effects on levels of trust in a society, given the type of interactions that take place as a result of the shock. Notably, it demonstrates homophily in networks in rural South India, where interactions that happen within a homogeneous group (neighborhoods for lower castes, kin and other caste members for upper castes) foster trust, while outside interactions or relying on marginal ties decrease it. This is in line with previous research demonstrating that Indians tend to trust those who are similar to themselves but not other linguistic or religious groups (Munshi, 2016a). The paper also showcases the importance of not relying only on broad measures of trust, such as generalized trust, when examining an environment characterized by tightly knit social groups. We do not find any results for our measure of generalized trust, but results turn significant once we consider measures of trust that more clearly define an in-group in comparison to an out-group (neighbors and non-neighbors, kin among employees and non-kin among employees). The paper further presents evidence that caste membership remains a significant determinant of social and economic outcomes in today's rural India.

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A Appendix: Tables and Figures

Table A1: Descriptive statistics of the individual level sample

	N	Mean	SD	Min	Max
Age	885	42.65	13.67	18	81
Married	885	0.82	0.39	0	1
Male	885	0.56	0.50	0	1
Dalit	885	0.48	0.50	0	1
Middle caste	885	0.42	0.49	0	1
Upper caste	885	0.10	0.30	0	1
Below primary	885	0.38	0.49	0	1
Primary completed	885	0.21	0.40	0	1
High school (8th-10th)	885	0.26	0.44	0	1
HSC/Diploma (11th-12th)	885	0.07	0.26	0	1
Bachelors (13th-15th)	885	0.06	0.23	0	1
Post Grad	885	0.02	0.14	0	1
Raven	885	13.21	8.84	0	36
Literacy	885	1.72	1.72	0	4
Numeracy	885	1.79	1.30	0	4
OP	885	2.76	0.67	1.1	4.71
CO	885	3.47	0.67	1.6	5.00
EX	885	3.36	0.59	1.4	4.71
AG	885	3.35	0.39	2.3	5.00
ES	885	3.29	0.48	2.0	5.00
Grit	885	3.06	0.58	1.3	5.00
Trust in neighborhood	885	3.92	1.02	1	5
Trust in kin	885	3.45	0.95	1	5
Generalized Trust	885	3.20	0.81	1	5
Actual SN size	885	1.39	1.75	0	10
Potential SN size	885	6.83	3.61	1	21
Total SN size	885	8.22	4.34	1	26
SN density	885	0.15	0.17	0	0.77

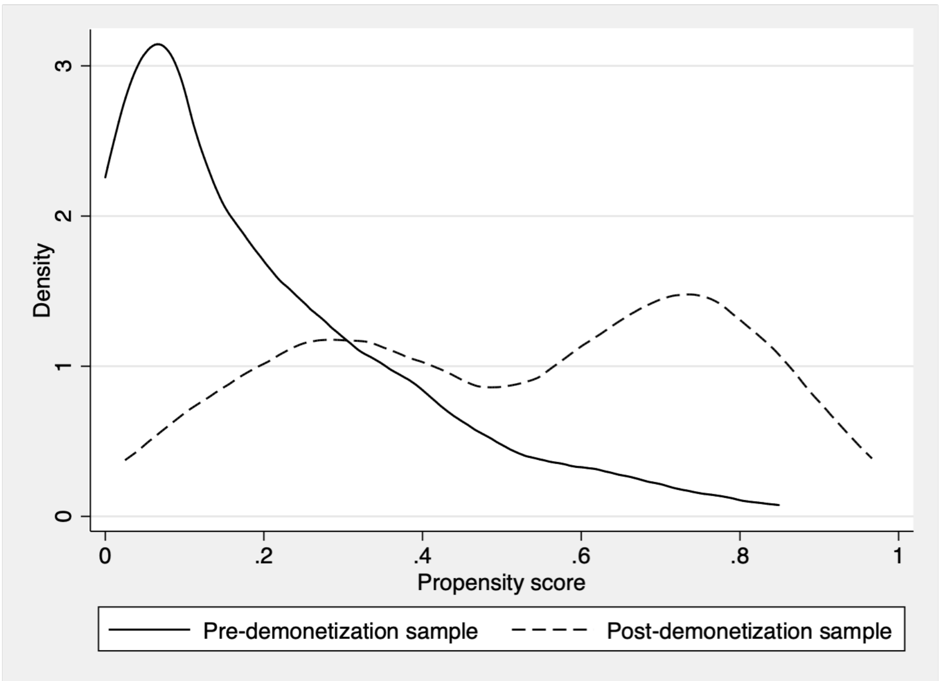
Source: NEEMSIS (2016-2017); authors' computations. The data is available on the NEEMSIS webpage `https://neemsis.hypotheses.org/`.
Notes: Sample restricted to those with non-missing cognitive and non-cognitive skills, and trust variables. The raw individual level data contains 954 individuals.

Table A2: Balance checks - unmatched samples

	Before demonetization			After demonetization				
	N	Mean	SD	N	Mean	SD	Diff	P-value
Age	630	43.13	13.92	255	41.48	13.01	1.64	0.12
Married	630	0.82	0.38	255	0.80	0.40	0.02	0.44
Male	630	0.53	0.50	255	0.63	0.49	-0.10	0.01
Dalit	630	0.49	0.50	255	0.46	0.50	0.04	0.37
Middle caste	630	0.40	0.49	255	0.45	0.50	-0.04	0.25
Upper caste	630	0.10	0.30	255	0.09	0.29	0.01	0.69
Below primary	630	0.40	0.49	255	0.33	0.47	0.07	0.06
Primary completed	630	0.21	0.41	255	0.19	0.39	0.02	0.53
High school (8th-10th)	630	0.26	0.44	255	0.29	0.45	-0.03	0.35
HSC/Diploma (11th-12th)	630	0.06	0.24	255	0.10	0.30	-0.04	0.07
Bachelors (13th-15th)	630	0.05	0.22	255	0.07	0.25	-0.02	0.35
Post Grad	630	0.02	0.13	255	0.02	0.15	-0.01	0.55
Raven	630	12.52	8.30	255	14.89	9.86	-2.36	0.00
Literacy	630	1.61	1.71	255	1.99	1.70	-0.37	0.01
Numeracy	630	1.71	1.32	255	1.96	1.23	-0.25	0.00
OP	630	2.90	0.57	255	2.96	0.48	-0.06	0.13
CO	630	3.56	0.66	255	3.77	0.71	-0.21	0.00
EX	630	3.49	0.49	255	3.56	0.45	-0.07	0.06
AG	630	3.47	0.36	255	3.58	0.39	-0.10	0.00
ES	630	3.41	0.61	255	3.52	0.62	-0.10	0.02
Grit	630	3.12	0.58	255	3.47	0.59	-0.36	0.00
Food expenses (HH)	630	7.02	0.50	255	6.73	0.44	0.30	0.00
Health expenses (HH)	630	9.12	1.09	255	9.00	1.00	0.13	0.11
Ceremonies expenses (HH)	629	9.16	0.83	255	9.04	0.58	0.12	0.04
Total HH income	629	11.49	0.95	255	11.87	0.70	-0.38	0.00
Trust in neighborhood	630	3.89	1.06	255	4.00	0.91	-0.11	0.15
Trust in kin	630	3.50	0.98	255	3.32	0.85	0.18	0.01
Generalized Trust	630	3.16	0.84	255	3.30	0.74	-0.14	0.02
Actual ties	630	1.42	1.84	255	1.33	1.50	0.09	0.51
Potential ties	630	7.40	3.81	255	5.42	2.56	1.98	0.00
Total SN size	630	8.82	4.64	255	6.75	3.02	2.07	0.00
SN density	630	0.14	0.16	255	0.18	0.19	-0.04	0.00

Source: NEEMSIS (2016-2017); authors' computations. Sample contains only those with non-missing cognitive and non-cognitive variables.
Notes: OP = Openness to Experience, CO = Conscientiousness, EX = Extraversion, AG = Agreeableness, ES = Emotional Stability. Personality traits are acquiescence corrected. Household expenses are in natural logarithms.

Figure A1: Common support for matching



Source: NEEMSIS (2016-17); based on authors' calculations.

Table A3: Balance checks - matched samples

	Before demonetization			After demonetization				
	N	Mean	SD	N	Mean	SD	Diff	P-value
Age	416	39.52	14.14	229	41.66	12.97	-2.14	0.18
Married	416	0.75	0.44	229	0.80	0.40	-0.05	0.30
Male	416	0.68	0.47	229	0.60	0.49	0.08	0.14
Dalit	416	0.45	0.50	229	0.45	0.50	0.00	0.96
Middle caste	416	0.43	0.50	229	0.44	0.50	-0.01	0.81
Upper caste	416	0.12	0.33	229	0.10	0.31	0.02	0.62
Below primary	416	0.32	0.47	229	0.33	0.47	-0.01	0.79
Primary completed	416	0.19	0.39	229	0.20	0.40	-0.01	0.85
High school (8th-10th)	416	0.22	0.42	229	0.28	0.45	-0.06	0.18
HSC/Diploma (11th-12th)	416	0.18	0.39	229	0.10	0.31	0.08	0.15
Bachelors (13th-15th)	416	0.06	0.24	229	0.06	0.23	0.00	0.88
Post Grad	416	0.03	0.16	229	0.02	0.15	0.00	0.78
Raven	416	1.93	1.75	229	2.01	1.71	-0.08	0.71
Literacy	416	1.93	1.27	229	1.98	1.22	-0.05	0.74
Numeracy	416	14.14	8.79	229	14.55	9.99	-0.40	0.72
OP	416	3.02	0.54	229	2.96	0.47	0.05	0.38
CO	416	3.54	0.65	229	3.71	0.71	-0.17	0.03
EX	416	3.44	0.50	229	3.54	0.45	-0.10	0.08
AG	416	3.42	0.41	229	3.54	0.38	-0.13	0.01
ES	416	3.36	0.61	229	3.47	0.62	-0.11	0.11
Grit	416	3.33	0.53	229	3.41	0.57	-0.08	0.18
Food expenses (HH)	416	6.71	0.57	229	6.76	0.44	-0.04	0.55
Health expenses (HH)	416	9.01	1.09	229	9.02	1.01	-0.02	0.91
Ceremonies expenses (HH)	416	9.08	1.03	229	9.04	0.58	0.03	0.78
Total HH income	416	11.86	0.84	229	11.84	0.72	0.02	0.82
Trust in neighborhood	416	3.64	1.06	229	3.99	0.93	-0.35	0.00
Trust in kin	416	3.43	0.95	229	3.28	0.84	0.16	0.13
Generalized Trust	416	3.10	0.98	229	3.25	0.73	-0.15	0.22
Actual ties	416	1.24	1.71	229	1.31	1.51	-0.08	0.66
Potential ties	416	7.80	3.82	229	5.39	2.66	2.40	0.00
Total SN size	416	9.03	4.46	229	6.71	3.14	2.33	0.00
SN density	416	0.12	0.15	229	0.17	0.19	-0.05	0.00

Source: NEEMSIS (2016-2017); Authors' computations. Sample contains only those with non-missing cognitive and non-cognitive variables.
Notes: OP = Openness to Experience, CO = Conscientiousness, EX = Extraversion, AG = Agreeableness, ES = Emotional Stability. Personality traits are acquiescence corrected. Household expenses are in natural logarithms.

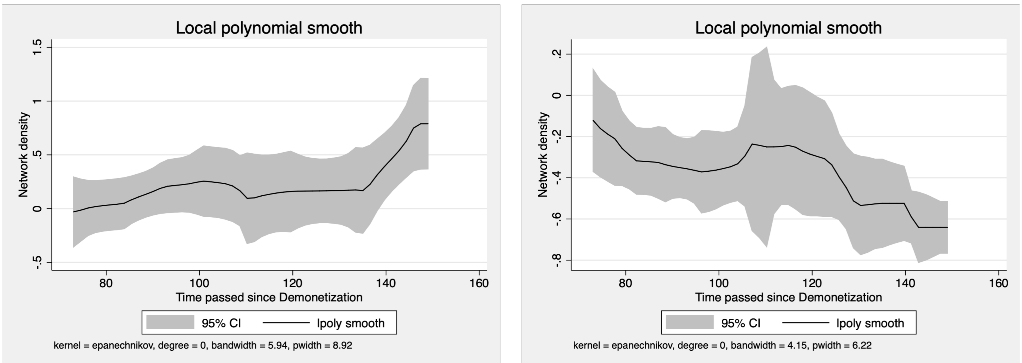
Table A4: OLS estimates of the determinants of trust

Trust measures	Neighborhood	Neighborhood	Kin employees	Kin employees	Gen. Trust	Gen. Trust
	(1)	(2)	(3)	(4)	(5)	(6)
Network density (std)	0.051		-0.007		-0.036	
	(0.044)		(0.046)		(0.041)	
Network size (std)		0.003		0.182		0.033
		(0.063)		(0.058)		(0.046)
Age	-0.000	0.001	0.003	0.000	-0.002	-0.003
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Female	-0.006	-0.033	0.054	0.138	-0.023	0.012
	(0.101)	(0.095)	(0.105)	(0.096)	(0.079)	(0.079)
Middle caste	0.110	0.095	-0.175	-0.133	-0.028	-0.009
	(0.165)	(0.165)	(0.253)	(0.251)	(0.182)	(0.182)
Upper caste	-0.038	-0.052	0.241	0.255	0.168	0.181
	(0.269)	(0.272)	(0.306)	(0.304)	(0.245)	(0.243)
Married	-0.095	-0.112	-0.026	-0.018	-0.169	-0.155
	(0.149)	(0.148)	(0.144)	(0.137)	(0.122)	(0.120)
Primary completed	-0.167	-0.165	-0.096	-0.087	-0.093	-0.093
	(0.133)	(0.132)	(0.146)	(0.139)	(0.121)	(0.121)
High school (8th-10th)	0.086	0.094	0.168	0.169	-0.085	-0.091
	(0.116)	(0.116)	(0.119)	(0.117)	(0.100)	(0.100)
HSC/Diploma (11th-12th)	-0.074	-0.083	0.112	0.087	0.095	0.096
	(0.184)	(0.185)	(0.193)	(0.185)	(0.174)	(0.173)
Bachelors (13th-15th)	-0.571	-0.579	-0.355	-0.402	-0.157	-0.160
	(0.277)	(0.278)	(0.228)	(0.225)	(0.207)	(0.204)
Post Grad	-0.046	-0.074	0.030	-0.138	0.083	0.070
	(0.457)	(0.465)	(0.310)	(0.322)	(0.339)	(0.334)
Food expenses	-0.197	-0.194	-0.308	-0.332	-0.074	-0.081
	(0.110)	(0.111)	(0.137)	(0.134)	(0.109)	(0.109)
Health expenses	-0.073	-0.072	0.042	0.028	-0.018	-0.021
	(0.046)	(0.046)	(0.040)	(0.040)	(0.040)	(0.040)
Ceremony expenses	0.183	0.186	0.003	0.009	0.016	0.015
	(0.078)	(0.078)	(0.078)	(0.075)	(0.070)	(0.069)
HH income	-0.085	-0.098	0.078	0.055	-0.039	-0.034
	(0.072)	(0.073)	(0.072)	(0.074)	(0.061)	(0.063)
N	645	645	645	645	645	645
R^2	0.369	0.367	0.330	0.351	0.593	0.593

Source: NEEMSIS (2016-2017); authors' computations based on the matched samples.
Notes: Robust standard errors in parentheses; Village-area fixed effects included. Base categories: caste = Dalit, education = no completed primary, sex = male. Household expense variables are in natural logarithm. Additional controls are cognitive and non-cognitive skills, occupational dummies, access to media and to savings account.

Figure A2: Relationship between days passed since demonetization and networks

(a) Network density (b) Network size



Source: NEEMSIS (2016-17); based on authors' calculations.

Table A5: Robustness: IV estimates of the determinants of trust, using days passed since demonetization as instrument

	First stage	Second stages			First stage	Second stages		
	Density	Neigh	Kin	Gen Trust	Size	Neigh	Kin	Gen Trust
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Density (std)		0.784	-0.630	-0.237				
		(0.396)	(0.317)	(0.269)				
Size (std)						-0.419	0.337	0.127
						(0.193)	(0.145)	(0.143)
Days passed	0.004				-0.007			
	(0.001)				(0.001)			
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-stat	11.7				53.3			
N	645	645	645	645	645	645	645	645
R^2	0.416	0.267	0.336	0.588	0.436	0.015	0.049	0.570

Notes: Table based on NEEMSIS (2016-2017). Robust standard errors in parentheses; Village-area fixed effects included.

Table A6: Robustness: IV estimates of the determinants of trust, without controlling for agreeableness

Trust measures	Neighborhood	Kin employees	Gen. Trust	Neighborhood	Kin employees	Gen. Trust
	(1)	(2)	(3)	(4)	(5)	(6)
Network density (std)	1.254	-0.587	0.370			
	(0.592)	(0.378)	(0.442)			
Network size (std)				-0.582	0.272	-0.171
				(0.199)	(0.146)	(0.191)
N	645	645	645	645	645	645
R^2		0.085	0.268	0.165	0.346	0.356

Notes: Table based on NEEMSIS (2016-2017). Robust standard errors in parentheses; Village-area fixed effects and the usual controls included. First stage F-statistics are for 7.03 network density and 45.1 for network size.

Table A7: Robustness: Second stage IV estimations with migration dummies

	(1) Neigh	(2) Neigh	(3) Kin employees	(4) Kin employees	(5) Gen. trust	(6) Gen. trust
Network density (std)	0.979		-1.282		-0.741	
	(0.998)		(1.035)		(0.756)	
Network size (std)		-0.417		0.545		0.315
		(0.304)		(0.290)		(0.270)
Migrant HH	0.104	0.181	0.472	0.371	0.443	0.385
	(0.449)	(0.244)	(0.489)	(0.254)	(0.350)	(0.248)
Indv is migrant	-0.272	-0.179	-0.053	-0.176	-0.274	-0.345
	(0.249)	(0.225)	(0.292)	(0.206)	(0.209)	(0.202)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	645	645	645	645	645	645
R^2		0.263		0.267	0.302	0.562

Notes: Table based on NEEMSIS (2016-2017). Robust standard errors in parentheses; Village-area fixed effects included. The usual control variables are included. First stage F-statistics are 2.2 for network density and 12.9 for network size.

Table A8: Robustness: Second stages of IV estimations of determinants of trust across the poverty distribution

	Poor			Non-poor		
	Neigh	Kin employees	Gen. trust	Neigh	Kin employees	Gen. trust
	(1)	(2)	(3)	(4)	(5)	(6)
Network density	0.508	-1.065	-0.848	1.789	0.710	1.056
	(0.467)	(0.515)	(0.456)	(1.060)	(0.548)	(0.666)
F-statistic	5.1			3.2		
N	324	324	324	321	321	321
R^2	0.304		0.098		0.209	0.349
Network size	-0.217	0.455	0.362	-1.181	-0.469	-0.697
	(0.200)	(0.154)	(0.160)	(0.346)	(0.313)	(0.247)
F-statistic	32.5			22.1		
N	324	324	324	321	321	321
R^2	0.321	0.411	0.406	0.089	0.270	0.633

Notes: Table based on NEEMSIS (2016-2017). Robust standard errors in parentheses; Village-area fixed effects included. The usual control variables are included.

Table A9: Robustness: Second stages of IV estimations of determinants of trust across the emotional stability distribution

	Lowest ES tertile			Highest ES tertile		
	Neigh	Kin employees	Gen. trust	Neigh	Kin employees	Gen. trust
	(1)	(2)	(3)	(4)	(5)	(6)
Network density	0.936	-1.640	-0.746	-0.392	-1.997	0.511
	(1.224)	(1.562)	(0.784)	(0.615)	(1.356)	(0.548)
F-statistic	0.9			1.9		
N	220	220	220	213	213	213
R^2	0.117		0.625	0.437		0.643
Network size	-0.290	0.507	0.231	0.244	1.241	-0.317
	(0.254)	(0.250)	(0.146)	(0.373)	(0.551)	(0.319)
F-statistic	10.8			8.4		
N	220	220	220	213	213	213
R^2	0.553	0.386	0.838	0.498	0.048	0.701

Notes: Table based on NEEMSIS (2016-2017). Robust standard errors in parentheses; Village-area fixed effects included. The usual control variables are included.