Essays on Networks and Development



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Declaration of Authorship

Chapters 1 and 3 are entirely my own work.

Chapter 2, titled "Misperceptions about Interpersonal Dialogue in Social Networks", is co-written with Ronak Jain, a PhD Candidate in Economics at Harvard University.

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Abstract

Social networks can impact individual outcomes by hampering social learning, propagating incorrect misperceptions, and upholding inefficient rules. This thesis studies how individual decisions can be impacted by the social networks they are embedded in. In the first chapter, I theoretically show that individual behavioural idiosyncrasies can adversely affect the choices of their peers and the long-run beliefs of society. I find that an individual's network position along with their behavioural type determines whether societal beliefs converge accurately and how quickly they do so. In the second chapter, my co-author and I use structural estimation techniques and experimental evidence to show that network-induced misperceptions can prevent individuals from engaging in inter-personal dialogue around mental health. We use secondary data to illustrate how belief-correction interventions can have network-dependent heterogeneous short-term and long-term impacts. Then, we run such an intervention with individuals affiliated to an NGO in New Delhi and find that it strengthens social ties by increasing engagement with the community. In the third chapter, I find that individuals who lie on multiple shortest paths in rural borrowing networks are less likely to take actions that can result in a loss of network links. I find that these agents are less likely to travel outside the village for work and that these decisions exhibit strategic complementarities.

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Introduction to the Thesis

"The sociological stream has what may be a fatal flaw as a theoretical enterprise: the actor has no 'engine of action'...The economic stream, on the other hand, flies in the face of empirical reality..."

Coleman (1988)

Social networks can influence outcomes by amplifying individual idiosyncrasies that hamper learning, propagating misperceptions that adversely affect choices, and imposing rules that create inefficiencies. A network-focused approach can capture various socio-economic inter-dependencies (Jackson, 2014) and can be used to provide policy prescriptions without necessarily having to invest in expensive data collection (Breza et al., 2019). I model, measure, and analyse social networks to address challenges in development economics. I theoretically model how social learning can be impacted by an individual's behavioural 'type', use structural estimation and experimental techniques to show how misperceptions can affect inter-personal dialogue about mental and financial health, and use secondary data to show how agents can leverage peer interactions and take actions that can restrict socio-economic mobility.

In Chapter 1, I derive and discuss theoretical results that show how individual learning idiosyncrasies can have multiplicative impacts on the long-run choices and beliefs of those in their network. How does an agent's under-reaction to new information or pessimism towards the source of information affect their own choices, the choices of their peers, and the long-run outcomes of the network? I answer these questions using tools from linear algebra and graph theory. In Chapter 2, my coauthor Ronak Jain and I study how individual misperceptions can affect inter-personal dialogue in social networks. We use structural estimation to highlight the potentially heterogeneous impacts of belief-shifting interventions and the dependence of the resulting equilibria on the structure of the network. We then present the results of a randomised controlled trial that we conducted with low-income individuals in New Delhi, India to improve engagement with mental and financial health and increase demand for community-led solutions. Finally, in Chapter 3, I discuss how agents in specific network positions benefit more from their rural networks and find it in their interest to not break any network rules themselves and prevent other agents from doing so. I test the predictions of the model on secondary data and find that the results can benefit policies that otherwise aim to address socio-economic mobility without taking network positions into consideration.

Learning in Networks with Idiosyncratic Agents

Individuals can under-react to information due to limited attention (Hanna et al., 2014; Schwartzstein, 2014). Poverty-induced "attentional demands" can also have negative impacts (Mani et al., 2013). Alternatively, individuals can overreact to their current information. Some might also be 'frustrated' and react negatively to positive signals spreading misinformation.[1] The first chapter shows how an individual's ways of responding to new information (affected by their

[1] I define these individuals as 'frustrated' because they are similar to those in Genicot and Ray (2017) whose investments decline despite rising aspirations when they are in the "frustration zone". Genicot and Ray (2020) describe this as "despair".

idiosyncrasies such as under-reaction, overreaction, or frustration) affect whether their long-run beliefs converge, converge accurately, and the speed with which they converge. Existing literature on behavioural learning focuses on the direct impact of various behavioural biases on individual outcomes and measures them mainly in laboratory settings. However, individual idiosyncrasies not only affect how they update their own beliefs but also impose an externality on the beliefs and choices of those they are connected to. They can feed into the choices and beliefs of those to whom the individuals are not even directly connected as learning takes place over infinite updating periods. I study the network-level impact of behavioural learning and contribute to (a) the existing literature on learning in networks that studies how network structure affects learning outcomes (Golub and Jackson, 2010; Acemoglu et al., 2010; Golub and Jackson, 2012) and (b) the literature on behavioural learning that shows how behavioural biases can affect individual learning outcomes (Kremer et al., 2019).

In the first part of the paper, I derive a sufficient condition that ensures that convergence takes place and show that the derived upper bounds on individual idiosyncrasies depend on both the structure of the network and the behavioural parameters. Golub and Jackson (2010) use a law of large numbers argument and find that beliefs in networks converge to the truth as the size of the population increases if and only if there do not exist agents who are disproportionately connected in the network. I use their approach to (a) show that beliefs may not converge to the accurate limit as the network grows even in the absence of such agents when agent idiosyncrasies also increase with the size of the network and (b) derive a measure of individual influence that determines whether long-run beliefs will be accurate. This measure of influence combines both the behavioural and network attributes of individuals.

Finally, I show how the slowness to update beliefs can create bottlenecks and have the same effect as that of two partitioned groups that do not transmit beliefs among each other. I suggest ways by which these bottlenecks can be tackled by interventions. These results have important applications to studying, for example, the evolution of beliefs about new technologies or attitudes towards vaccination. While the results of this paper are useful in predicting characteristics of long-run beliefs if one can accurately measure both the networks and agent behavioural types, I also discuss normative findings that can be used to guide policy in the absence of such precise measurement. I also simulate the model on artificial and real-world networks to check the derived relationships and the tightness of the derived bounds.

Misperceptions about Dialogue in Social Networks

This paper is co-written with Ronak Jain, a PhD student at Harvard University.

Individuals may not engage in inter-personal dialogue and seek advice from their peers. For example, Chandrasekhar et al. (2018) find that signalling and shame related concerns affect individual decisions to seek advice in rural India and Walker and Bantebya-Kyomuhendo (2014) discuss that poverty-induced shame can negatively affect willingness to interact and reduce social capital. In this paper, we show that low inter-personal dialogue about mental and financial health-related concerns might be driven by incorrect beliefs about the community's willingness to engage. We find among our experimental sample of low-income individuals in New Delhi, India that roughly 54% of individuals report that they rarely or never have had a conversation about mental health-related concerns with their peers in the last two weeks. 64% of individuals reveal a willingness to do so and 68% underestimate the willingness of other members in their community. We apply the models in Jackson and Yariv (2007); Jackson (2019) to examine how such

misperceptions can naturally arise in a network where individuals choose whether or not to engage in dialogue. The costs of engaging in dialogue are proportional to the expected disengagement in their neighbourhood so that individuals have an incentive to conform. Then, as in Jackson (2019), we apply the friendship paradox to show that individuals can underestimate average dialogue in their network if they treat the dialogue among their peers as a proxy for it. This is because an individual's peers, on average, are more connected than they are (Feld, 1991) and being more connected implies higher costs of dialogue if the majority choose to not do so.

We provide empirical evidence in favour of the model by constructing two proxies for disengagement by using the data on multiple networks among the same set of individuals collected by Banerjee et al. (2013) and studying differences between these networks. We use the instrument strategy proposed by Bramoullé et al. (2009); De Giorgi et al. (2010) to show that these network-based proxies of disengagement exhibit positive peer effects. Next, we structurally estimate the model using this data to (a) emphasise the role played by networks in affecting the equilibrium disengagement in the model and (b) highlight the importance of this heterogeneity in the short run and long-run impact of belief correcting interventions. We find that majority of the villages have three equilibria of disengagement: a stable equilibrium of zero disengagement, a low non-zero unstable equilibrium, and a high stable equilibrium suggesting the existence of a tipping point. We use policy counterfactuals to then show that the degree distribution of the network, as predicted by the model, affects the short run and long-run impact of an intervention that shifts individual beliefs. This highlights the importance of timing in the measurement of treatment effects after such an intervention and the dependence of this on the underlying network structure.

Finally, we present the results of a randomised controlled trial we conducted among low-income individuals affiliated with an NGO in New Delhi, India. We document that individuals underestimate the willingness of their community to engage in inter-personal dialogue about mental and financial health. We find that the gaps between their overall and advice networks (i.e. networks that capture all interactions v/s interactions specific to advice pertaining to personal problems) are correlated with whether individuals severely underestimate their community's willingness to engage in a dialogue. We shift these beliefs by providing individuals with accurate information about the true average beliefs across the communities and find immediate impacts in terms of (a) higher willingness to participate in potential savings groups, (b) higher willingness to volunteer for a community mental health listening service, and (c) higher contributions made towards a public good. Conditional on agreeing to donate to the public good, we find that those who are categorised as stigmatised against mental health in the baseline are more likely to contribute when they are in the treatment group. We also document spillover effects on physical health-related dialogue. In addition to this, we find evidence that an individual's investment in their mental health (in terms of participation in the enumerator-conducted depression scoring and willingness to listen to helpline numbers) and the assistance they expect from their community can be substitutes. The positive impact of a shift in beliefs on take-up for potential savings groups and other community-level activities suggests that beliefs may be one of the constraints preventing individuals from making full use of their social network. We also present the results of the follow-up survey conducted during the peak of the COVID-19 crisis in India in April-May 2021.

Network Rules and Network Intermediaries

Munshi and Rosenzweig (2009) find that caste networks can reduce mobility- those in richer caste-

networks are less likely to migrate or marry outside their caste. I study how an agent's network position can affect (a) the benefits they obtain from the network and (b) the probability that they break network rules that risk loss or dilution of existing network links. I modify and apply existing theoretical models by Goyal and Vega-Redondo (2007); Choi et al. (2017) to show that (a) agents lying on many shortest paths can benefit from being providers of access and be less likely to leave the network, (b) these central agents can be more likely to impose a credible threat on those whose decisions impose a negative externality, and (c) that the decisions to invest in shortest paths can be strategic substitutes. I test these three empirical predictions using the data on individual characteristics and networks of 75 Indian villages collected by Banerjee et al. (2013). I find that agents who lie on many shortest paths (i.e. have a high betweenness centrality) are less likely to travel for work outside the village and more likely to open a savings account, which I argue, signals a commitment to stay in the village and preserve the status quo. I address the endogeneity of the network variables by using a theoretically motivated instrumental variables approach motivated by prediction (c) stated above.

I check if the centrality-migration relationship is robust to the type of network, the computational unit (individual or household), and the inclusion of other centrality measures. I find that the relationship is robustly negative when I consider other networks such as the economic network that assumes a link if individuals report any economic relationship or the overall network that assumes a link if individuals report any relationship at all. I also find that despite the correlation with other centrality measures, betweenness centrality continues to have a robustly negative effect even after degree and eigen vector centrality are included in the empirical specification. I also measure endogenous and exogenous peer effects and use the instrument strategy proposed by Bramoullé et al. (2009); De Giorgi et al. (2010) to identify the former. I find that decisions to commute to work outside the village are strategic complements.

Finally, I discuss how the network position of an individual's peers can affect their decision to travel to work outside their village. I discuss the implications of the endogeneity of this variable and the mechanisms through which it can have an effect and report correlational evidence to check if individuals located in networks containing agents endowed with disproportionately large market power (i.e. having a high betweenness centrality) are less likely to travel to work outside the village. To this effect, I compute the market power of an agent in the network as the difference in the connectedness of the network, measured by computing the difference in the network's Fiedler value (Fiedler, 1973) when the agents are present in the network and removed from it. I suggest that policymakers can achieve an increase in the take-up of lucrative employment outside the villages and a consequent increase in mobility by reducing the influence of the between-central brokers. Mobility can be increased if individuals can access information and transact with each other without having to rely on the information brokers and if the competition among these brokers is increased to reduce their market power.

Chapter 1

Learning in Networks with Idiosyncratic Agents [1]

Vatsal Khandelwal [2]

Individuals can be slow to update beliefs and may respond to new information in idiosyncratic ways. Since their beliefs affect the choices of those they interact with, the idiosyncrasies that affect their capacity to learn information also affect how information accumulates across society. This paper shows how an individual's under-reaction to new information (for example, due to lack of attention) and idiosyncratic ways of responding to new information (due to overreaction or frustration) affect (a) the ability of society to reach an agreement, (b) the ability of society to reach the correct agreement, and (c) the speed with which such an agreement is reached. I derive sufficient conditions for convergence in beliefs in the form of network-dependent upper bounds on idiosyncrasies for all networks of individuals with heterogeneous biases, placing heterogeneous weights on their neighbours. Then, I show that the absence of very connected influential agents is not sufficient to ensure that beliefs converge to the truth when idiosyncrasies also change with network size. I also show how under-reaction can affect the speed with which societies learn by deriving upper bounds on bottlenecks for regular networks dependent on the extent of individual under-reaction. I use this to bound convergence times and briefly discuss how such analyses can be used to understand and tackle the persistence of norms. Finally, I simulate the model on real and artificial networks and find that the results are validated.

[1] I thank Stefan Dercon and Alexander Teytelboym for their suggestions and guidance. I also thank James Duffy, Ben Golub, Willemien Kets, Margaret Meyer, Stephen Nei, Aidan Smith, Bassel Tarbush, Séverine Toussaert, Peyton Young, and the participants at the Oxford Student Micro Theory Workshop for their comments and suggestions.

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1 Introduction

The behavioural characteristics of an individual do not only affect their own beliefs and choices but also the beliefs and choices of their peers. Individuals may be slow to respond to new information, they might overreact to recent events and not place enough weight on the past, or might be mistrusting or cynical. Some might also deliberately try to sabotage information accumulation by responding to it in counter-intuitive ways. This paper studies the indirect, multiplicative impacts of such idiosyncrasies on the ability of a society to learn and reach an agreement. For example, how does learning take place among under-reacting, cynical, misinformation-spreading, or over-reacting individuals who, for example, want to learn the true benefits of a new technology? What magnitude of individual idiosyncrasy can a society tolerate to reach an agreement about an unknown state of the world? How does it affect the ability of a society to reach an accurate consensus and the speed with which such a consensus is reached? I show that learning idiosyncrasies affect social learning along these dimensions when individuals are embedded in a network and make inferences based on the choices of those they are connected to. I suggest that interventions interested in social learning and long-run belief formation must jointly take *both* network structure and individual behavioural idiosyncrasies into consideration to ensure that beliefs converge accurately and quickly.

I use 'idiosyncrasy' as a broad term to capture an individual's behavioural type. I categorize these idiosyncrasies as under-reaction, over-reaction, and frustration respectively. These idiosyncrasies enter the model as weights that individuals place on their current and past information while forming their new belief. Individuals can be status quo biased (Samuelson and Zeckhauser, 1988) and consequently update their beliefs slowly. This under-reaction can also arise due to a lack of attention to new information. This relates to a strand of literature in behavioural economics that studies the impact of cognitive load such as Mani et al. (2013) and limited attention such as Schwartzstein (2014) and Hanna et al. (2014).[3] An under-reacting individual in the model places weights α_i and $1-\alpha_i$ with $\alpha_i \in (0,1)$ on their past and current beliefs to form the belief on the basis of which they make choices. Instead of being slow, some individuals might overreact to their current beliefs, undermining the beliefs they've held in the past. Some might be frustrated and place a high weight on their past beliefs instead. Frustration, borrowing the term from Genicot and Ray (2017), can be interpreted in two ways.[4] Frustrated individuals can be pessimistic and mistrusting due to past experiences and may react negatively (positively) to good (bad) news.[5] Alternatively, frustrated individuals can be interpreted as 'contrarians' i.e. those who

[3] See Gabaix (2019) for an extensive review of the literature on limited attention.

[4] The first interpretation is inspired by agents in Genicot and Ray (2017) whose investments decline when their aspirations improve when they're in the "frustration zone". Genicot and Ray (2020) describe this as 'despair'.

[5] This behaviour can also be related to the "backfire effect" found among the subjects of the experiments in Nyhan and Reifler (2010) whose misperceptions became worse after they were given correct information.

deliberately try to derail the learning process by behaving in a manner that sends incorrect signals to the observers.[6] A frustrated agent, as the model will illustrate, is one for whom $\alpha_i > 1$ so that they place a disproportionately high weight on their past beliefs.

I specify two standard environments in which individuals update their beliefs. In the first case, labelled, *regular information*, an individual's belief depends on privately received signals and the choices of those they are connected to. This can, for example, be used to explain a process in which individuals form beliefs about a technology and choose an adoption intensity after observing their private returns and the adoption intensity of their friends. For example, Conley and Udry (2010) find that farmers in Ghana learn the benefits of using fertilizers while growing pineapples from their own and their friend's experiences. This learning setup, where individuals learn from both their private signals and information from their networks, has also been studied in papers such as Jadbabaie et al. (2012) and Molavi et al. (2018).

In the second case, labelled, *one-off information*, individuals make choices based on the choices of those whom they are connected to but do not receive any private signal except a one-off initial signal which affects their first period beliefs. They only learn from whom they interact with and receive no additional private information. This is a more standard setting studied in the existing literature. Jackson (2010) and Golub and Sadler (2017) provide an extensive review of this learning model. In both the regular and one-off cases, individuals observe the choices of their network neighbours, infer their beliefs, form their own beliefs using these inferences and their private signal (if observable). They update their beliefs by taking a weighted average (DeGroot, 1974) and the process is repeated over infinite periods. I study how idiosyncrasies such as under-reaction, frustration, or overreaction, affect social learning in both cases. A critical assumption is that agents are not aware that their neighbours are idiosyncratic and interpret their neighbour's choices wholly as a signal about the state of the world. This generates network-level externalities of individual idiosyncrasies in that they affect the convergence of beliefs in society, the accuracy of the long-run belief, and the speed with which it converges.

I find three main sets of results.

First, I find that when individuals receive regular information, beliefs converge to a societal agreement if (a) the magnitude of over-reaction and frustration in agent network neighbourhoods is below a derived upper bound and (b) agents situated around over-reacting or frustrated peers in the network trust their beliefs enough. The derived upper bound depends on both the network and behavioural characteristics of certain identifiable agents in the network. Sufficient conditions for convergence are derived for all networks whose members exhibit heterogeneous idiosyncrasies and place heterogeneous weights on the beliefs of their neighbours. I also extend the convergence theorems to

[6] Fake news and foreign interventions in election campaigns are prominent examples. For example, see "Chaos Is the Point': Russian Hackers and Trolls Grow Stealthier in 2020", *The New York Times*, January 10, 2020.

study convergence in beliefs among individuals whose idiosyncrasies are more persistent i.e. they do not only place a weight on their past period beliefs but place a weight on their beliefs over several periods. The threshold is analogous to the baseline case.

Figure 1.1 shows how different levels of idiosyncrasies can affect the convergence of beliefs in the giant component of a rural Indian advice-taking network from Banerjee et al. (2013). Figure 1.2 shows how different levels of trustworthiness of own beliefs can affect the convergence of beliefs. I find that the intuition that a more idiosyncratic network is likely to have divergent beliefs may not always be correct. Beliefs in a network with more idiosyncratic agents may not necessarily diverge if the agents trust themselves enough. This point is illustrated by the network on the right in Figure 1.2 which is just as idiosyncratic as the divergent networks in Figures 1 and 2 except that individuals trust themselves enough. Similarly, beliefs may not converge if there exist agents who do not place a high enough weight on their own signal. This can be true even if agent idiosyncrasies are not very high. The upper bound depends on both the magnitude of the idiosyncrasies and the weights agents place on each other in the network.

Second, I demonstrate how the three types of idiosyncrasies can affect the accuracy of the convergent beliefs. I find that convergent beliefs are accurate when individuals form new beliefs by taking a linear combination of their current and past beliefs and receive regular information. The weights can be negative but must sum to one. A trivial implication is that beliefs in networks with under-reacting individuals always converge to the truth. However, this also means that conditional on convergence, beliefs always converge to the truth even if the network contains frustrated agents. I also discuss an outlier case in which this is not true i.e. where (a) a social agreement is not reached even if individual beliefs converge and (b) individual beliefs converge to an inaccurate value.

The one-off information case is more involved. Golub and Jackson (2010) call networks "wise" if the convergent beliefs of its agents are correct. They find that society becomes asymptotically wise as network size increases if the influence of the most influential agent goes to zero. I use their approach to derive an idiosyncrasy-dependent measure of agent influence and a sufficient condition for wisdom when agents place equal weight on their neighbour's beliefs. While the derived sufficient condition is subsumed in their result, it emphasizes that agent idiosyncrasies and their interactions with the network structure must be taken into account while studying wisdom. Idiosyncrasies do not affect the wisdom of growing networks if they are constant as network size increases. However, I highlight that individuals may not reach an accurate convergent belief if their idiosyncrasies respond to network size. I find that while both frustration and over-reaction cause beliefs to diverge if they cross a certain threshold, growing overreaction can initially help the network approach wisdom.[7] This is because, unlike overreaction, a disproportionate increase in frustration can make the *past self* of an

[7] Golub and Jackson (2010) use Chebyshev's inequality while relating agent influence to wisdom. Here, whether the network "approaches" wisdom, is gauged in terms of changes in the Chebyshev upper bound.

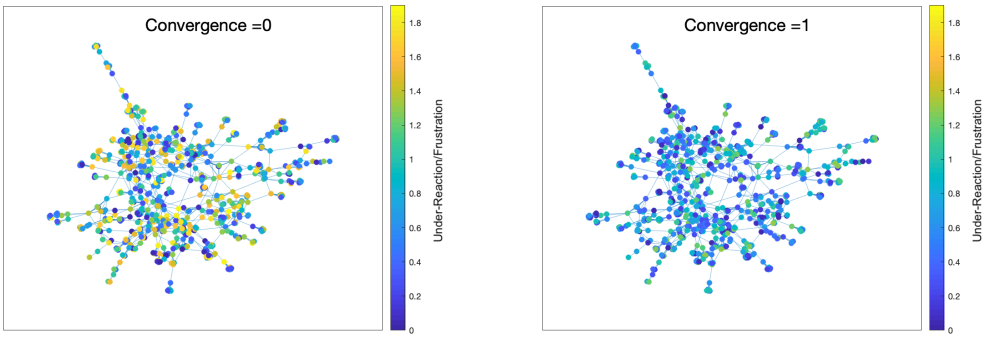


Figure 1.1: Individuals in the same advice network (village 15) from Banerjee et al. (2013) are assumed to have idiosyncrasies α_i randomly picked from uniform distributions characterized as "low" $[0, 1.3]$ i.e. under-reacting or frustrated (on the right) or "high" $[0, 1.9]$ i.e. very frustrated (on the left). They are assumed to place an equal weight on their private signals and their friend's choices.

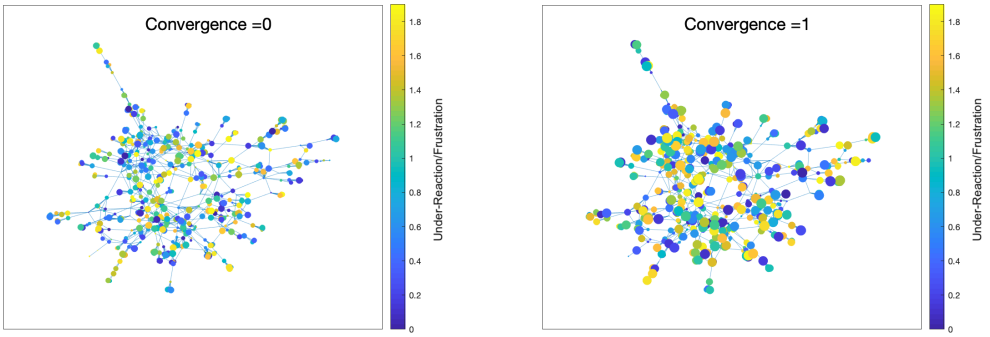


Figure 1.2: Individuals in the advice network (village 15) from Banerjee et al. (2013) are assumed to place a weight on their own beliefs, randomly picked from uniform distributions characterized as "low" $[0, 0.5]$ (on the left) or "high" $[0, 1]$ (on the right). Idiosyncrasies are picked from the "high" $[0, 1.9]$ distribution. The size of the marker is proportional to the weight agents place on their own beliefs.

agent very influential. This can raise their total influence on others' beliefs and inhibit wisdom. Crucially, this can be true even if the agent stays just as influential or becomes less influential in the network sense. This illustrates again that the interaction between an individual's network position and behavioural characteristics cannot be ignored especially while studying processes that involve social learning. Simulated examples verify this intuition.

Third, I show that an individual's under-reaction i.e. slowness in updating their beliefs affects the speed with which societies reach an agreement in the one-off information model. I show that making a network where each agent has the same number of connections (i.e. a regular network) more connected is equivalent to reducing or eliminating the under-reaction of its members. The literature on convergence times of Markov processes suggests that the bottleneck ratio can be used to provide a lower bound for the time it takes the process to converge (Levin and Peres, 2017). The bottleneck ratio is computed by finding the worst partition of the network such that each partitioned group pays minimum attention to the beliefs of the other (Levin and Peres, 2017). Golub and Sadler (2017) also discuss how this measure relates to the speed of convergence. I compute analytical expressions for the upper bounds of the bottleneck ratio for regular networks in terms of under-reaction and network connectivity. These bounds are used to construct a lower bound on the time it takes individual beliefs to converge in any regular network. I find that a reduction in under-reaction and an increase in connectedness can reduce learning bottlenecks and convergence times. I also find that these bottleneck bounds are more responsive to changes in under-reaction when agents have more connections.

Finally, I randomly endow idiosyncrasies to the agents in the advice networks collected by Banerjee et al. (2013) to test the tightness of the sufficient condition derived for convergence. I find that networks that are more likely to satisfy the sufficient condition are more likely to have convergent beliefs. Maximal agents in these networks are not necessarily those with the highest conventional measures of centrality.[8] Careful measurement of learning idiosyncrasies is needed to identify these agents. This can then be a first step towards predicting learning outcomes in real-world networks with idiosyncratic agents. This also points towards the need to develop augmented notions of network importance that account for behavioural characteristics.

I also provide additional evidence to support the predictions on bottlenecks and speed by computing convergence times for randomly generated regular networks and the irregular networks in Banerjee et al. (2013). I check how well the empirical relationship between under-reaction, connectedness, and convergence time matches the theoretical predictions. I find that the derived lower bound on mixing time is tight for sufficiently connected d-regular networks and that convergence time in both d-regular and village networks responds to under-reaction as per the predictions of the model. I also find evidence supporting the claim that convergence times become more responsive to changes in

[8] See Jackson (2010) for a discussion on various ways to measure an agent's importance in the network.

under-reaction as regular networks become more connected. Convexity of convergence times as a function of under-reaction cannot be conclusively established in irregular networks although there is evidence pointing in that direction.

The paper is structured as follows. I discuss the contributions to existing literature in Section 2. The setup of the model is discussed in Section 3. In Section 4, I derive and discuss the results on convergence. I discuss the results on the accuracy of the convergent beliefs in Section 5. The results on speed of convergence are covered in Section 6. In Section 7, I run simulations to investigate (a) how well the sufficient condition predicts convergence and (b) the tightness of the bounds derived on the speed of convergence. Section 8 discusses the implications of the results and Section 9 concludes. The proofs of the lemmas and theorems are provided in the appendix.

2 Contribution

This paper is related to the existing theoretical work on learning in networks. I complement this literature by incorporating behavioural idiosyncrasies in the learning process and studying how these get amplified by the network and affect learning outcomes.

First, existing literature shows how network structure affects whether beliefs converge and converge accurately. Golub and Jackson (2010) find that beliefs converge correctly i.e. the network is "wise" if there exists no agent with non-decreasing 'influence' as the network size increases. Acemoglu et al. (2010) find that converged beliefs are most inaccurate when there exist many "forceful" agents who only listen to those who listen to them. I illustrate that idiosyncrasies can affect Golub and Jackson (2010)'s measure of agent influence and prevent accurate learning if they grow with the size of the network. Incorporating idiosyncrasies in the learning process also allows me to emphasise that *both* the network structure and the behavioural type of the individuals *interactively* affect social learning. To this effect, I also make a methodological contribution to the literature on social learning by applying the theoretical results of Gershgorin (1931); Taussky et al. (1948) to study how behavioural idiosyncrasies affect the largest eigen-value of the matrix that determines the weight agents place on each other's beliefs.[9]

Unlike the literature that studies how individuals exhibiting an affinity towards a fixed belief can affect social learning (Friedkin and Johnsen, 1999; Acemoglu et al., 2010; Bloch et al., 2018; Della Lena, 2019), agents in this paper do not have fixed beliefs and their idiosyncrasy does not affect whom they pay attention to. Instead, they continuously update their beliefs in a manner that is in line with the learning idiosyncrasy they exhibit. For example, frustrated agents in my model do not have a fixed pessimistic belief that they are too stubborn to change. Instead, they are persistently mistrusting and/or eager to spread misinformation and update their beliefs accordingly. [10] This allows me to relate

[9]The magnitude of this eigen-value determines whether beliefs converge.

[10]Similarly, over-reacting agents place a weight (larger than one) on their current beliefs and a

long-run learning outcomes with the behavioural type of the individual.

Second, I contribute to the literature on the speed of learning. Golub and Jackson (2012) suggest a new "spectral" measurement of homophily and find that homophily reduces the speed with which beliefs converge. I find that the negative effect of under-reaction on the speed of learning is analogous to partitioning the network into two groups that do not pay attention to each other. Existing literature also discusses how such bottlenecks can reduce the speed of learning (Golub and Sadler, 2017). I show that learning bottlenecks induced by agent under-reaction can have a similar negative effect as bottlenecks induced solely by the network structure. I also briefly discuss the implications of these results on norm-shifting interventions. Young (2001, 2015) discuss norm persistence and how norms can be locally homogeneous but exhibit global variation. I discuss that social learning can be accelerated to tackle norm persistence by reducing the derived learning bottlenecks. I discuss that this can be achieved in regular networks either by reducing under-reaction or equivalently, by increasing the number of connections.

Third, this paper also complements the growing literature on "behavioural learning" reviewed in Kremer et al. (2019). Kremer et al. (2019); Benjamin (2019) review issues that individuals can face while forming beliefs after observing new information. While an agent's idiosyncrasy affects their beliefs and choices in the model considered here, it is only able to have a multiplicative impact across the network because of an underlying issue of interpretation. Individuals incorrectly assess that their peers are not idiosyncratic and interpret their peers' choices to be perfectly indicative of their underlying beliefs. Hence, they incorrectly infer their peers' underlying beliefs after observing their choices without accounting for their peers' idiosyncrasies. I also contribute to the literature on limited attention reviewed in Kremer et al. (2019). Under-reaction affects an individual's belief formation rule in this paper as the attention parameter affects the individual's subjective world-view in Gabaix (2019). I explicitly add a network dimension to study the multiplicative, society-level impacts of such attentional constraints. The impact of these constraints on long-run beliefs is especially important to study given the empirically documented negative effects of limited attention in other contexts such as the one in Hanna et al. (2014) who find that farmers do not pay attention to specific inputs.

3 Setup

Each agent i belongs to a finite set of agents N s.t. $\mid N \mid = n$. All agents are embedded in a network of agents G where $g_{ij} = 1$ if a link exists between i and j and 0 otherwise. The set of agent i's neighbours $N(i)$ includes all the agents to whom agent i is linked. The network G is assumed to be (a) undirected i.e. a link between agents i and j implies a link between agents j and i and (b) strongly connected i.e. there exists a path between any two agents i

positive/negative weight on their past beliefs and keep updating in this manner. I find that networks can tolerate such persistent idiosyncrasies up to a limit and still reach an agreement.

and j in the network. I will refer to d_i as the number of neighbours of agent i and $d_{i:condition}$ as the number of neighbours of agent i who satisfy a given *condition*. Individual i places a strictly positive DeGroot weight w_{ij} (DeGroot, 1974) on her neighbour j's opinions and w_{ii} on herself such that $\sum_{i\in N(i)} w_{ij} + w_{ii} = 1$. These weights will be specified to be equal across i's neighbours and herself (i.e. $w_{ij} = \frac{1}{d_i+1}\ \forall j \in N(i)$) as and when necessary.

In each discrete time period t, every agent i makes a choice e_{it} based on the set of her beliefs $\{r_{ik}\}_{k=0}^{k=t}$ about an unknown return r. After every agent has made their choice, they observe the choices made by her network neighbours and infer their beliefs about r. In addition, each agent may also observe a private signal s_{it+1} which is independently and identically distributed around the mean r across all agents in N. Based on the information from their network and their private signal (if visible), every agent i forms a new belief about r labelled r_{it+1}. Then, agents make a choice based on the set of current and past beliefs $\{r_{ik}\}_{k=0}^{k=t+1}$ in period $t+1$. This process continues for infinite time periods. I assume that agents only use their current and past beliefs, $\{r_{ik}\}_{k=t-1}^{k=t}$ to make their choice in period t but this assumption can be relaxed and the results are analogous. I discuss this case in the appendix. The details of this setup are explained below.

3.1 Choices

The utility of an agent i in time period t is a function of her choice e_{it} given the return she *expects* to receive at the end of period t and the cost associated with her choice. The returns she expects from choice e depend on the agent's beliefs about the true return r. The individual's expectation of the true return, based on which they make choices, is assumed to be a linear combination of their beliefs about the returns in time t and $t-1$. The weights α_{1i} and α_{2i} placed on the current and past beliefs determine the specific type of idiosyncrasy. An individual's idiosyncrasy refers to the specific value of the two parameters α_{1i} and α_{2i} that affect the formation of the 'expected return' on the basis of which they make their choice. An individual i is said to exhibit no idiosyncrasy when they place a weight equal to 1 on their most recent information $\alpha_{1i} = 1$ and $\alpha_{2i} = 0$.

Let $f : \mathbb{R} \to \mathbb{R}^+$ be an injective function that maps the expected return in period t to a positive real number such that $f'(x) > 0\ \forall x$ and let f be commonly known among all agents.[11] Let c be the increasing, strictly convex cost associated with the choice e_{it}. The utility function can be written as follows-[12]

$$U_{it} = \big[f(\alpha_{1i}r_{it} + \alpha_{2i}r_{it-1})\big]e_{it} - c(e_{it}) \tag{1.1}$$

[11]The commonly known function f is introduced to ensure that the agent's choice is always informative. For instance, if f weren't introduced, then $e^*_{it} = 0\ \forall\ \alpha_{1i}r_{it} + \alpha_{2i}r_{it-1} < 0$. By mapping these negative expected returns to a unique positive number, f ensures that effort is always informative of beliefs.

[12]The payoff function below can be interpreted as a rewritten version of that in Kőszegi and Rabin (2006) if we place additional restrictions on f. Individuals are not loss averse here, but as in Kőszegi and Rabin (2006), they treat their last period belief as a reference point and respond to differences between this and their current belief as per their idiosyncrasy.

where $\alpha_{1i}, \alpha_{2i} \in \mathbb{R}$, $c''(e_{it}) > 0 \; \forall \; i, \; t$

Idiosyncrasies

As defined above, an individual's idiosyncrasy affects the value of the two parameters α_{1i} and α_{2i} and determines the expected return on the basis of which they make their choice. I distinguish between the following types of idiosyncrasies:

1. *Under-reaction*- In this case, agent idiosyncrasies α_{1i} and α_{2i} are such that $\alpha_{1i}, \alpha_{2i} \in (0, 1)$ and $\alpha_{1i} + \alpha_{2i} = 1$. These agents are assumed to react slowly to new information in that they form their belief r_{it} about the true return r in period t but instead of using this belief, they take a linear combination of their beliefs r_{it} and r_{it-1} while making their choice. I argue that this can arise due to a resistance to changing their baseline opinion due to status quo bias (Samuelson and Zeckhauser, 1988) or because they do not pay enough attention to the variable in the first place (Gabaix, 2019). In the latter case, α_{1i} can be interpreted as the probability with which the individual pays attention to this variable and updates their belief in period t. For example, if $r_{it} > r_{it-1}$ for an agent i, their choice e_{it}, affected by $\alpha_{1i} r_{it} + \alpha_{2i} r_{it-1}$ will not be as high as it would be if they were placing full weight on r_{it}.

2. *Over-reaction* - In this case, agent idiosyncrasies α_{1i} and α_{2i} are such that $\alpha_{1i} > 1$, and $\alpha_{2i} < 0$ and $\alpha_{1i} + \alpha_{2i} = 1$. Existing literature shows, for example, that prices of stocks can be affected by individual overreaction to unexpected news (De Bondt and Thaler, 1985) and that individual predictions using macroeconomic data are error-prone due to overreaction (Bordalo et al., 2020). Similar to this, agents in my model over-react to new information in every period. For example, if such an agent has beliefs $r_{it} > r_{it-1}$, their choice e_{it} will be higher than the case in which they were placing a weight of 1 on r_{it} or if they were under-reacting.[13]

3. *Frustration* - In this case, agent idiosyncrasies α_{1i} and α_{2i} are such that $\alpha_{1i} < 0$, and $\alpha_{2i} > 1$ and $\alpha_{1i} + \alpha_{2i} = 1$. These agents react positively to negative information and vice versa. For example, if such an agent has beliefs $r_{it} > r_{it-1}$, their choice e_{it} will be lower than the previous period. The term frustration is borrowed from the agents in Genicot and Ray (2017) who in the 'frustration zone' reduce their investments when their aspirations improve. These agents can also be interpreted as contrarians or misinformation-spreading. Conspiracy theorists with "self-insulating" beliefs that are strengthened further when presented with contradictory information (Sunstein and Vermeule, 2009) are also similar to the frustrated agents here.

Note that these three cases only include parameter values α_{1i} and α_{2i} such that $\alpha_{1i} + \alpha_{2i} = 1$. However, note that $\mid \alpha_{1i} \mid + \mid \alpha_{2i} \mid > 1$ for frustrated and over-reacting agents. For the remainder of the paper, α_{1i} and α_{2i} will be loosely referred to as the agent i's 'behavioural

[13] See Barberis (2018) for a review of behavioural models that can explain both over *and* under-reaction.

parameter' or 'idiosyncrasy'.[14]

First Order Condition

Given these idiosyncrasies, the first order condition can be written as follows:

FOC: Optimal effort for agent i solves the equation:

$$e^*_{it} = c'^{-1}(f(\alpha_{1i} r_{it} + \alpha_{2i} r_{it-1})) \tag{1.2}$$

This implies that if the agent is under-reacting and $r_{it} > r_{it-1}$ then she will increase her choice of e but not by as much as she would have if she were not under-reacting. If she is frustrated and $r_{it} > r_{it-1}$, she will choose a lower e in period t as compared to period $t-1$. If she overreacts to current beliefs and $r_{it} > r_{it-1}$, she will choose a higher e in period t as compared to period $t-1$ and this will be more than what she would have chosen if she were not over-reacting.

For example, let e be the effort exerted in supporting a political party and r be the expected rate of return of such support. An individual who under-reacts would change their political support slower than an individual without any such bias whereas an individual with frustration would reduce their political support to the party if the perceived returns improve. This could be a deliberate choice to spread misinformation or be a result of cynicism inbuilt from past experiences of hearing positive news but seeing negative results. An individual who overreacts will increase or decrease political support a lot more than they should.

The model applies to a variety of different settings but I choose the effort-choice setting for purposes of exposition. The choice variable e and the return variable r will be referred to as effort and payment rate respectively.

3.2 Beliefs

I assume that every agent's cost function c is quadratic and commonly known to their neighbours. I also assume that the function f is also commonly known to all agents. So, agents can transform their neighbour's observed effort into the belief based on which their neighbours made that choice. Agents are assumed to be unaware of their neighbour's learning idiosyncrasy and function as if $\alpha_{1j} = 1$, $\alpha_{2j} = 0$ for their neighbours j. This is how an individual's idiosyncrasy begins to affect the choices of their neighbours. Every agent i would ideally like to include their neighbour j's belief r_{jt-1} while forming their own beliefs in period t. However, because they're unaware of their neighbour's idiosyncrasies and only observe their neighbour's choice e_{jt-1}, they include the linear combination $\alpha_{1j} r_{jt-1} + \alpha_{2j} r_{jt-2}$ while updating their own beliefs thereby allowing their neighbour's idiosyncrasies

[14] While the paper only deals with the cases where $\alpha_{1i} + \alpha_{2i} = 1$, I very briefly discuss an outlier case in Section 5.1 in which there exist agents for whom $\alpha_{1i} + \alpha_{2i} > 1$ and both parameters are additionally strictly positive. I interpret what this means for their behaviour and show how it can affect learning outcomes.

to affect their choices. It is important to emphasise here that while the cost $c(e)$ of the choice e is assumed to be quadratic and common knowledge, this does not preclude heterogeneity in cost functions across agents if agents have perfect information about these cost functions and there is a one-to-one mapping between j's observable effort and the belief that i infers j has from observing their effort.

Individuals are assumed to update their beliefs using the DeGroot learning rule (DeGroot, 1974) in both environments. I use the DeGroot model due to the following reasons. *First*, individuals in a DeGroot setup form their belief about the present state of the world by taking a weighted average of their own previous belief and the inferred beliefs of their neighbours in the previous period. Browning et al. (2015) find that in accordance with the Bayesian response, non-anxious individuals rely more on very recent information while learning in an environment where the state of the world is not fixed. Even though the state of the world i.e. the distribution of the underlying variable, is fixed in my model, it can be argued that habitually relying on most recent information can be a valid learning model for agents who may otherwise inhabit an unstable environment. *Second*, unlike Bayesian agents who would place differing weights on their peers with the weights changing over time, agents in this model place an unchanging constant weight on their neighbour's inferred beliefs. DeMarzo et al. (2003) find that DeGroot-style learning can naturally arise if individuals update their beliefs in a Bayesian manner but are susceptible to 'persuasion' bias in that they do not update their weights after the first period.[15] *Third*, individuals in the DeGroot setup do not question the usefulness of information that they receive from their network neighbours who may also be paying attention to each other. This is in line with redundancy neglect that is extensively documented in existing literature (Eyster and Rabin, 2010; Kremer et al., 2019) and detected in experimental settings (Eyster et al., 2018). *Finally*, Bayesian learning models are not easy to apply to complicated settings (Jackson, 2010) which is why the DeGroot assumption that the weights placed on neighbour's beliefs do not change over time can be appealing. In an experimental setting, Chandrasekhar et al. (2020) find that the proportion of Bayesian agents learning a binary state is as low as 10% among their sample of rural Indian villagers from Karnataka.[16]

I now specify how individuals update their beliefs in two learning environments which differ only by whether or not they receive private signals.

Model with Regular Information

In this case, individuals form beliefs about the true return by observing both the effort level of those they are connected to in their network and a private, noisy, signal s_{it} of the true return r such that $E[s_{it}] = r$. Agents place weights on their private signal and the inferred rates from their neighbour's efforts. Then, they form their belief r_{it} as a weighted

[15] This motivation for the DeGroot model is also discussed in Golub and Sadler (2017).

[16] Choi et al. (2016) discuss other lab-settings where the DeGroot model has been tested.

average (DeGroot, 1974) as per the following *belief formation rule*-[17]

$$r_{it} = w_{ii}s_{it} + \sum_{k \in N(i)} w_{ik} f^{-1}(c'(e^*_{kt-1})) \tag{1.3}$$

This equation implies that the individual's belief r_{it} is formed by taking an average of their own signal s_{it} and the inferred beliefs of their peers. These beliefs are inferred by observing the peers' effort in the previous period. Individuals are assumed to know the cost function c and the function f both of which are used recover the inferred belief of their peers from their observed effort. As discussed earlier, the function f ensures that the observed effort is informative of the underlying beliefs in that it one-to-one maps the subjective belief on the basis of which the choice was made (i.e. the expected return) to a unique positive number. This rules out cases where the effort choice is zero. I also assume that the choices made by the agent are continuous since a discrete, binary choice of effort, for example, will not be entirely indicative of the peer's underlying belief and only that it is either positive or negative. Rewriting the RHS of the equality above, we get:

$$r_{it} = w_{ii}s_{it} + \sum_{k \in N(i)} w_{ik} \left[\alpha_{1k} r_{kt-1} + \alpha_{2k} r_{kt-2}\right] \tag{1.4}$$

This does not imply that the agents are aware of their peers' idiosyncrasies. Instead, they can infer the expected return on the basis of which their peer made their choice i.e. the scalar $\alpha_{1k} r_{kt-1} + \alpha_{2k} r_{kt-2}$ and then use this to update their beliefs. The assumption that agents are not aware of their peers' idiosyncrasies is critical to illustrate the multiplicative impact of idiosyncrasies because it is due to this assumption that an agent i does not try to disentangle r_{kt-1} and r_{kt-2} from the inferred belief of neighbour k.

Now, we can stack r_{it} across all agents to get $R_t = W_1 S_t + W_2 R_{t-1} + W_3 R_{t-2}$ where R_t is the vector of beliefs in period t and S_t is the vector of observed (noisy) signals in period t. W_1, W_2 and W_3 are square matrices I is the identity matrix, and 0 is the null matrix, all of order n . The matrices W_1, W_2 and W_3 information about the weights that agent's place on each other's beliefs and the idiosyncrasies they exhibit while learning new information and are constructed by stacking the belief formation rule across all agents. We can rewrite this difference equation as follows-

$$\begin{bmatrix} R_t \\ R_{t-1} \end{bmatrix}_{2n \times 1} = \begin{bmatrix} W_1 S_t \\ 0 \end{bmatrix}_{2n \times 1} + \begin{bmatrix} W_2 & W_3 \\ I & 0 \end{bmatrix}_{2n \times 2n} \begin{bmatrix} R_{t-1} \\ R_{t-2} \end{bmatrix}_{2n \times 1}$$

[17] Agent i thinks that her neighbour k doesn't exhibit any idiosyncrasies so incorrectly believes that $\alpha_{1k} = 1$ and $\alpha_{2k} = 0$. This is why she inadvertently includes $c'(e^*_{kt-1}) \neq r_{kt-1}$ in her belief. Consider relaxing the assumption concerning i's naivety and allow every agent to guess their neighbour's idiosyncrasies. If the guesses were always correct, idiosyncrasies would not affect the affect the belief formation rule and learning outcomes of society. Agent i could observe $c'(e^*_{kt-1})$ and infer the exact value of r_{kt-1}.

$$\implies \mathbf{R}_t = \mathbf{S}_t + \Omega \mathbf{R}_{t-1} \tag{1.5}$$

Model with One-off Information

In this case, individuals do not receive any private signal in any period and only observe the choices of those around them. Their first-period beliefs are drawn from the same distribution as the signals in the regular information model and are distributed around the true rate r. A distinction can be made between individuals who are aware of their idiosyncrasies and individuals who aren't. I assume that individuals are aware of their own idiosyncrasies and do not have to infer their beliefs from their effort. Consequently, they place no weight on their beliefs in $t-2$.

This implies the following *belief formation rule*-

$$r_{it} = w_{ii} r_{it-1} + \sum_{k \in N(i)} w_{ik} \left[\alpha_{1k} r_{kt-1} + \alpha_{2k} r_{kt-2} \right] \tag{1.6}$$

As before, we can stack r_{it} across all agents i to get- $R_t = W_2 R_{t-1} + W_3 R_{t-2}$. We can then rewrite this second order difference equation in the following manner.

$$\begin{bmatrix} R_t \\ R_{t-1} \end{bmatrix}_{2n \times 1} = \begin{bmatrix} W_2 & W_3 \\ I & 0 \end{bmatrix}_{2n \times 2n} \begin{bmatrix} R_{t-1} \\ R_{t-2} \end{bmatrix}_{2n \times 1}$$

$$\implies \mathbf{R}_t = \Omega \mathbf{R}_{t-1} \tag{1.7}$$

4 Convergence

4.1 Convergence with Regular Information

I will first discuss the necessary definitions and assumptions before proceeding to discuss the sufficient condition that guarantees convergence of beliefs.

Consider the stacked belief formation rule derived in the previous section. Taking an expectation over t, we get, $E[\mathbf{R}_t] = S + \Omega E[\mathbf{R}_{t-1}]$ where S is now a static column vector whose i'th row equals $w_{ii} r \ \forall i \leq n$ and equals $0 \ \forall n < i \leq 2n$. R_t is the $2n \times 1$ stacked beliefs vector containing beliefs of all individuals in periods t and $t-1$. Ω is a stacked $2n \times 2n$ matrix containing the square sub-matrices W_2, W_3, I and the null matrix.

I now define what it means for beliefs to converge in this setting. I use the standard notion of stochastic convergence because there is a continuous inflow of noisy information in every period.

Definition 1 *Beliefs of agents in network G converge to a vector R in expectation if and only if*

$$\lim_{t\to\infty} \mid E[\boldsymbol{R}_t] - R \mid = \boldsymbol{0}$$

The spectral properties of Ω determine if beliefs converge. In particular, convergence will take place if and only if the largest absolute eigen-value $\rho(\Omega)$ of matrix Ω i.e. the spectral radius, is less than 1 (Meyer, 2000). This is shown in the following lemma.

Lemma 1 *(Meyer, 2000) Beliefs of agents in network G converge if $\rho(\Omega) < 1$*

The proof for Lemma 1 is provided in the appendix.

However, to be able to use this result, I will first have to prove that Ω is irreducible. A matrix A is said to be *irreducible* if its graph is strongly connected i.e. every node can be reached via a directed path from every other node (Meyer, 2000).

The following lemma relates the irreducibility of Ω to agent idiosyncrasies.

Lemma 2 *: Ω is irreducible if the underlying network G is strongly connected and if $\alpha_{2i} \neq 0 \ \forall i$.*

The proof for Lemma 2 is provided in the appendix.

This is a sufficient condition for irreducibility and it ensures that every agent in the graph generated by Ω can reach every other agent via a directed path. These include both the network agents in the first n rows and columns, whom we can refer to as the "current selves", and also the remaining n nodes whom we can refer to as the "past selves" of the network agents. The result relies on the assumption that the underlying network G is strongly connected so the n network agents can reach each other. The restriction on idiosyncrasies is only to ensure that the network agents can also reach and be reached by their past selves. $\alpha_{2i} \neq 0$ implies that every agent in the network must place at least some non zero weight on their past opinion. As I will discuss, irreducibility of Ω is needed to make claims about convergence.

Now, I define the average idiosyncrasy in an agent's neighbourhood and then discuss what it means for an agent to be maximal. Crucially, whether or not an agent is maximal depends on both their network, their behavioural parameters, and the behavioural parameters of their peers. As I will show, the characteristics of these maximal agents will determine if beliefs in the network converge.

Definition 2 *: The average idiosyncrasy $\bar{\alpha}_i$ in an agent i's neighbourhood is the average $\mid \alpha_{1j} \mid + \mid \alpha_{2j} \mid$ where $j \in N(i)$ and $\mid \alpha_{1j} \mid + \mid \alpha_{2j} \mid > 1$. Average idiosyncrasy in i's neighbourhood is equal to-*

$$\frac{\sum_{j\in N(i):|\alpha_{1j}|+|\alpha_{2j}|>1} \mid \alpha_{1j} \mid + \mid \alpha_{2j} \mid}{\sum_{j\in N(i)} \boldsymbol{1}\big[\mid \alpha_{1j} \mid + \mid \alpha_{2j} \mid > 1\big]}$$

Definition 3 *: The maximal agent(s) of a network G are defined as the set of agents*

$$i^* = \{i : i = \arg\max_{i \in N} \sum_{j \in N(i), |\alpha_{1j}|+|\alpha_{2j}|=1} w_{ij} + \sum_{j \in N(i), |\alpha_{1j}|+|\alpha_{2j}|>1} w_{ij}(\mid \alpha_{1i} \mid + \mid \alpha_{2i} \mid)\}$$

Recall that $\sum_{j \in N(i), |\alpha_{1j}|+|\alpha_{2j}|=1} w_{ij}$ can be rewritten as $1 - w_{ii} - \sum_{j \in N(i), |\alpha_{1j}|+|\alpha_{2j}|>1} w_{ij}$ because $\sum_{j \in N(i)} w_{ij} = 1$ by construction.

Thus, the maximand in the above definition can be written as

$$1 - w_{ii} + \sum_{j \in N(i), |\alpha_{1j}|+|\alpha_{2j}|>1} w_{ij}(\mid \alpha_{1j} \mid + \mid \alpha_{2j} \mid -1) \tag{1.8}$$

Who are the maximal agents?

Maximal agent(s) are those who (a) put less weight on their own beliefs *and* (b) have neighbours who are very frustrated or overreact a lot. These agents could be those who live in neighbourhoods that are very frustrated or prone to over-reaction and who don't trust their own private signals enough. They could also be agents who live in under-reacting or status quo biased neighbourhoods. However, an agent living in such a neighbourhood needs to be more untrustworthy of their private signal to qualify as a maximal agent than an agent living in a frustrated or overreacting neighbourhood.[18] Figure 1.3 plots two village networks from Banerjee et al. (2013), identifies the maximal agents and highlights their characteristics. Maximal agents place less weight on their own beliefs and are located around other agents who are very frustrated i.e. they are not necessarily frustrated themselves.

Sufficient Conditions for Convergence

Theorem 1 *: Beliefs in any network G converge if*

$$\sum_{j \in N(i^*): |\alpha_{1j}|+|\alpha_{2j}|>1} w_{i^*j}(\mid \alpha_{1j} \mid + \mid \alpha_{2j} \mid -1) \leq w_{i^*i^*}$$

.

The proof for Theorem 1 is provided in the appendix.

I use Gershgorin's theorem (Gershgorin, 1931) and the extension of this result by Taussky et al. (1948) to prove this theorem.[19] I express the radius of the Gershgorin circles of Ω in

[18] This can be established by comparing the maximands. The maximal agent(s) among those living in under-reacting neighbourhoods maximize $1 - w_{ii}$ whereas maximal agent(s) among those living in frustrated/overreacting neighbourhoods maximize $1 - w_{ii} + \sum_{j \in N(i), |\alpha_{1i}|+|\alpha_{2i}|>1} w_{ij}(\mid \alpha_{1i} \mid + \mid \alpha_{2i} \mid -1)$. The maximal agents(s) of the network will live in under-reacting neighbourhoods only if are very sceptical of their own private signals. Those living in frustrated neighbourhoods don't have to be so untrustworthy of their private information to qualify as maximal agents.

[19] Meyer (2000) traces the history of this theorem not only to the Soviet mathematician S.A. Gershgorin but to earlier papers written by L Levy, H. Minkowski and J. Hadamard.

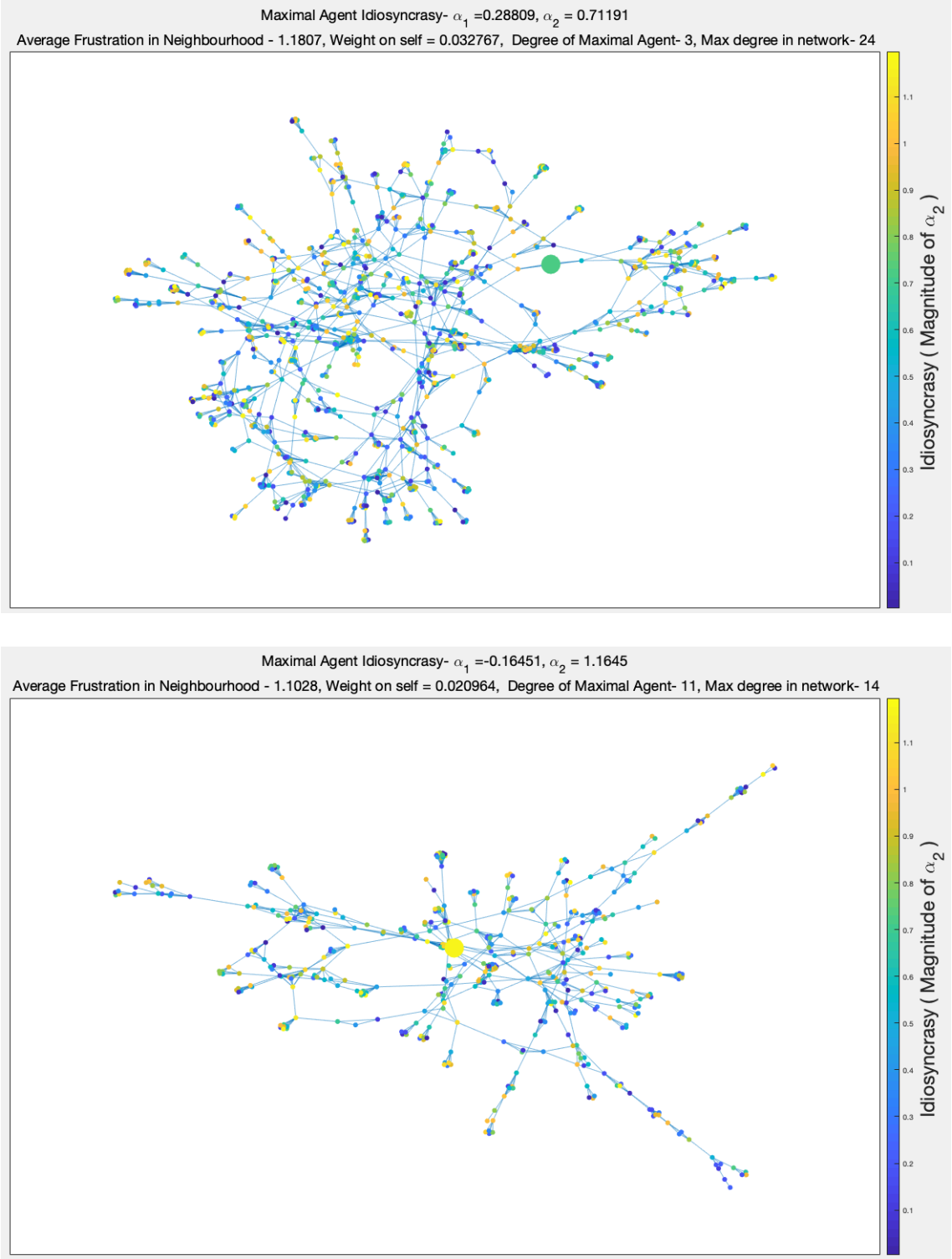


Figure 1.3: Maximal Agents in a rural Indian advice network obtained from Banerjee et al. (2013). Heterogeneous DeGroot weights and agent idiosyncrasies are picked *iid* from uniform distributions. Agents are assumed to be either under-reacting or frustrated. The overreaction case is analogous. Maximal agents (see the large circles in both figures) are those who place less weight on their own beliefs and live in frustrated neighbourhoods. These agents do not necessarily have a very high degree and may not be frustrated themselves (as shown in the top figure).

terms of agent idiosyncrasies and then derive the conditions under which this radius is less than 1. Convergence is then established by noting that Ω is irreducible. The advantage of this approach is that it does not rely on Ω being a non-negative matrix and hence allows me to study the long-run effects of frustration and over-reaction. Convergence results that rely on the Perron Frobenius theorem require Ω to be non-negative.[20]

Interpretation of Theorem 1

The condition in the theorem is violated if the maximal agent does not place enough weight on their own beliefs. It is also violated if they place a very high weight on the beliefs of their frustrated or over-reacting neighbours instead of themselves. Consider a network of agents who are under-reacting ($\alpha_{1i} < 1$, $\alpha_{2i} < 1$), frustrated ($\alpha_{2i} > 1$) or overreacting ($\alpha_{1i} > 1$). In this case, the condition in Theorem 1 suggests that if the maximal agents in the network are those whose neighbourhoods only have under-reacting agents, they only need to place a positive weight on their own private signals to ensure convergence.[21] On the other hand, the condition suggests a strictly positive lower bound on the weights that the maximal agents place on their own information if their neighbourhoods also include frustrated and overreacting individuals. Intuitively, agents who live in frustrated or overreacting neighbourhoods must trust their own information enough and more than those living in under-reacting neighbourhoods.

The magnitude of an agent i's idiosyncrasy (relative to under-reacting agents) can be written as $\mid \alpha_{1i} \mid + \mid \alpha_{2i} \mid -1$. This can be interpreted as a measure of the extent of their frustration or overreaction. Consider the case where the maximal agent's frustrated neighbourhood is such that $\alpha_{1j} = -1$ and $\alpha_{2j} = 2 \; \forall \; j \in N(i^*)$. In this case, the sufficient condition demands that the weight the maximal agents place on their own signal should be twice as large as the total weight they put on the beliefs of all their neighbours. If their neighbours weren't as frustrated, for example, if $\alpha_{1j} = -0.5$ and $\alpha_{2j} = 1.5 \; \forall \; j \in N(i^*)$, then the weight the maximal agents place on their own signal must be at least as large as the total weight they put on their neighbours.

In general, the maximal agent must place more weight on their private signals than the sum of the weight they place on their neighbours, weighted by the extent of their neighbours' idiosyncrasy. This is an intuitive condition. Convergence in networks with such agents requires individuals to not be too untrustworthy of their private information. If those who live in the most idiosyncratic neighbourhoods are sufficiently trustworthy of their own information, then beliefs will converge. Thus, Theorem 1 suggests that the kind of individuals one listens to (in terms of the magnitude of their idiosyncrasies) and how much one listens to them (in terms of how much they trust their own information) determines whether societies can learn or not. The following corollaries verify this intuition.

[20] See Jackson (2010); Golub and Jackson (2010) for these results. Agents in such models do not typically exhibit idiosyncrasies and matrix entries are non-negative.

[21] By the definition of a maximal agent, this also implies that all other agents in the network should also place a non-zero weight on their own beliefs.

Consider the following corollaries.

Corollary 1 *Beliefs in a network G with homogeneous α_1 and α_2 converge if*

$$\mid \alpha_1 \mid + \mid \alpha_2 \mid -1 < \frac{w_{i^*i^*}}{\sum_{j \in N(i^*):|\alpha_{1j}|+|\alpha_{2j}|>1} w_{i^*j}}$$

Corollary 2 *Beliefs in a network G of agents who place equal weights on their own private signals and the beliefs of their neighbours, converge if*

$$\bar{\alpha_{i^*}} \leq \frac{1 + d_{i^*:j \in N(i^*),|\alpha_{1j}|+|\alpha_{2j}|>1}}{d_{i^*:j \in N(i^*),|\alpha_{1j}|+|\alpha_{2j}|>1}}$$

where i^* is the maximal agent, $d_{i^*:j \in N(i^*),|\alpha_{1j}|+|\alpha_{2j}|>1}$ is the number of frustrated or overreacting neighbours of i^*, and $\bar{\alpha_{i^*}}$ is the average idiosyncrasy in $i^{*\prime}s$ neighbourhood.

Consider what corollary 2 implies for networks that contain some under-reacting agents and in addition, contain some frustrated and overreacting agents. As before, I assume that $\alpha_{1j} + \alpha_{2j} = 1 \ \forall$ such agents j. $\alpha_{1j} < 0, \alpha_{2j} > 1$ those who are frustrated and $\alpha_{1j} > 1, \alpha_{2j} < 0$ for those who overreact. The sum of the absolute values of the scalars is larger than 1 in both cases.

The inequality in corollary 2 can then be written to derive an upper bound on the frustration and overreaction in the maximal agent's neighbourhood-

$$\sum_{j \in N(i^*):|\alpha_{1j}|+|\alpha_{2j}|>1, \alpha_{2j}>1} \alpha_{2j} + \sum_{j \in N(i^*):|\alpha_{1j}|+|\alpha_{2j}|>1, \alpha_{1j}>1} \alpha_{1j}$$

$$\leq \frac{1 + 2d_{i^*:j \in N(i^*):|\alpha_{1j}|+|\alpha_{2j}|>1}}{2} \tag{1.9}$$

If the network did not contain any overreacting agents, then the sufficient condition for convergence in beliefs would be an upper bound on the average frustration in the maximal agent's neighbourhood i.e. average $\alpha_{2j} \ \forall \ j \in N(i^*)$. This means that-

$$\text{Avg Frustration in } i^*\text{'s Neighbourhood} =$$

$$\frac{\sum_{j \in N(i^*):|\alpha_{1j}|+|\alpha_{2j}|>1, \alpha_{2j}>1} \alpha_{2j}}{d_{i^*:j \in N(i^*):|\alpha_{1j}|+|\alpha_{2j}>1}} \leq \frac{1 + 2d_{i^*:j \in N(i^*):|\alpha_{1j}|+|\alpha_{2j}|>1}}{2d_{i^*:j \in N(i^*):|\alpha_{1j}|+|\alpha_{2j}>1}} \tag{1.10}$$

Analogously, if the network did not contain any frustrated agents, the sufficient condition would contain an analogous upper bound on the average overreaction in the maximal agent's neighbourhood i.e. average $\alpha_{1j} \ \forall \ j \in N(i^*)$ This means that-

$$\text{Avg Overreaction in } i^*\text{'s Neighbourhood} =$$

$$\frac{\sum_{j \in N(i^*):|\alpha_{1j}|+|\alpha_{2j}|>1, \alpha_{2j}>1} \alpha_{1j}}{d_{i^*:j \in N(i^*):|\alpha_{1j}|+|\alpha_{2j}>1}} \leq \frac{1 + 2d_{i^*:j \in N(i^*):|\alpha_{1j}|+|\alpha_{2j}|>1}}{2d_{i^*:j \in N(i^*):|\alpha_{1j}|+|\alpha_{2j}>1}} \tag{1.11}$$

The upper bounds on frustration and overreaction are analogous but are placed on the average α_2 in the first case (which conveys the magnitude of frustration) and the average α_1 in the second case (which conveys the magnitude of overreaction). Both frustration and overreaction affect the ability of the network to reach convergence in beliefs in a similar manner.

As discussed earlier, convergence always implies consensus to the true r since the network includes agents i whose scalars α_{1i} and α_{2i} sum to 1.

Networks with persistent idiosyncrasies

What happens when agent idiosyncrasies persist over time and agents weight $k > 1$ past periods instead of just weighing the immediate past? The theorem is presented in the appendix and the bounds on idiosyncrasies are analogous. This generalisation can also be used to understand cases where there are specific events associated with specific time periods which some agents might overweight or underweight. The result continues to allow for agent heterogeneity and I find that networks reach a consensus if the sum of an agent's idiosyncrasies across all time periods is sufficiently low. As before, this is easier to hold if agents place a high enough weight on their own private information.

4.2 Convergence with One-off Information

Let us now consider the case where information is one-off i.e. individuals only observe the choices of their network neighbours and do not receive any private signals? Recall that in this case, the learning process is defined by the following belief formation rule $R_t = \Omega R_{t-1}$ where the diagonal elements of Ω are *not* necessarily zero anymore since individuals do not receive any separate private information and weight their own beliefs like they weight the inferred beliefs of their neighbours. As discussed earlier, I assume that every individual i is aware of their under-reaction so they place the entire weight w_{ii} on r_{it-1}.

Convergence does not take place in expectation in this learning environment and is obtained when the system reaches the deterministic steady state $R = R_t = R_{t-1}$. The following theorem provides a result for idiosyncratic networks which learn in this environment.

Theorem 2 *Beliefs in any network of individuals who do not receive private signals in* $t > 1$ *will converge if* $\alpha_{1i} \in [0, 1)$, $\alpha_{2i} \in (0, 1]$ *and if* $\alpha_{1i} + \alpha_{2i} = 1 \ \forall i \in N$.

The proof for Theorem 2 is provided in the appendix. Recall that we can interpret Ω as the adjacency matrix of a network where each agent's current and past self can be interpreted as a different agent. This theorem is then contained within the existing result by Golub and Jackson (2010) if we can show that Ω is non negative, irreducible, row-stochastic, and aperiodic. The restriction on agent idiosyncrasies ensures this. We already know that beliefs in under-reacting networks converge when information is regular. This theorem implies that beliefs in under-reacting networks converge in the one-off information case

as well. While under-reaction doesn't affect convergence in either scenario, I will show in Section 6 that it necessarily affects the speed of convergence by exacerbating learning bottlenecks when information is one-off.

The absence of frustrated and overreacting individuals is sufficient but not necessary for convergence. Even though I cannot derive an upper bound on frustration or overreaction in the one-off case, networks which can tolerate these idiosyncrasies do exist. This means that agents who do not receive any private signals and live among moderately frustrated and overreacting peers can still reach an agreement. I will use examples to illustrate this in Section 5.2.

5 Wisdom

The previous section studied how idiosyncrasies affect convergence of beliefs.It is important to check if these converged beliefs are correct. Now, I study how learning idiosyncrasies affect the ability of the network to reach an *accurate* consensus in both the regular and one-off information case. While this has been studied in existing literature in the context of DeGroot learning models (DeMarzo et al., 2003; Golub and Jackson, 2010), I study the learning process in which individual idiosyncrasies augment the DeGroot weights and affect the ability of society to reach an accurate long-run belief. I will first discuss the results that relate idiosyncrasies with long-run accuracy in the case where individuals receive regular information. Then, I follow the exact technique described in Golub and Jackson (2010) to study this in the one-off information case.

5.1 Model with Regular Information

Theorem 3 *: A convergent network G converges in mean to the true rate r $\forall$ $i \in N$.*

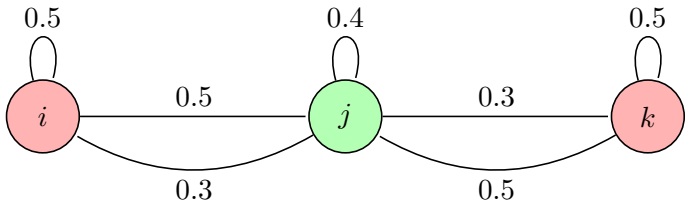
The proof for Theorem 3 is provided in the appendix and relies on the assumption that $\alpha_{1i} + \alpha_{2i} = 1$ $\forall$ $i \in N$.

We know from the previous section that individual beliefs converge in expectation since $\alpha_{1i} + \alpha_{2i} = 1$ $\forall$ $i \in N$. This theorem implies that they must converge to the same, accurate, limit i.e. $(I - \Omega)^{-1}S$ will be a column vector containing identical long-run beliefs equal to the expected value of the individual private signals. This means that convergence necessarily implies an accurate consensus in networks with under-reacting agents, frustrated agents, and/or overreacting agents.

Example of inaccurate long-run beliefs in a network with optimistic agents

Let us very briefly consider an outlier case, outside the purview of the introduced model, to see the dependence of the above result on the assumption that $\alpha_{1i} + \alpha_{2i} = 1$ for all individuals i in N. Consider optimistic overreacting agents who place a high positive weight on current beliefs and also a small positive weight on past beliefs, such that the idiosyncrasy scalars α_{1i} and α_{2i} sum to more than 1 and are both strictly positive. These

1. $\alpha_{1i} = \alpha_{2i} = 0.5 \ \forall i$ (Under-Reaction)



2. $\alpha_{1i} = 1.6, \alpha_{2i} = 0.2 \ \forall i$ (Optimistic)

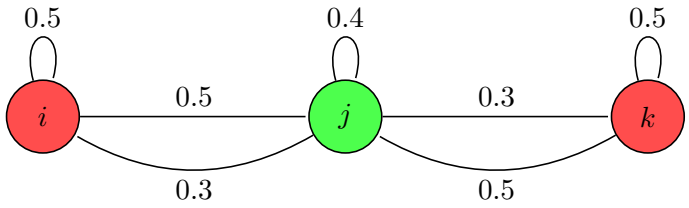


Figure 1.4: Examples of two line networks with the same network structure and DeGroot weights but different idiosyncrasies. Individual beliefs converge in expectation in both cases but converge to the inaccurate limit when agents are very optimistic.

individuals over-react to positive information in that if $r_{it} > r_{it-1}$, then the belief on the basis of which they make a choice is even greater than r_{it}. Depending on the magnitude of α_{1i}, when these individuals hear negative information so that $r_{it} < r_{it-1}$, they either under-react to it such that their choice-inducing belief is greater than r_{it} or they become even more optimistic than before such that it is greater than r_{it-1}. If there exist such optimistic individuals who (a) over-react to positive information and (b) either under-react to negative information or over-react in the positive direction, then individual beliefs may converge but consensus may not be reached. There may not be any agent whose beliefs converge to the accurate level r. This is shown in the following example.

Consider two identical line networks with 3 agents exhibiting different idiosyncrasies. (see Figure 1.4 below) Assume that network 1 contains under-reacting agents with homogeneous parameters $\alpha_1 = \alpha_2 = 0.5$. These agents slowly respond to new information. Assume that network 2 contains optimistic agents described above with homogeneous idiosyncrasies $\alpha_1 = 1.6$ and $\alpha_2 = 0.2$. We know that beliefs converge if the largest eigen-value of Ω is less than 1. The vector of convergent beliefs can be written as $(I - \Omega)^{-1}S$. I verify that the eigen-value of Ω for both the networks discussed in this example is less than 1. Then, I compute $(I - \Omega)^{-1}S$ for both cases.

1. In the case of the network with under-reacting agents ($\rho(\Omega) = 0.6779$)

$$\left[I - \begin{pmatrix} 0 & 0.25 & 0 & 0 & 0.25 & 0 \\ 0.15 & 0 & 0.15 & 0.15 & 0 & 0.15 \\ 0 & 0.25 & 0 & 0 & 0.25 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \end{pmatrix}\right]^{-1} \begin{pmatrix} 0.5r \\ 0.4r \\ 0.5r \\ 0 \\ 0 \\ 0 \end{pmatrix} = \begin{pmatrix} r \\ r \\ r \\ r \\ r \\ r \end{pmatrix}$$

2. In the case of the network with optimistic agents ($\rho(\Omega) = 0.9873$)

$$\left[I - \begin{pmatrix} 0 & 0.8 & 0 & 0 & 0.1 & 0 \\ 0.48 & 0 & 0.48 & 0.06 & 0 & 0.06 \\ 0 & 0.8 & 0 & 0 & 0.1 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \end{pmatrix}\right]^{-1} \begin{pmatrix} 0.5r \\ 0.4r \\ 0.5r \\ 0 \\ 0 \\ 0 \end{pmatrix} = \begin{pmatrix} \frac{215}{7}r \\ \frac{235}{7}r \\ \frac{215}{7}r \\ \frac{215}{7}r \\ \frac{235}{7}r \\ \frac{215}{7}r \end{pmatrix}$$

As shown in this example, when agents under-react or are frustrated, convergence of individual beliefs implies consensus and this consensus is necessarily accurate. However, when agents are optimistic and overreact to their current information (such that their idiosyncrasy parameters sum to a number greater than 1), convergence in individual beliefs does not imply either a collective agreement or an accurate long-run belief. In the above example, beliefs of such individuals converge, but converge in expectation to a rate approximately 30 times the true rate. Further, beliefs do not converge in expectation to the same limit so there is long-run disagreement.

5.2 Model with One-off Information

Consider the one off information model where individuals do not observe a signal of the true rate r every period. Do beliefs converge to the right level despite the presence of idiosyncrasies? The argument in this section follows the same trajectory as the general case discussed in Golub and Jackson (2010) except that agents will be allowed to exhibit learning idiosyncrasies. I will go through the setup and definitions in their paper altering the notation in accordance with the model considered here wherever necessary. I will mention if the properties of Ω and the incorporation of agent idiosyncrasies require any additional qualifications. As in their paper:

- Let $\Omega_{n=1}^{\infty}$ be a sequence of adjacency matrices of networks of size n. Networks are indexed by their size n and any variable p related to this network will be written as $p(n)$. Define the degree of agent i in this network as $d_i(\Omega_n)$. The degree, here, does not include the agent themselves i.e. the total number of agents i places a positive weight on is $d_i + 1$. Additionally, define the idiosyncrasies of agent i in this network

as $\alpha_{1i}(\Omega_n)$ and $\alpha_{2i}(\Omega_n)$.

- The vector of initial beliefs of the n agents can be written as $s(n) = [s_1, s_2 ... s_n, s_{n+1} ..., s_{2n}]^T$ where $s_i = s_{n+i}\ \forall i \in N$. The beliefs $\{s_1, s_2, ...s_n\}$ are independently distributed on the interval $[0, 1]$ with finite mean r and variance, bounded below for all $i \in N$. The vector is of length $2n$ here since beliefs are updated as per the second order difference equation.

- Consider a strongly connected, row-stochastic, positive adjacency matrix M. As Golub and Jackson (2010) define, the learning process $R_t = MR_{t-1}$ 'converges' if limiting beliefs exist i.e. $\lim_{t\to\infty} M^t s$ exists $\forall s$ whose elements lie in $[0, 1]$. These beliefs $r_{i\infty}$ can be written in terms of the initial signals s and a unique vector v whose i'th element describes the influence of agent i's original belief on the limiting beliefs of other agents, so $r_{i\infty} = vs$.[22]

  The matrix M is different from Ω in that Ω is strongly connected and row stochastic but can contain negative entries when agents are frustrated or when they overreact. Recall that we cannot apply the Gershgorin theorem to derive the upper bound for idiosyncrasies below which consensus is reached in the one off information model. However, even though we cannot comment on convergence, we do know that these convergent matrices exist. In that case, the influence of each agent $i \in N$ will be equal to $v_i + v_{n+i}$ since this is the total weight placed on their initial beliefs s_i and s_{n+i} where $s_i = s_{n+i}$. I will now give an example of a convergent matrix Ω which has negative entries when agents exhibit frustration.

  Consider the following example of a network where the three agents are located on a line and put equal weights on themselves and their friends. $\lambda = 1.5$, so these agents are frustrated.

$$\Omega = \begin{bmatrix} 0.5 & -0.3 & 0 & 0 & 0.8 & 0 \\ -0.2 & 0.33 & -0.2 & 0.53 & 0 & 0.53 \\ 0 & -0.3 & 0.5 & 0 & 0.8 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix}$$

[22] The vector v is the unique (normalised) left eigen-vector of M corresponding to the eigen-value 1 and it exists when matrix M is convergent (Kemeny and Snell, 1960; Golub and Jackson, 2010).

$$\Omega^{\infty} = \begin{bmatrix} 0.15 & 0.22 & 0.15 & 0.12 & 0.24 & 0.12 \\ 0.15 & 0.22 & 0.15 & 0.12 & 0.24 & 0.12 \\ 0.15 & 0.22 & 0.15 & 0.12 & 0.24 & 0.12 \\ 0.15 & 0.22 & 0.15 & 0.12 & 0.24 & 0.12 \\ 0.15 & 0.22 & 0.15 & 0.12 & 0.24 & 0.12 \\ 0.15 & 0.22 & 0.15 & 0.12 & 0.24 & 0.12 \end{bmatrix}$$

Here, we can distinguish between the present and past selves of the agents. The past self of the network agent $i \in N = \{1, 2, ...n\}$ is the $n + i$'th node of Ω.[23] The influence vector v of the past and present selves of the agents on this line is $[0.15, 0.22, 0.15, 0.12, 0.24, 0.12]$. The total influences of the three agents on the line can be found by adding the influence of their past and present self since that is the total weight placed on their initial belief. This is equal to $[0.27, 0.46, 0.27]$. As expected, the agent in the centre of the line is the most influential. Similar examples can show that networks with idiosyncratic agents which learn via the process defined in the one off information model can tolerate some frustration and/or overreaction and reach a consensus.

I assume that agents put equal weight on themselves and their friends. As before, I assume that agent idiosyncrasies are heterogeneous and that agents are aware of their idiosyncrasies so they do not place any weight on their past selves while forming their belief r_{it}.

As in Golub and Jackson (2010), a network is wise if and only if-

$$\text{plim}_{n\to\infty} \max_i \mid r_{i\infty}(n) - r \mid = 0 \tag{1.12}$$

where $r_{i\infty}(n)$ is the vector of steady-state beliefs for network n and r is accurate consensus.

How do idiosyncrasies affect wisdom?

While the standard case in Golub and Jackson (2010) only allows network statistics to vary with the size of the networks in the sequence, idiosyncrasies matter when $\alpha_{1i}(\Omega_n)$ and $\alpha_{2i}(\Omega_n)$ are allowed to change with n as well. Can societies attain wisdom if agents become more under-reacting as societies expand? Can they attain wisdom if agents become more frustrated? Is the condition of dying network influence derived by Golub and Jackson (2010) sufficient to ensure wisdom even if agents become more frustrated or overreact more as societies expand? I will describe results for both the case in which the behavioural parameters are unaffected by network size and the case where it changes as the network becomes larger.

[23] Individuals in period t place a weight on their peer's beliefs in $t-1$ but not $t-2$ which is why there is only one past self. In general, if under-reaction is more persistent, then there will k past selves. The total influence of an agent will be summed across all their past selves and the results of this section will be analogous.

Following is the key result of this section which shows how idiosyncrasies affect the accuracy of convergent beliefs.

Theorem 4 *A sequence of convergent networks* $\Omega_{n=1}^{\infty}$ *is wise if and only if-*

$$\max_{i\in N}\left\{\frac{d_i(\Omega_n)+1}{\sum_{i\in N} d_i(\Omega_n)+1+\alpha_{2i}(\Omega_n)d_i(\Omega_n)}+\frac{\alpha_{2i}(\Omega_n)d_i(\Omega_n)}{\sum_{i\in N} d_i(\Omega_n)+1+\alpha_{2i}(\Omega_n)d_i(\Omega_n)}\right\}\xrightarrow{n}0$$

The proof for Theorem 4 is provided in the appendix.

This theorem implies that networks are wise if and only if the maximum total influence tends to zero. This statement and proof of this theorem are the same as in Golub and Jackson (2010) except that the agents in their network do not exhibit any under-reaction, frustration, or overreaction and there are no past selves. When agents exhibit no idiosyncrasy (i.e. $\alpha_1 = 1$ and $\alpha_2 = 0$), then the result from Golub and Jackson (2010) applies i.e. a growing network is wise when every agent's degree, relative to the rest of the network, falls as the network increases in size. In my case, agents exhibit idiosyncrasies and these idiosyncrasies can also change as the network grows. I will first define what it means for growing idiosyncratic networks to approach wisdom.

Definition 4 *A sequence of convergent networks* $\Omega_{n=1}^{\infty}$ *is said to 'approach' wisdom if*

$$\frac{\partial\left[v_i(n)+v_{n+i}(n)\right]_{max}}{\partial n}<0$$

A growing network is said to 'approach' wisdom if the total influence of the most influential agent always falls as the network size increases. This means that a rise in n is always accompanied by a fall in the upper bound proposed by Chebyshev. The following examples show that networks with frustrated and overreacting agents may not unambiguously approach wisdom even if the relative degree of the most influential agent falls. Both these examples suggest that a rise in the influence of the agent's past self (i.e. the $n+i$'th node of Ω for the i'th network agent) can prevent the network from approaching wisdom, even if the agents become less influential in the network sense.

Example 1- Networks with under-reacting/frustrated agents

Consider a network with under-reacting and frustrated agents. The most influential agent is the one with a very high degree and a high level of under-reaction/frustration i.e. a high value of α_{2i}. Let all network agents be such that their degree relative to the total degree in the network goes to zero as the size of the network increases. This is the condition guaranteeing wisdom in Corollary 1 in Golub and Jackson (2010). This condition implies that the first term in the above expression must fall to zero assuming $\alpha_{2i}(\Omega_n)$ isn't falling for any i. If $\alpha_{2i}(\Omega_n)$ is constant as n rises, networks in the sequence $\Omega_{n=1}^{\infty}$ will be wise.

What if we allow $\alpha_{2i}(\Omega_n)$ to rise as the network grows in size? This would imply that agents get more under-reacting and consequently frustrated as networks become larger. Ω_n will

not be convergent as α_{2i} continues to rise above a certain threshold so the question about being wise becomes redundant. Let us restrict our attention to the interval containing all candidate values of α_{2i} $\forall i$ where Ω_n is convergent. Let us only consider a rise in n until the upper limit $\bar{n}$ beyond which a further increase will push α_{2i} outside this interval and make Ω_n diverge. What happens as n increases?

Let α_{2i} be constant as n grows for all agents except the one with the highest degree. Now assume that α_{2i} grows at a rate faster than the corresponding fall in the relative degree for this agent. The influence of the current self of this agent will fall because of both the fall in their degree (compared to the total degree in their network) and because of the rise in their frustration. However, the influence of the past self could rise more than this fall in the influence of the current self if α_{2i} rises a lot. The maximum total influence will not tend to 0 if the most influential agent's $\alpha_{2i}(\Omega_n)$ increases in this manner as the network grows. So if the rise in n is accompanied by a disproportionate rise in the frustration of the most influential agent, the upper bound for the probability in Chebyshev's inequality will rise and networks will not necessarily approach wisdom. If the size of the network rises above $\bar{n}$, then beliefs will fail to converge.

Simulated Example: Consider a complete network with 100 agents and an under-reaction parameter of 0.01 each i.e. they place a weight of 0.01 on their past belief. In every time period, I increase the network size by adding an agent with an under-reaction parameter of 0.01 and allowing them to link with each of the existing agents. It is easy to note that the relative degree of the existing agents ($\frac{d_i}{\sum_{i \in N} d_i}$) falls as new agents are added to the network. If agents weren't idiosyncratic or if their idiosyncrasies remained constant as network size increased, Golub and Jackson (2010)'s result shows that this growing network will be wise. Now, let there exist an influential agent k whose under-reaction increases by 0.02 as the network size increases so that they eventually become frustrated. Plugging these values into the above expression shows that the influence of k's current self falls after every new agent is added. However, the influence of their past self increases faster causing their total influence to increase. This causes the upper bound in Chebyshev's inequality to rise and the network does not approach wisdom. The first sub-figure in Figure 1.5 plots the influence of the most influential agent, their under-reaction/frustration, and their relative degree at each step as the network grows.

So, rising frustration can prevent the network from approaching wisdom even if agents become less powerful in terms of their network position.

Example 2- Networks with over-reacting agents

Now, consider convergent networks which contain overreacting and under-reacting agents. Recall that $\alpha_{1i} > 1$ and $\alpha_{2i} < 0$ for all agents i who overreact. In this case, v_{n+i} can be negative for some $i \in N$. Let us restrict our attention to cases where the total influence of every agent i is positive even if $v_{n+i} < 0$. This means that we restrict attention to

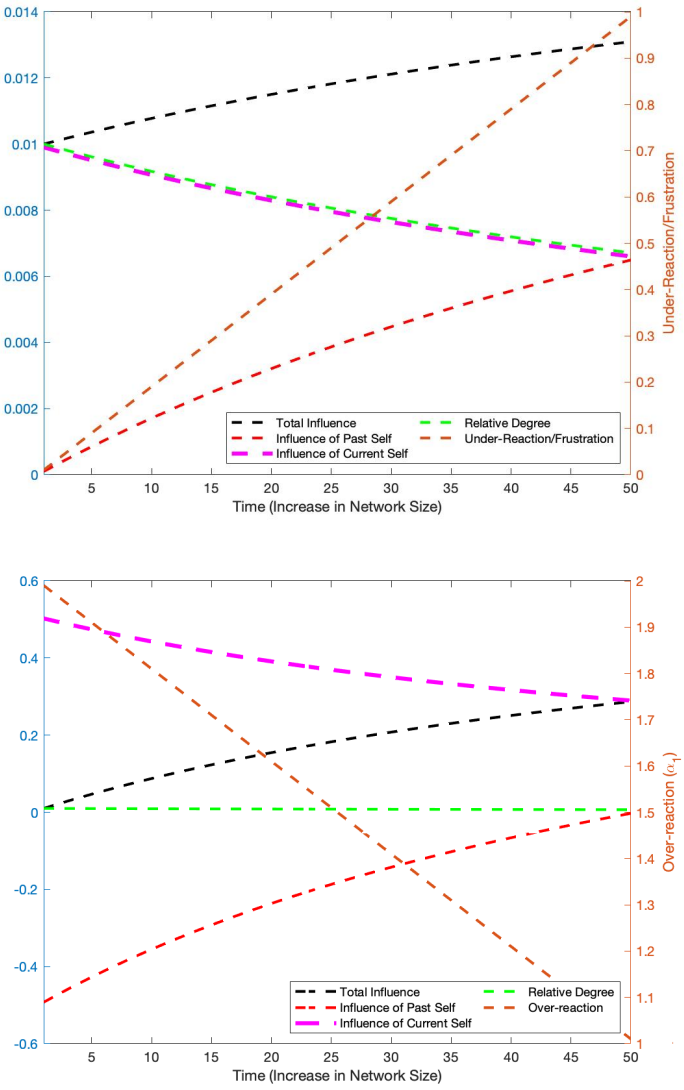


Figure 1.5: What happens to the influence of the most influential agent as agents are added in the network? The two graphs show the case where their frustration rises and overreaction falls respectively. Frustration and over-reaction are plotted on the right y axis respectively. Total influence rises despite the fall in relative degree because the influence of the past self rises faster.

$\alpha_{1i} \in (1, 2)$ and $\alpha_{2i} \in (-1, 0)$. This is an important restriction as it prevents agents from having a negative total influence on the limiting belief if at all the network converges. As an example, consider a three-person line network in which every agent overreacts to their current information such that $\alpha_{1i} = 1.3$ and $\alpha_{2i} = -0.3$ $\forall i$. Agents place half the weight on their own beliefs and equally divide the rest among their neighbours.

In this case, the influence of the past selves of the three agents is negative but the total influence of each agent is given by the vector $[v_1 + v_4, v_2 + v_5, v_3 + v_6] = [0.25, 0.5, 0.25]$. As before, the final agreement reached by this network with size $n = 3$ can be written as $\sum_{i=1}^{3}(v_i + v_{n+i})s_i$.

An increase in α_2 implies a fall in agent overreaction. As we know from the previous example on frustration, if α_2 rises faster than relative degree falls, then the total influence rises. This means that the total influence of the most influential agent can rise if they overreact less as network size increases. While the effects go in the same direction as frustration, the interpretation is different. A disproportionate rise in α_2 increases total influence and the upper bound in Chebyshev's inequality. This means that networks are harmed by increasing frustration but approach wisdom when overreaction increases. Beyond a limit, an increase in both causes beliefs to diverge.

Simulated Example: Consider the same network as in the previous example and let us assume that the initial 100 agents have an $\alpha_1 = 1 - \alpha_2 = 1.99$ i.e. they overreact a lot. As before, let there exist an agent k whose overreacts less as network size increases and their overreaction reduces by 0.02 each time a new agent is added. This causes the influence of the current self of this agent to fall but the influence of their past self rises faster causing their total influence to increase. The second sub-figure in Figure 1.5 plots the influence of this agent, their overreaction, and their relative degree as the network grows. If agent overreaction falls fast enough, then it can increase the influence of their past self and prevent the network from approaching wisdom. Unlike frustration, an increase in overreaction can help the network approach wisdom. Beliefs will diverge if overreaction increases beyond a limit.

While the condition of reducing network influence derived by Golub and Jackson (2010) needs to hold for a network to be wise, the magnitude of agent idiosyncrasies and the responsiveness of these idiosyncrasies to the size of the network have implications on whether networks approach wisdom. Growing frustration poses a threat to convergence and wisdom but growing overreaction may help the network approach wisdom. Both will ultimately cause beliefs to diverge if they cross a threshold.

6 Speed of Convergence

How quickly do individual beliefs converge to a consensus? How does under-reaction affect bottlenecks in social learning and the speed of convergence? How does this depend on how connected the network is? How can interventions be designed to improve learning

and reduce norm persistence in under-reacting networks? I answer these questions in this section.

The relationship between network structure and speed of convergence has been studied by Acemoglu et al. (2010) and Golub and Jackson (2012). The role played by the second eigen-value of the transition matrix in determining the speed of convergence of a Markov process is discussed in Levin and Peres (2017) and applications of this to social learning are discussed in Golub and Sadler (2017). Levin and Peres (2017); Golub and Sadler (2017) also define the Cheeger constant as a measure of bottlenecks i.e. the worst-case inter-group communication between two mutually exclusive groups of the network chosen to minimize the same. I complement the literature on social learning by explicitly deriving an upper bound for this measure of bottlenecks as a function of the under-reaction of the agents in the network. Then, I use this bound to study how under-reaction affects the speed with which beliefs converge in a network and how this depends on network connectivity. I also run simulations on d regular networks and the Indian village networks from Banerjee et al. (2013) to test the predictions of the model and tightness of the derived bounds in the next section. Finally, I use these results to discuss why interventions which aim to induce the adoption of new behaviours or technologies among under-reacting individuals are unable to do so. I suggest how these interventions can benefit from targeting network connectivity as making regular networks more connected leads to the same effects as reducing the under-reaction of its members.

I restrict the model environment for simplicity. I only consider the one-off information model where the individual does not observe any noisy realisation of the parameter. This is because the standard results for mixing times in Markov chains are readily applicable to stochastic transition matrices but the process in which agents receive private signals involves matrices whose rows do not sum to 1. I also assume that agents are homogeneous and exhibit the same magnitude of under-reaction i.e. $\alpha_{1i} = \alpha_1$, $\alpha_{2i} = \alpha_2$ $\forall i \in N$, $0 < \alpha_1 < 1, 0 < \alpha_2 < 1$ and $\alpha_1 + \alpha_2 = 1$. There are no frustrated or overreacting agents in these networks. Agents place equal weight on the beliefs of those they are connected to in Ω including themselves. Every agent is assumed to place a weight $\frac{1}{d_i+1}$ on their own beliefs and as before, their degree d_i does not include this self loop. Agents do not place a weight on their past self since they're assumed to be aware of their exact past period belief r_{it-1} and do not have to infer it from their effort. In this sense, as before, agents are assumed to be aware of their under-reaction.

I will now define the cheeger constant of a network and a measure for the time it takes beliefs in the network to converge. The aim is to use express the former in terms of under-reaction and then use it to bound the latter.

6.1 The Cheeger Constant

Definition 5 *(Levin and Peres, 2017; Golub and Sadler, 2017) The Cheeger constant* c^*

is defined as follows-

$$c^* = \min_{M:\sum_{i\in M} v_i \leq \frac{1}{2}} \frac{\sum_{i\in M, j\in M'} v_i w_{ij}}{\sum_{i\in M} v_i}$$

M and M' are the two partitions that minimize inter-partition links. v_i is the influence of agent i as defined in the previous section. This is the i'th entry of the left eigen-vector of Ω and measures the extent to which agent i's initial opinion affects the limiting belief of all agents. The Cheeger constant is low if there exists a group of agents who place very low weight on the beliefs of others outside the group and have at most half the total influence. As before, we can classify the rows of Ω as the adjacency vectors of the current and past selves of the network agents $i \in N$ i.e. the first n rows of Ω list directed links of the current selves group (CSG) and the next n rows list the directed links of the past selves group (PSG). If the j'th row of Ω corresponds to links of an agent's current self, then the $n+j$'th row will correspond to links of the agent's past self.

The influence vector v can be computed just as before by solving $v\Omega = v$. The influence of agent i in CSG and agent $n+i$ in PSG can be written as follows.

$$v_i = \frac{d_i + 1}{\sum_i (d_i + 1) + \alpha_{2i} d_i} \text{ and } v_{n+i} = \alpha_{2i} \frac{d_i}{d_i + 1} v_i \tag{1.13}$$

Consider a regular network (such that each agent in CSG is connected to an equal number of agents in CSG) and allow agents to place equal weight on their neighbours. This means that each agent in CSG will have equal influence v and each agent in PSG will have equal influence $\alpha_2 \frac{d}{d+1} v$. Using the definition of the Cheeger constant and the computed elements of influence vector v, we can rewrite the Cheeger constant in the following manner-

$$c^* = \min_{M:\sum_{i\in M} v_i \leq \frac{1}{2}} \frac{\#_{CSG_M, CSG_{M'}} + \alpha_2 \left[\#_{CSG_M, PSG_{M'}} + \#_{PSG_M, CSG_{M'}} d - \#_{CSG_M, CSG_{M'}}\right]}{\#_{CSG_M}(d+1) + \#_{PSG_M} \alpha_2 d} \tag{1.14}$$

I will now derive an upper bound for the Cheeger constant of the transition matrix Ω. I will use this to comment on how under-reaction can affect bottlenecks and then provide a bound on the time it takes networks to learn. I focus on d regular networks as they provide illustrations of networks with zero clustering (circle), networks with positive clustering (d regular, $d < n$), and networks with maximum clustering (complete, $d = n-1$). Throughout this section, I write that an agent has degree d when the agent has d individuals they listen to excluding themselves. So, for example, $d = 2$ for a circle and $d{=}n$ for a complete network.

Cheeger constant in regular lattices with under-reacting agents

Consider a $d \geq 2$-regular lattices with n agents where n is an even integer and is sufficiently large. The following lemma derives an expression for an upper bound for the Cheeger

constant for such a network.

Lemma 3 *1. The upper bound for the Cheeger constant for a d-regular lattice with n under-reacting individuals, where n is even, $2 \leq d$, $2d \leq n$ can be written as*

$$\bar{c} = \frac{2k(d)}{n(d+1+\alpha_2 d)}$$

where $k(d)$ is a function rising in degree d.

2. The upper bound for the Cheeger Constant for a complete network with n individuals where n is even, can be written as

$$\bar{c} = \frac{n}{2(n+(n-1)\alpha_2)}$$

The proof for Lemma 3 is provided in the appendix.

I derive the upper bound by dividing the current and past selves into two groups hypothesized to have minimum interaction between them. Since agents are identical in terms of network links and under-reaction, I hypothesize that the partitions determining the bottleneck ratio should have equal influence and equal number of past and current selves. The rationale behind these assumptions is explained in more detail in the proof in the appendix.

I find that this upper bound is better than other competing bounds. For instance, if we start with all current selves in one group and all past selves in the other and then start moving the current/past selves out of one group into the other, the Cheeger candidates will necessarily be higher than the Cheeger upper bound computed above. This is shown in Figure 1.13 in the appendix. I also discuss why deviations from the suggested partitions may not reduce the Cheeger constant.

I now discuss how this bound depends on under-reaction, network size, and degree. These comparative statics are informative of how under-reaction and connectivity may affect learning bottlenecks and consequently the time it takes beliefs to converge. As I will discuss later, some of the intuition developed here is validated when the model is simulated on artificial and real-world networks. The empirical relationship between under-reaction and speed of learning in these networks is predicted by the comparative statics that make use of the derived Cheeger constant.

Comparative Statics

Theorem 5 *Consider the Cheeger constant c^* minimized at partitions M^* and M'^* such that $\sum_{i \in M^*} v_i \leq \frac{1}{2}$ for a d regular network in which agents place equal weights on each other.*

Let $\bar{c}$ be the derived upper bound for c^*. Then,

1. *The upper bound decreases as under-reaction increases.*

$$\frac{\partial \bar{c}}{\partial \alpha_2} < 0$$

2. *The upper bound decreases at an increasing rate as under-reaction increases i.e. bottlenecks can be convex in under-reaction.*

$$\frac{\partial^2 \bar{c}}{\partial \alpha_2^2} > 0$$

3. *The upper bound increases as the network size increases keeping connectivity constant and decrease as connectivity increases keeping network size constant.*

$$\frac{\partial \bar{c}}{\partial n} < 0, \frac{\partial \bar{c}}{\partial d} > 0$$

4. *The upper bound becomes more responsive to changes in under-reaction (i.e. it is more convex) if (a) network size decreases, (b) connectivity increases.*

$$\frac{\partial^2 \bar{c}}{\partial \alpha_2^2 \partial n} < 0, \frac{\partial^2 \bar{c}}{\partial \alpha_2^2 \partial d} > 0$$

The proof follows when we take derivatives of the bounds derived in the previous lemma with respect to under-reaction, network size, and degree.

The contour plots in Figure 1.6 illustrate the relationship between the upper bound for the Cheeger constant, network size, and degree for different levels of under-reaction. The bound decreases when under-reaction increases implying that the network is likely to be more bottlenecked. The bound is higher when the network is small and more connected. Further, bottleneck bounds become less responsive to changes in under-reaction as networks become less connected or as they increase in size. This implies that bottlenecks and convergence times in smaller and more connected networks may be more responsive to changes in under-reaction.

6.2 Mixing Time

A standard result in the literature on the speed of convergence of reversible Markov processes suggests that the Cheeger Constant can be used to bound the second eigen-value of the transition matrix (Levin and Peres, 2017). The Markov process considered here is not reversible. Reversibility implies that $v_i \Omega_{i\ n+i} = v_{n+i} \Omega_{n+i\ i}\ \forall i \in N$ where v is the stationary distribution of the process (Levin and Peres, 2017). We know that v is the influence vector suggesting how much each agent's initial beliefs affect the agreement reached by the network. Both v_i and v_{n+i} are non zero because of the irreducibility of Ω i.e. the past and current self of an agent have at least some influence

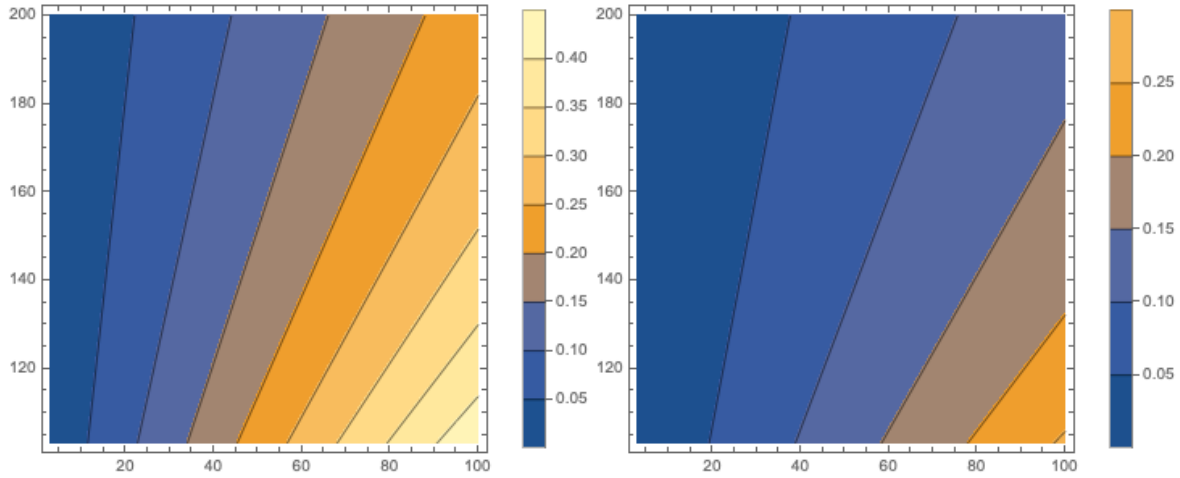


Figure 1.6: Cheeger constant upper bound contour plots for d regular networks as a function of total degree $d+1$ (on the x-axis) and network size (on the y axis). The first plot corresponds to networks with low under-reaction of $\alpha_2 = 0.1$ and the second corresponds to high under-reaction of $\alpha_2 = 0.9$. Darker shades imply a lower value of the Cheeger upper bound i.e. the graph is likely to be more bottlenecked.

over other agents. We also know that $\Omega_{i\ n+i} = 0$ and $\Omega_{n+i\ i} = 1$ by construction. This implies that the Markov process is not reversible.

The mixing time of the Markov process as per Levin and Peres (2017) can be defined as follows.

Definition 6 *The mixing time of a Markov process is defined as-*

$$t^* = \min\{t : \max_{i \in \{1,2,..,2n\}} \mid \Omega^t(i,:) - v \mid_{TV} \leq \frac{1}{4}\}$$

$\mid . \mid_{TV}$ refers to the total variation distance and measures the closeness between two probability distributions (Levin and Peres, 2017). In this case, these are the stationary distribution of the learning process and the distribution implied by the i'th row of Ω^t.

Despite non-reversibility, as Levin and Peres (2017) mention, the Cheeger constant (and consequently its upper bound) can still be used to provide a lower bound for the mixing time of Ω since Ω is both irreducible and aperiodic. The lower bound for the mixing time of such a Markov process can be written as follows:

$$t^* \geq \frac{1}{4c^*}. \tag{1.15}$$

Levin and Peres (2017) prove that this inequality holds for any transition matrix that is both aperiodic and irreducible and even if the underlying Markov process is non-reversible. Adjacency matrices like Ω are aperiodic when there exists at least one individual with positive self-weight (Jackson, 2010). Ω is irreducible as per the previously proven Lemma if $\alpha_1, \alpha_2 > 0$ which we have assumed to be true.

I now discuss the relationship between the derived Cheeger upper bound and convergence time.

Theorem 6 *Consider a d regular lattice with individuals who exhibit a positive under-reaction* $\alpha_2 \in (0,1)$. *Then,*

$$t^* \geq \frac{1}{4\ c^*} \geq \frac{1}{4\ \bar{c}} = \frac{n(d+1+\alpha_2 d)}{4k(d)} = \bar{t}$$

Further,

$$\frac{\partial \bar{t}}{\partial \alpha_2} > 0,\ \frac{\partial \bar{t}}{\partial d} < 0 \ \textit{and}\ \frac{\partial \bar{t}}{\partial n} > 0\ .$$

This directly follows by substituting $\bar{c}$ in the expression for the lower bound for mixing time. The theorem shows that the lower bound for mixing time rises as under-reaction rises and points towards a potentially positive relationship between mixing time and under-reaction and a potentially negative relationship between mixing time and network connectivity. This follows from the previous lemma. A rise in under-reaction is likely to increase bottlenecks and reduce the speed of convergence. A rise in connectivity is likely to reduce bottlenecks, increase the speed of convergence, and make the bottlenecks (and consequently mixing times) more responsive to changes in under-reaction.

It is important to note that movements in these bounds do not necessarily reflect movements in the actual Cheeger constant. I will simulate the model on artificial d regular networks and the Indian village networks and validate some of these hypothesized relationships in the next section to alleviate this concern. The application to the d regular case is straightforward. However, in order to apply it to the Indian village networks, I will have to treat the computations made in the d regular case as coarse approximations for the general case with heterogeneous degree.

7 Simulations

I use randomly generated networks and the rural Indian networks in Banerjee et al. (2013) throughout this section. The networks data from Banerjee et al. (2013) contains adjacency matrices of various types of networks from 75 villages in rural India. These networks include various kind of relationships such as borrowing, lending, advice-taking, visiting each other's houses. I will use the advice-giving network G where a link between i and j exists, so $g_{ij} = 1$ when i takes advice from j. The network is assumed to be undirected and I proxy for an advice-related relationship. So, $g_{ij} = g_{ji} \forall i, j \in N$.[24]

[24]The choice of the network is not critical to the analysis conducted here since the aim is to simulate the model and test the results on any real-world network. I am only concerned with inter-village comparisons for a given choice of network. Even the model results that depend on network structure, such as speed of convergence, are studied by making comparisons across villages.

7.1 Convergence

First, I simulate the regular information model on the advice networks in rural Indian villages from Banerjee et al. (2013) to see how well the sufficient condition derived in Theorem 1 predicts convergence. I run $\sim$ 1200 iterations and each iteration proceeds in the following manner.

1. A village advice network v is randomly chosen from all advice networks. The giant component of this network is retained and the iteration proceeds if it contains more than 10 agents.
2. Networks in each village are randomly categorised into one of the following types-
   (a) Type 1- with very low idiosyncrasies, so $\alpha_{2i} \sim U[0, 1.1]$
   (b) Type 2- with low idiosyncrasies, so $\alpha_{2i} \sim U[0, 1.3]$
   (c) Type 3- with medium idiosyncrasies, so $\alpha_{2i} \sim U[0, 1.5]$
   (d) Type 4- with high idiosyncrasies, so $\alpha_{2i} \sim U[0, 1.7]$
   (e) Type 5- with very high idiosyncrasies, so $\alpha_{2i} \sim U[0, 1.9]$
3. Individual i in network v is then endowed with an idiosyncrasy α_{2i} randomly chosen from the uniform distribution selected for their village v. Individuals are assumed to either be under-reacting or frustrated. The over-reaction case is analogous but is not covered in these simulations.
4. Individuals begin learning with an individual-specific prior randomly chosen from $U[0, 20]$ in time $t = 0$. In each period t, individuals observe a private signal about the true rate $r = 10$. The signals are a realisation from the normal distribution $N(10, 0.01)$. Individuals form their beliefs in period t by placing a weight on their private signals and the inferred beliefs of their neighbours as per the belief formation rule. They place an equal weight on their own beliefs and the inferred beliefs of their neighbours. This weight is equal to $\frac{1}{d_i+1}$ for every individual $i \in v$.
5. The iteration continues for 1000 time periods. Beliefs are said to converge in time t if the average beliefs in the network do not differ from the true rate $r = 10$ in t, $t-5$, $t-10$ and $t-20$ by a number greater than 10^{-3}.

I check if beliefs in these networks converge in expectation and how successfully the derived sufficient condition predicts convergence. I identify the maximal agent in these networks and check if the sufficient condition is satisfied. The degree and eigenvector centrality of the maximal agents from these networks are plotted in Figure 1.7 below. Maximal agents are not necessarily the most degree or eigenvector central individuals in the network. The simulations assume that individuals place an equal weight on their own beliefs and that of their neighbours, so more number of neighbours necessarily implies a lower weight on their own opinions. This is why, in this case, there is a positive correlation between an

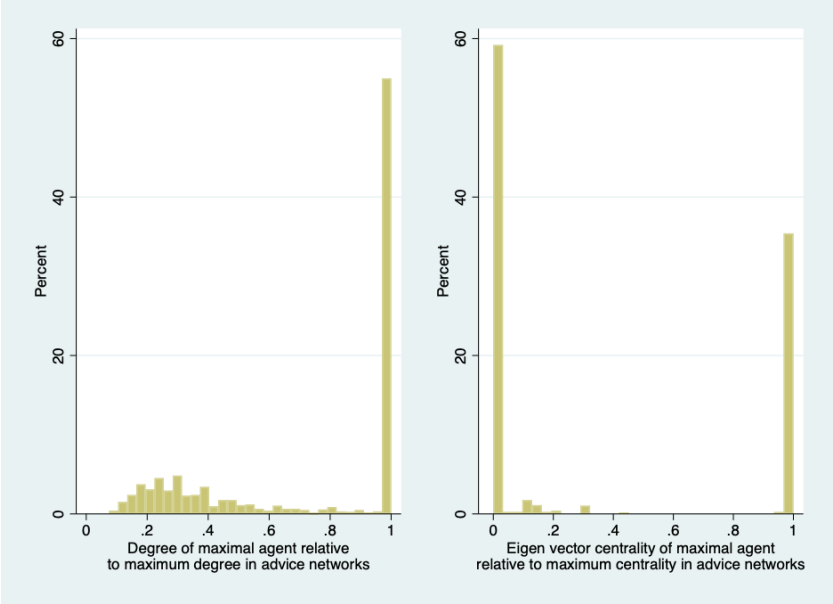


Figure 1.7: Degree and Eigenvector centrality of maximal agents across all iterations.

agent's degree and whether or not they are the maximal agent. Such a positive correlation may not necessarily hold with unequal weights.

Since convergence is always ensured whenever the sufficient condition is satisfied, I am particularly interested in identifying cases where convergence is reached but the sufficient condition is violated. For these cases, I check how far the average frustration in the maximal agent's neighbourhood is from the upper bound derived in Corollary 2. Figure 1.8 plots the difference between the actual radius of the union of the Gershgorin row circles and the required radius (=1) for networks that are not predicted to converge but still do. This difference is less than 0.4 for 95% of the cases.

As expected, beliefs always converge when the sufficient condition predicts convergence. However, the sufficient condition predicts convergence for 80 % of the actual convergent networks and convergence does not take place for 65% of the cases for which the condition is violated.

To check if the sufficient condition is too tight, I identify the types of networks whose beliefs converge despite the violation of the condition.

Figure 1.9 plots the fraction of simulations for which the sufficient condition is satisfied and the fraction for which convergence takes place, for each network- plotted all together and plotted by different levels of frustration. The sufficient condition predicts convergence or the lack of convergence accurately when maximum frustration is either very low (type 1) or very high (type 5). Networks of type 2 frustration always converge and the sufficient condition only predicts some of these cases. Networks of type 3 and 4 always violate the sufficient condition but some of them do converge. Convergence becomes less likely as we move from type 3 to type 4 networks and the sufficient condition correspondingly becomes

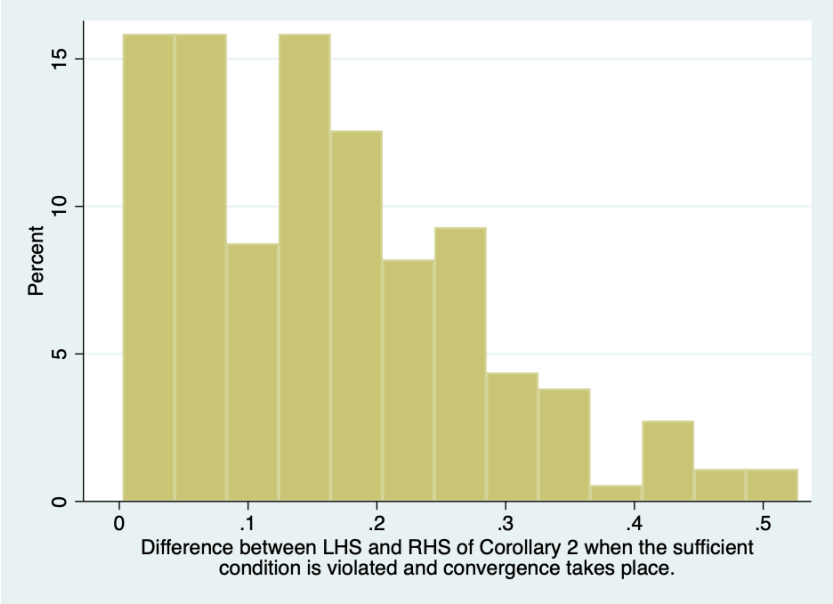


Figure 1.8: Histogram of the difference between the actual and required Gershogorin rowsum of convergent networks where the sufficient condition is violated.

a better predictor of divergence. It perfectly predicts divergence in networks of type 5. Satisfying the derived bound ensures convergence but violating it does not necessarily indicate divergence in beliefs in networks of types 2,3, and 4.

The monotonic relationship between the magnitude of idiosyncrasy and convergence observed here is due to equal weights. While we can compare the tightness of the sufficient condition across networks with different levels of idiosyncrasies here, such comparisons will be more involved without the assumption of equal weights. In that case, very frustrated networks with maximal agents who trust themselves a lot might converge but less frustrated networks with more gullible maximal agents may not. The derived sufficient condition will also be a useful indicator of convergence in these complicated settings where an obvious monotonic relationship between frustration and convergence cannot be necessarily established.

7.2 Speed of Convergence

Now, I test the tightness of the bounds on 'mixing time' derived in Theorem 6 on randomly generated d regular networks and real-world networks from Banerjee et al. (2013).

d regular networks

I consider small d-regular networks of size $n = 20$ and $d \in \{2, 4, 6, 8\}$ where agents are endowed with a randomly chosen homogeneous under-reaction $\alpha_2 \in (0, 1)$. Agents place an equal weight on themselves and their friends. I generate 2000 such networks, construct transition matrices, and compute the mixing times. To do the latter, I compute the total variation distance between the stationary distribution of Ω and the worst distribution

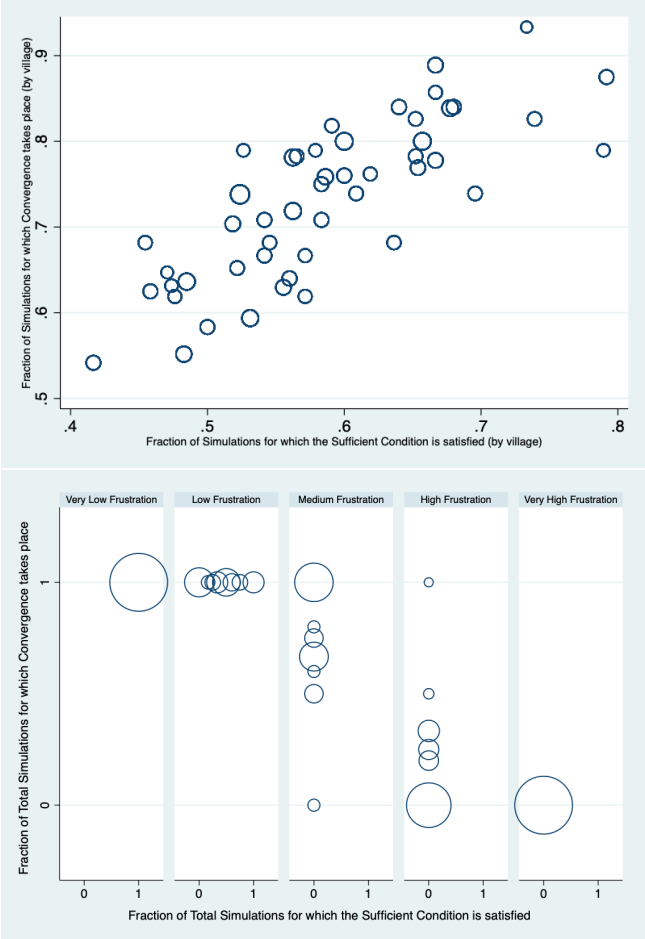


Figure 1.9: Fraction of simulations for which the sufficient condition is satisfied v/s the fraction for which convergence takes place in the Banerjee et al. (2013) networks endowed with different idiosyncrasies (left: for each village, right: for each village and network type.) The size of the marker in each subplot is proportional to the frequency of the observations in that group.

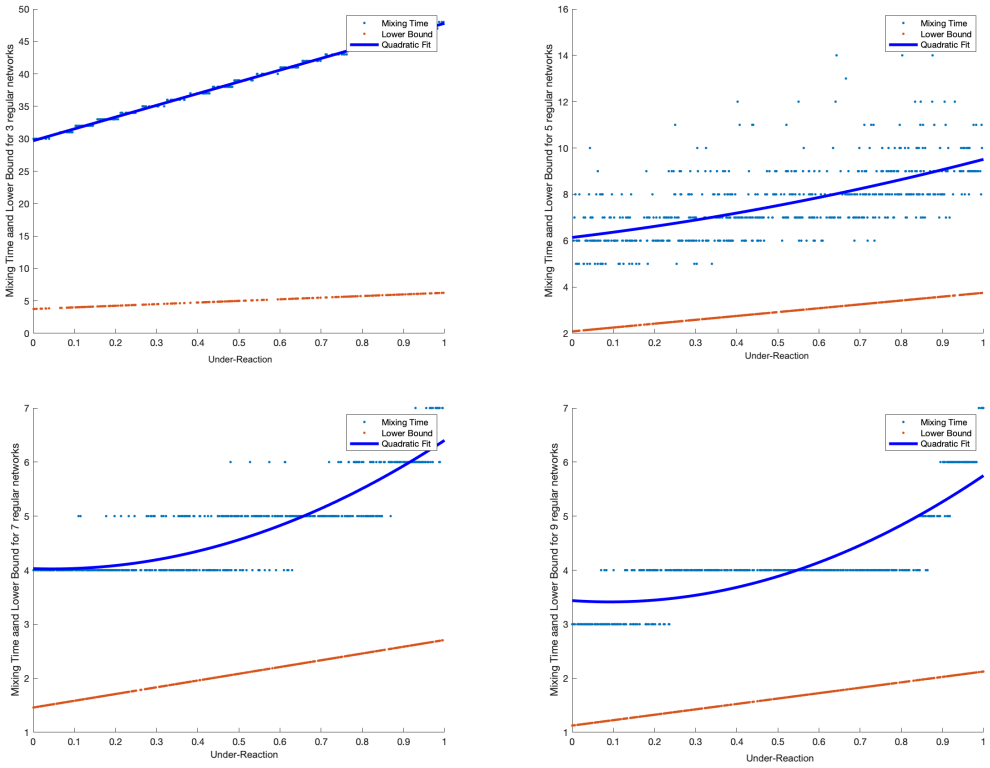


Figure 1.10: The above figures plot mixing bounds and the derived lower bounds as a function of under-reaction for ~ 2000 d regular networks with $n = 20$ and $d + 1 \in \{3, 5, 7, 9\}$.

implied by Ω^t at time period t. Applying the definition in Levin and Peres (2017), the mixing time t^* of matrix Ω can be written as follows:

$$t^* \leq \bar{t^*} = \min\{t : \max_{i \in \{1,2,..,2n\}} \frac{1}{2} \sum_{j \in \{1,2,..,2n\}} \mid \Omega^t(i,j) - v(j) \mid \leq \frac{1}{4}\} \tag{1.16}$$

I also compute the lower bound for mixing times of these d regular networks using the expressions for the Cheeger bound derived in the previous section. Mixing time (numerically computed) and mixing time lower bounds (analytically derived) are plotted against under-reaction for different d regular networks in Figure 1.10. We can make the following observations-

1. t^* is rising in under-reaction and falling in degree. Both these findings are consistent with the comparative statics derived in the previous section where I found that the (a) upper bound for the Cheeger constant for d regular networks is falling in under-reaction and rising in degree and consequently (b) the lower bound for the mixing times is rising in under-reaction and falling in degree.

2. t^* becomes more convex in under-reaction as degree increases. This is in line with the previous result that the upper bound for bottlenecks becomes more responsive

to changes in under-reaction as the network becomes more connected. It also corroborates the intuition that interventions which seek to increase the speed of convergence of beliefs by reducing under-reaction can be more successful in well-connected networks.

3. The lower bound is close to t^* when $\frac{d}{n}$ is sufficiently high. This is most evident in the graph for 3 regular networks in which case the bounds do not provide a close approximation for the true mixing time.

Now, I will check if the relationships between mixing time, biases, and connectedness hold in the Indian village networks from Banerjee et al. (2013).

Villages in rural India

I check if the predictions for the d regular case apply to the Indian village dataset from Banerjee et al. (2013). In each iteration, I randomly choose a village advice network and construct Ω by (a) endowing the agents with a homogeneous under-reaction chosen uniformly from $(0, 1)$ and (b) assuming that agents place an equal weight on each other's opinions. I find the average degree of these networks and compute the lower bound for mixing time as per the derived equation. This is an approximation since these networks are not regular and the lower bound was only defined for regular networks. As in the d regular case, I compute the mixing time under these assumptions. I also compute how connected the network is by taking the ratio of average degree and size and classify networks into quartiles based on how connected they are. Figure 1.11 plots the computed upper bound of mixing time against under-reaction for different quartiles of network connectedness. I make the following observations.

1. The derived lower bound for mixing time and the actual mixing time have a large gap between them but both are rising in under-reaction. This provides evidence that beliefs in under-reacting networks converge slowly. The positive relationship between mixing time and under-reaction can be seen in 1.11. The coefficient on under-reaction is positive when mixing times are regressed on under-reaction, holding connectedness constant.

2. As per the results for the d regular case, a rise in connectedness should lead to a fall in mixing time, holding under-reaction constant. This is because the Cheeger constant in the d regular case falls as network size rises and as degree falls. The coefficient on connectedness is negative when mixing time is regressed on under-reaction and connectedness.

3. I also find evidence to suggest that mixing times may become more responsive to under-reaction as networks get more connected. This can be inferred from Figure 1.11. However, there is not enough variation in average degree among the 75 villages to explore this further.

The results of these simulations support the hypothesized negative relationship between

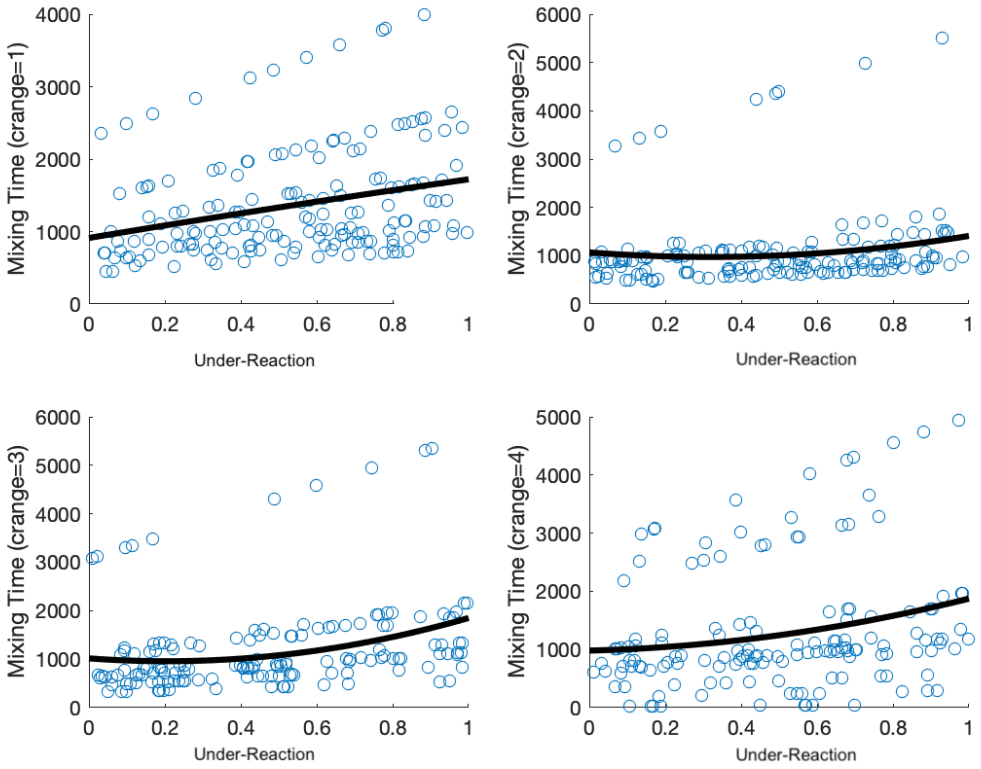


Figure 1.11: Mixing time plotted against under-reaction for village networks grouped by different quartiles of connectedness labelled 1 to 4. Mixing times are rising in under-reaction #iterations=713.

under-reaction and speed of convergence. Connectedness has a positive effect on the speed of convergence, as expected. However, we cannot necessarily conclude that networks become more responsive to under-reaction as they become more connected.

8 Discussion

Now, I briefly discuss (a) the implications of the results on convergence on interventions that aim to improve social learning and (b) how the relationship between under-reaction, learning bottlenecks, and speed of convergence relates to the literature on social norms.

The empirical usefulness of the results on convergence depends on whether the researcher can accurately measure networks and identify the behavioural type of the agent. The results illustrate different ways through which interventions can improve the convergence of beliefs in different settings where different behavioural types might be a more prominent concern. For example, frustrated agents might affect beliefs about vaccination while under-reacting agents might affect technology adoption. An intervention that aims to improve convergence outcomes can either (a) target individual idiosyncrasies, especially among those agents who are located around gullible agents in the network, (b) target gullibility by increasing the weight individuals put on their signals rather than the choices of their network neighbours, or (c) inform individuals about the idiosyncrasies of their peers thereby removing the channel through which these negative externalities affect societal outcomes. The derived upper bounds show that the network can tolerate some over-reaction and frustration but the tolerance is higher as discussed if agents are not very gullible. Intervention techniques (a) and (b) directly affect these bounds. The results that link an individual's idiosyncrasies with convergence are dependent on an assumption that individuals are not aware that their neighbours are under-reacting, over-reacting, or frustrated. Intervention technique (c) counters this assumption by making individuals aware of the idiosyncrasies of those they learn from. The link between convergence and the magnitude of idiosyncrasies (via the Gershgorin circles) allows us to obtain these results for any network where agents place heterogenous weights on the beliefs of their peers. While these results can be used to predict the convergence of beliefs using accurate measurements, they are also helpful in understanding the more normative aspects of social-learning interventions.

The derived relationships between network connectedness, individual under-reaction, bottlenecks and mixing times, can be used to understand why social norms persist and how interventions that seek to alter social norms can be designed. The literature on social norms finds that norms are persistent and hard to alter (Young, 2015). Young (2001, 2015) give examples of community structures affecting social norms such as the finding by Munshi and Myaux (2006) that an individual's use of contraceptives is positively correlated with its use in their religious community but not correlated with its use in other religious communities. Young (2015) also mention the hypothesis by Kohler et al. (2001) that more connected networks can inhibit learning because of the repetition

of information and because they have a greater ability to apply pressure. Kohler et al. (2001)'s empirical results from Kenyan households suggest that network density may have negative and positive effects on adoption of contraceptives when adoption is below or above a certain value. The results here suggest that higher density (i.e. lower network size and higher degree) has a positive impact on the speed of convergence in regular networks when agents under-react. I also find evidence pointing towards the positive effect of connectedness on the speed of convergence of beliefs in irregular networks when I simulate the model using data from Banerjee et al. (2013). I also show that slowness in convergence of beliefs can arise due to network bottlenecks. These bottlenecks prevent learning among the agents' past and current selves and are exacerbated by the magnitude of under-reaction. These 'behavioural' bottlenecks have a similar effect as the bottlenecks that arise, for example, due to religious boundaries among the agents in Munshi and Myaux (2006).

Consider the case where individuals begin with some consensus about the underlying state of the world in period 0 (i.e. the baseline) after which they're provided with a new signal in period 1 (i.e. the intervention). While individuals will update their beliefs accordingly, a new consensus may take time to be reached depending on how bottlenecked the learning process is. Changing beliefs from the old consensus (i.e. the old norm) to a new potential consensus (i.e. the new norm) can be a long drawn process because of the presence of such bottlenecks. I show that these bottlenecks arise because of individual under-reaction and can be reduced by targeting both under-reaction and the network structure. Bottlenecks in learning can be large in very under-reacting networks for a given network size and degree. If under-reaction is high, then the past selves of the agents may have undue influence, leading to a low Cheeger constant. Bottlenecks then increase the lower bound on mixing times implying that the network is likely to learn slowly. Partitioning the learning network into two groups that do not listen across is similar to "local conformity" and "global diversity" in beliefs documented by Young (2015) i.e. the presence of disparate norms across communities and similar norms within communities.

I find that these bottlenecks can respond to network connectivity and size. Bottlenecks in regular networks might increase as network size increases, decrease as network connectivity increases, and become more responsive to changes in under-reaction as network size decreases or connectivity increases. Networks which are large but very sparsely connected will then be less responsive to norm-altering interventions. Interventions that aim to reduce under-reaction and alter norms should aim to simultaneously change network connectivity and agent under-reaction. Improving network connectivity will directly reduce bottlenecks and also make them more responsive to changes in under-reaction.

The results on speed of convergence are limited in that they are based on the derived upper bound of the Cheeger Constant. While the simulations suggest that these comparative statics may hold, the results are also only applicable to d regular networks

where individuals place equal weights on each other. The simulations on irregular networks also assume equal weights. However, this does not take away from the key point that both the direct and interaction effects of under-reaction and network connectivity must be considered while designing interventions that target norms. If the network is fairly regular, then a combined approach of increasing the number of connections and targeting under-reaction will be most useful.

Additionally, if we observe the time it takes beliefs to converge (and for individuals to adopt a new technology, for example), then we can use these results to run the opposite exercise. We can measure convergence times in various networks and measure the network structure. Then, under the assumptions of the model, we can use this information to compute an upper bound for the under-reaction parameters of the members of the network. A similar exercise can be conducted to compute a lower (upper) bound on frustration or over-reaction after observing whether beliefs diverge (converge) in a given network. Note that this exercise relies on the assumption that individuals are updating their beliefs exactly in the manner considered here.[25]

9 Conclusion

This paper shows that individual idiosyncrasies can impose social costs in that they impact (a) the ability of a society to reach an agreement, (b) the accuracy of the agreement, and (c) the speed with which it is reached. I distinguish between three types of idiosyncrasies that span the parameter space. Individuals in my model can include, for example, farmers learning the benefits of a new technology, voters learning the benefits of a government policy, or parents learning the benefits of investing in their child's education. Under-reaction, frustration, and overreaction are likely to affect how these agents make choices and how their choices then affect the beliefs and choices of those who observe them.

The agents in this paper are of certain types and continuously update their beliefs as per their type. It might be useful to consider cases where agent idiosyncrasies change in every time period while keeping the network constant. For example, agents might under-react to new information in early periods and then become frustrated over time. This would imply that the adjacency matrix would endogenously change in every period.[26] Endogenously evolving adjacency matrices will also allow us to consider the impact of other kinds of behaviour such as loss aversion. While the current approach places strong restrictions on agent behaviour, it highlights how individual idiosyncrasies can interact with the network structure and impose macroeconomic costs.

[25] Chandrasekhar et al. (2020) find evidence in favour of Degroot learning among villagers in rural India but note that the proportion of Bayesians is higher among Mexican students.

[26] Golub and Sadler (2017) mention constant weights as one of the major drawbacks of the DeGroot model. See their paper for a review of the existing literature on updating processes with stochastic transition matrices.

Appendix

9.1 Convergence

Proof of Lemma 1

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Proof: This is a standard result proven in the existing literature (Meyer, 2000). The belief formation rule in the regular information case can be written as follows.

$$\mathbf{R}_t = \mathbf{S}_t + \Omega\mathbf{R}_{t-1} = \sum_{j=0}^{t} \Omega^j \mathbf{S}_{t-j} + \Omega^t \mathbf{R}_0 \implies E[\mathbf{R}_t] = \sum_{j=0}^{t} \Omega^j E[\mathbf{S}_{t-j}] + \Omega^t \mathbf{R}_0$$

Taking limits, we get

$$\lim_{t\to\infty} E[\mathbf{R}_t] = \sum_{j=0}^{\infty} \Omega^j S + \lim_{t\to\infty} \Omega^t \mathbf{R}_0 \overset{\text{if } \rho(\Omega)<1}{=} (I-\Omega)^{-1} S$$

The last equality follows from two known results about the spectral radius. (1) The sum $[I + \Omega + \Omega^2 + \Omega^3 ...]$ converges to $(I-\Omega)^{-1}$ and (2) $\lim_{t\to\infty} \Omega^t = 0$ if $\rho(\Omega) < 1$. Thus, convergence in mean takes place if $\rho(\Omega) < 1$.

Proof of Lemma 2

Click to go back.

Proof: I will show that the matrix Ω is irreducible if the underlying network G is connected and if $\alpha_{1i}, \alpha_{2i} \neq 0 \ \forall i$. The second assumption implies that if the underlying network G has a connection between agents i and j, then i places a strictly non zero weight on j's beliefs in times $t-1$ and $t-2$ in forming their own beliefs in the time t. Conversely, if i places a zero weight on j's opinion in either period, then it implies that i and j are not linked in G.[27]

Recall that Ω is a square matrix of order $2n \times 2n$ of which is composed of four $n \times n$ sub-matrices W_2, W_3, I, and 0. The first n rows and column entries of matrix Ω are non-zero if and only if the corresponding network adjacency matrix entries are non-zero i.e. the digraph of the $n \times n$ sub matrix W_2 is strongly connected if the network G is strongly connected. This implies that the digraph of Ω contains a strongly connected component containing links among the first n nodes. I only have to show that the remaining n nodes of this matrix (i.e. nodes from columns $n+1$ to $2n$) are a part of this connected component.

[27]The assumption that i has to weight j's beliefs in $t-1$ *and* $t-2$ and cannot set one of them equal to zero is not a restrictive assumption. If i does not pay attention to j's beliefs in period $t-2$, they can place a weight *almost* equal to 0. However, Ω is irreducible even if, for instance, $\alpha_{1i} = 0 \forall i$ but $\alpha_{2i} \neq 0 \forall i$. I ignore these cases for simplicity.

This will constitute the proof.

Let us first consider the case where α_{1i}, $\alpha_{2i} > 0 \ \forall i \in N$.

The $n + k$'th node of matrix Ω has a unique outgoing link to agent k for all $k \in N$ but no incoming link from agent k. This is because matrix Ω contains the identity sub matrix in its bottom left corner and the diagonals in the sub-matrix W_3 are zero. To show that these remaining nodes also belong to the connected component, we only have to show that there also exists an incoming link that connects each of the nodes $n + 1...2n$ to at least one member $i \in N$ in the connected component. We can prove this by contradiction. Assume that there is no incoming link to the $n + k$'th node of matrix Ω for $k \in N$. This implies that the $n+k$'th column of Ω is a zero vector. However, this also implies that k'th column vector of Ω is a zero vector. Since we have assumed that $\alpha_{1i} \neq 0 \ \forall i$, a zero column vector k in W_2 necessarily means that agent k has no links in G- which contradicts the assumption that G is strongly connected.

So, for every node $n+k$, there exists *at least* one incoming link and only one outgoing link, generating at least one cycle. This implies that these nodes also belong to the connected component and there exists a directed path between any two nodes of matrix Ω. Thus, matrix Ω is irreducible if the underlying network is strongly connected and if α_{1i} , $\alpha_{2i} \neq 0$ $\forall \ i$.

Special Case- Now, consider the special case where $\alpha_{2i} \neq 0$ and $\alpha_{1i} = 0 \ \forall i \in N$. An example of this case would be where all agents have the under-reaction parameter α_{2i} equal to 1.

In this case, W_2 is a null matrix. I will distinguish between a node and an agent to ensure clarity.[28] The former will refer to the rows and columns of matrix Ω and the latter will refer to agents in the network. To understand this, relabel the first n rows and columns of matrix Ω as nodes $a_1, a_2...a_n$ and the last n rows and columns as nodes $b_1, b_2....b_n$ where the subscripts are the labels of the network agents. In order to prove irreducibility, we have to show that-

1. $\forall i, j \in N$, Node a_i can reach any other node b_j- Since the network is strongly connected, each agent $i \in N$ in the network should be able to reach each agent $j \neq i$. This implies that each node a_i must be able to reach each node b_j via the entry in W_3. If this were not the case, the network agent j corresponding to node b_j would not be a part of the strongly connected component. For example, if node a_i has to reach some b_j, they can do so within one step if agent i is connected to agent j since $\alpha_{2i} \neq 0 \ \forall i \in N$. If this is not the case, by strong connectivity, there has to be some agent l who is connected to agent j. Let us define a network path between agents i and l without any loss of generality $i \to k \to l \to j$. This means that in the matrix Ω, $a_i \to b_k \to a_k \to b_l \to a_l \to b_j$. Thus, there always an outgoing path

[28] In fact, nodes j $\in \{n + 1, ..2n\}$ can be interpreted as the 'past selves' of the corresponding node $j - n \in N$ This terminology is also used later.

between a_i and $b_j \forall i, j \in N$. This is because every node b_k is connected to a unique node a_k with a unique outgoing link via the identity matrix.

2. $\forall i, j \in N$, Node b_i can reach any other node b_j- Each b_i can reach the unique a_i it is connected to, via the identity matrix in the bottom left corner of matrix Ω. As argued above, each node a_i can then reach every node b_j via a directed path.

3. $\forall i, j \in N$, Node a_i can reach any other node a_j. This would have been easy to show (via connectedness) if $\alpha_{1i} \neq 0 \forall i \in N$. When $\alpha_{1i} = 0$ for all agents, then we need to look for a path via the nodes $\{b_i, b_2, ...b_n\}$. As shown above, node a_i can reach node b_j via a directed path. b_j is uniquely connected to a_j via the identity matrix.

4. $\forall i, j \in N$, Node b_i can reach any other node a_j- Each b_i can reach the unique a_i it is connected to (via the identity matrix), which as shown, can reach the unique b_j connected to node a_j.

So even in the extreme case where matrix W_2 is a null matrix, Ω is irreducible if the network is strongly connected and if $\alpha_{2i} \neq 0$.

Proof of Theorem 1

Click to go back.

Proof:

Define the union of the 'row circles' of any matrix A, $\mathbb{R}_{\mathbb{A}}$, as the union of all circles centered at the diagonal entry a_{ii} with a radius equal to the sum of all other elements in the row i.e. $\sum_{j:j\neq i} a_{ij}$. Define the union of the 'column circles' of A, $\mathbb{C}_{\mathbb{A}}$, as the union of all circles centered at the diagonal entry a_{jj} with a radius equal to the sum of all other elements in the column i.e. $\sum_{i:i\neq j} a_{ji}$. Gershgorin's circle theorem (Gershgorin, 1931) states that all eigen-values of matrix A must lie inside the intersection of the union of all row circles and the union of all column circles i.e. all eigen-values must lie inside $\mathbb{R}_{\mathbb{A}} \cap \mathbb{C}_{\mathbb{A}}$. The extension of the theorem by Taussky et al. (1948) proves that if a matrix is irreducible, then an eigen-value lies on the boundary of one of the circles if and only if it lies on the boundary of all the circles. I now derive a condition on Ω that ensures that the radius of the Gershgorin circle is atmost 1.

The matrix Ω can be written as follows

$$\Omega = \begin{bmatrix} 0 & \alpha_{1j}w_{ij} & \alpha_{1k}w_{ik} & \dots & 0 & \alpha_{2j}w_{ij} & \alpha_{2k}w_{ik} & \dots \\ \alpha_{1i}w_{ji} & 0 & \alpha_{1k}w_{jk} & \dots & \alpha_{2i}w_{ji} & 0 & \alpha_{2k}w_{jk} & \dots \\ \vdots & & \ddots & & & & \ddots & \\ \alpha_{1i}w_{ni} & \dots & 0 & & \alpha_{2i}w_{ni} & \dots & & 0 \\ 1 & 0 & 0 & \dots & 0 & 0 & \dots & \\ 0 & 1 & 0 & \dots & 0 & \ddots & & \\ \vdots & \ddots & & \dots & & & & \\ 0 & \dots & 1 & & 0 & \dots & & 0 \end{bmatrix}$$

Define r_1 as the radius of the largest row circle among the first n row circles centered at the origin i.e. the maximum absolute sum of the first n rows of Ω. We can separate the agents into two groups- those who for whom $\mid \alpha_{1i} \mid + \mid \alpha_{2i} \mid = 1$ and those for whom $\mid \alpha_{1i} \mid + \mid \alpha_{2i} \mid > 1$. So,

$$r_1 = \max_{i \in N} \sum_{j \in N(i), |\alpha_{1i}|+|\alpha_{2i}|=1} w_{ij} + \sum_{j \in N(i), |\alpha_{1i}|+|\alpha_{2i}|>1} w_{ij}(\mid \alpha_{1i} \mid + \mid \alpha_{2i} \mid)$$

$$= 1 - w_{ii} + \sum_{j \in N(i^*), |\alpha_{1j}|+|\alpha_{2j}|>1} w_{i^*j}(\mid \alpha_{1j} \mid + \mid \alpha_{2j} \mid -1)$$

where i^* are the maximal agent(s) who maximizes the first expression. The second equality follows by recalling that the weights must sum to 1 i.e. $\sum_{j \in N(i)} w_{ij} + w_{ii} = 1 \; \forall i \in N$

Define r_2 as the radius of the largest row circle among the next n row circles centered at the origin.

$$r_2 = \max_{i \in \{n+1, \dots 2n\}} \sum_{j : j \neq i} \Omega_{ij} = 1$$

Next, define the radii of the column circles. Define r_3 as the radius of largest column circle among the first n column circles, all of which are centered at the origin.

$$r_3 = \max_{j \in N} \sum_{i : i \neq j} \Omega_{ij} = \max_{j \in N} \Big[\sum_{i \in N(j)} w_{ij} \mid \alpha_{1j} \mid \Big] + 1$$

Similarly, define r_4 as the radius of the largest column circle among the remaining n column circles, all of which are centered at the origin.

$$r_4 = \max_{j \in \{n+1, \dots 2n\}} \sum_{i : i \neq j} \Omega_{ij} = \max_{j \in \{n+1, \dots 2n\}} \sum_{i \in N(j)} w_{ij} \mid \alpha_{2j} \mid$$

The radius of the union of the column circles will always be greater than 1. The radii of

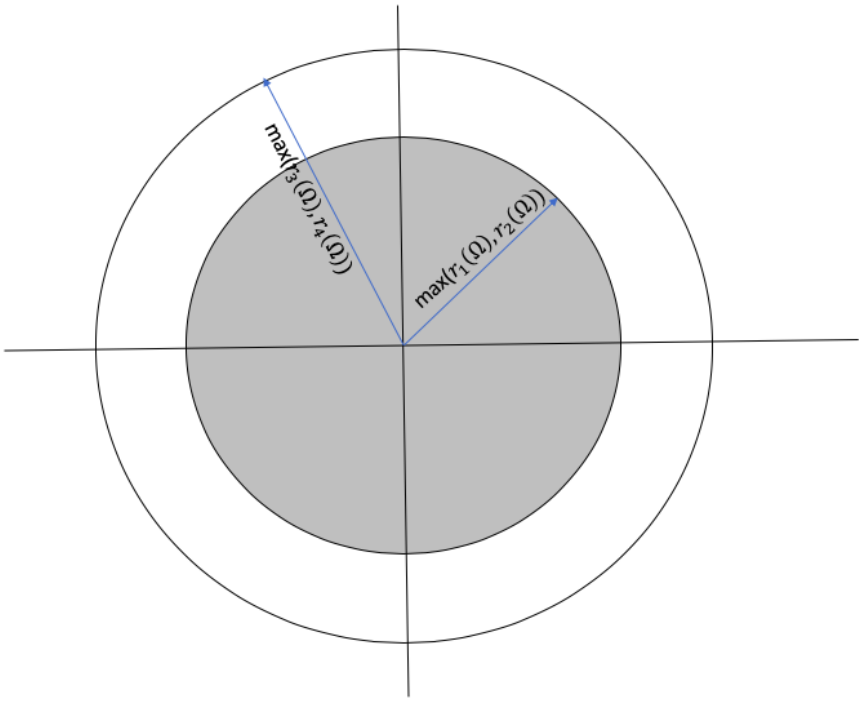


Figure 1.12: The radii of the union of the row and column Gershgorin circles depend on α_{1i} and α_{2i} $\forall i \in N$. max $\{r_1, r_2\} = 1$ when the sufficient condition is satisfied. Irreducibility of Ω and the application of Tausky's theorem ensure that all eigen-values lie strictly inside the shaded circle.

the union of the row circles will 1 iff

$$r_1 \leq r_2 \implies \sum_{j \in N(i^*), |\alpha_{1j}|+|\alpha_{2j}|>1} w_{i^*j}(\mid \alpha_{1j} \mid + \mid \alpha_{2j} \mid -1) \leq w_{ii}$$

Under this condition, the radius of the union of the row circles is equal to 1 and the radius of the intersection of the column and row circles is also equal to 1. Since Ω is irreducible as per Lemma 2, we can use Taussky's theorem to infer that the eigen-values of Ω must lie strictly inside this circle i.e. the eigen-values must strictly be less than 1 in absolute value.

This ensures convergence and completes the proof. Figure 1.12 plots the Gershgorin circles of Ω.

Corollary 1 and 2

The corollaries can be derived by making appropriate substitutions in Theorem 1.

Networks with persistent idiosyncrasies

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Throughout the paper, I assume that individuals consider a linear combination of their

current and last period belief while making their choice i.e. individuals place weights on r_{it} and r_{it-1}. Here, I allow idiosyncrasies to be more persistent by allowing individuals to exhibit learning lags i.e. they place weights on r_{it} r_{it-1}, r_{it-2}.. r_{it-k} for some fixed k. Let functions f and c be defined as before. Then, the utility function and first order conditions can be written in the following manner-

$$U_{it} = f(\sum_{m=1}^{k} \alpha_{mi} r_{it-m}) e_{it} - c(e_{it}) \text{ where } \alpha_{mi} > 0 \ \forall m \in \{1, ..k\}, \forall i \in N$$

$$c'(e^*_{it}) = f(\sum_{m=1}^{k} \alpha_{mi} r_{it-m})$$

As before, beliefs time t are formed by observing the personal realisation of the noisy rate and the efforts of the neighbours in period $t-1$.

$$r_{it} = w_{ii} s_{it} + \sum_{k \in N(i)} w_{ik} f^{-1}(c'(e^*_{kt-1})) = w_{ii} s_{it} + \sum_{k \in N(i)} w_{ik} \big[\sum_{m=1}^{k} \alpha_{mi} r_{it-m} \big]$$

We can stack these equations for r_{it} and r_{it-1} $\forall i$ to get-

$$\begin{bmatrix} R_t \\ R_{t-1} \\ R_{t-2} \\ \vdots \\ Rt-k \end{bmatrix} = \begin{bmatrix} W_1 S_{t-1} \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix} + \begin{bmatrix} W_2 & W_{31} & W_{32} & W_{33} & \dots & \dots & W_{3k} \\ I & 0 & 0 & 0 & \dots & 0 & 0 \\ 0 & I & 0 & 0 & \dots & 0 & 0 \\ \vdots & & \ddots & & & & \\ 0 & 0 & 0 & & \dots & I & 0 \end{bmatrix} \begin{bmatrix} R_{t-1} \\ R_{t-2} \\ R_{t-3} \\ \vdots \\ Rt-k-1 \end{bmatrix}$$

$\implies \mathbf{R}_t = \mathbf{S}_t + \Omega \mathbf{R}_{t-1}$ W_1 and S_{t-1} are as defined as before. The $n \times n$ matrices W_2 and matrix W_{3m} $\forall m \in \{2, 3..k\}$ can be written analogously as follows-

$$W_2 = \begin{bmatrix} 0 & \alpha_{1j} w_{ij} & \alpha_{1k} w_{ik} & \dots \\ \alpha_{1i} w_{ji} & 0 & \alpha_{1k} w_{jk} & \dots \\ \vdots & & \ddots & \\ \alpha_{1i} w_{ni} & \dots & & 0 \end{bmatrix} \quad W_{3m} = \begin{bmatrix} 0 & \alpha_{mj} w_{ij} & \alpha_{mk} w_{ik} & \dots \\ \alpha_{mi} w_{ji} & 0 & \alpha_{mk} w_{jk} & \dots \\ \vdots & & \ddots & \\ \alpha_{mi} w_{ni} & \dots & & 0 \end{bmatrix}$$

As before, I have to show that Ω is irreducible to be able to use the Gershgorin theorem. This directly follows from Lemma 2 under the assumption that G is strongly connected and if $\alpha_{ki} \neq 0$ $\forall i \in N$, $\forall k \geq 1$. Maximal agents can be defined analogously and the interpretation of a maximal agent is the same as before.

Definition 7 *: The maximal agent(s) of a network G in which agents exhibit learning lags up to k periods are defined as the set of agents*

$$i^* = \{i : i = \arg\max_{i \in N} \sum_{j \in N(i), \sum_{m=1}^{k} |\alpha_{mj}| = 1} w_{ij} + \sum_{j \in N(i), \sum_{m=1}^{k} |\alpha_{mj}| > 1} \big[w_{ij} \sum_{m=1}^{k} \mid \alpha_{mj} \mid \big]$$

The theorem can be stated as follows.

Theorem 7 *: Beliefs in any network G with learning lag k converge if*

$$\sum_{j\in N(i^*):\sum_{m=1}^{k}|\alpha_{mj}|>1} w_{i^*j}((\sum_{m=1}^{k} \mid \alpha_{mj} \mid) - 1) \leq w_{i^*i^*}$$

.

Proof- The proof is analogous to the proof for Theorem 1. As before, beliefs converge if individuals living in idiosyncratic neighbourhoods place a high enough weight on their own private signals. The difference is that the average idiosyncrasy in a neighbourhood is computed by summing idiosyncrasies (in excess of 1) across all peers and crucially, across all lags. Substituting $k = 2$ gives the condition in Theorem 1.

Proof of Theorem 2

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Proof- We know from Kemeny and Snell (1960); Golub and Jackson (2010) that convergence is ensured for an irreducible, aperiodic, row-stochastic, non negative adjacency matrix. Ω is a non negative and row stochastic when there exists no frustrated or overreacting agent so $\alpha_{1i} + \alpha_{2i} = 1$ and both α_{1i} and α_{2i} lie in the unit interval. It is irreducible when $\alpha_{2i} \neq 0 \ \forall i \in N$. Further, Ω is aperiodic by construction.

In order to show aperiodicity, we just have to show that there exists at least two cycles of even and odd length in Ω. Pick agent j $\in \{n+1, ..2n\}$. Agent j corresponds to the past self of an agent i' and places a weight of 1 on them. Agent i' in turn must have a friend $i'' \in N$ who must place a weight on j. This is because i" is assumed to be unaware that i is under-reacting and so they will inadvertently weight i's past self. $j \to i' \to i'' \to j$ is a cycle of length 3. Since the underlying network is undirected, we also always have cycles of length 2. Thus, Ω is aperiodic. We have already shown that it is irreducible. Hence Ω can tolerate any amount of under-reaction and consequently beliefs will converge.

9.2 Wisdom

Proof of Theorem 3

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Proof: Consider the belief formation rule-

$$r_{it} = w_{ii}s_{it} + \sum_{k\in N(i)} w_{ik}\left[\alpha_{1k}r_{kt-1} + \alpha_{2k}r_{kt-2}\right]$$

. Taking expectations on both sides, we get-

$$\mathbb{E}[r_{it}] = w_{ii}r + \sum_{k\in N(i)} w_{ik}\left[\alpha_{1k}\mathbb{E}[r_{kt-1}] + \alpha_{2k}\mathbb{E}[r_{kt-2}]\right]$$

Let individual i's beliefs converge in expectation to some value $c_i \in R$.

Substituting, $\mathbb{E}[r_{it}] = \mathbb{E}[r_{it-1}] = c_i$, we get-

$$c_i = w_{ii}r + \sum_{k \in N(i)} w_{ik}\left[\alpha_{1k}c_k + \alpha_{2k}c_k\right]$$

Solving the belief formation equations simultaneously for $c_i \forall i \in N$ and imposing $\alpha_{1i} + \alpha_{2i} = 1$, we get the solution $c_i = r \ \forall \ i \in N$. This is easiest to see when there are only 2 agents. When idiosyncrasies sum to 1, they do not affect the convergent beliefs, and all individuals reach the correct consensus. This completes the proof.

Proof of Theorem 4

Click to go back.

Proof: As per the result in Golub and Jackson (2010), the necessary and sufficient condition for wisdom is that the maximum element of the influence vector v should tend to zero as the network size increases. I compute the elements of v for the matrix Ω where agents have heterogeneous biases and place equal weight on their private signals and the information inferred from their neighbour's choices. The elements of the eigen-vector v for a network of size n can be written as follows-

$$v_i(\Omega_n) = \frac{d_i(\Omega_n) + 1}{\sum_i d_i(\Omega_n)} \text{ if i } \in \{1, ...n\} \text{ and } v_i(\Omega_n) = \frac{\alpha_{2i}(\Omega_n)d_i(\Omega_n)}{\sum_i d_i(\Omega_n)} \text{ if i } \in \{n+1, ...2n\}$$

This can be derived by solving $v\Omega = v$ since v, as discussed in Golub and Jackson (2010), is the left hand eigen vector of Ω. Compared to Golub and Jackson (2010) however, the influence of an individual in this setup is additionally impacted by the presence of their past self.

We can normalize v by dividing each element by the sum of all elements.

$$v_i(\Omega_n) = \frac{d_i(\Omega_n) + 1}{\sum_i d_i(\Omega_n) + 1 + \alpha_{2i}(\Omega_n)d_i(\Omega_n)} \text{ if i } \in \{1, ..n\} \text{ and}$$

$$v_i(\Omega_n) = \frac{\alpha_{2i}(\Omega_n)d_i(\Omega_n)}{\sum_i d_i(\Omega_n) + 1 + \alpha_{2i}(\Omega_n)d_i(\Omega_n)} \text{ if i } \in \{n+1, ...2n\}$$

Recall that Ω is a square matrix of order $2n$ when the size of the underlying network is n. The total influence of agent i in the network n is $v_i(n) + v_{n+i}(n)$. Golub and Jackson (2010) use Chebyshev's inequality to show that networks become wise as their size increases only if the largest entry in the influence vector goes to zero. I use the same approach in this case where there are two graph nodes (the current and past self) for each network agent. In this case, the first n entries of the initial belief vector s are independently distributed

and the last n are element-wise identical to the first n entries. Chebyshev's inequality can be applied to independently distributed variables so we need to rewrite the final beliefs in terms of the first n entries of the initial belief vector s. Final beliefs can be written as $\sum_{i\in\{1,2,..,2n\}} v_i(n)s_i(n) = \sum_{i\in\{1,2,..,n\}}(v_i(n) + v_{n+i}(n))s_i(n)$.

Let σ^2 be the maximum variance among the variances of s_i, $i \in N$.

We know from Chebyshev's inequality that for any strictly positive ϵ,

$$\mathbb{P}(|\sum_{i=1}^{n}\Big(v_i(n) + v_{n+i}(n)\Big)s_i(n) - r\ |> \epsilon) \leq \frac{var(\sum_{i=1}^{n}(v_i(n) + v_{n+i}(n))s_i(n))}{\epsilon^2}$$
$$\leq_{(1)} \frac{\big[v_i(n) + v_{n+i}(n)\big]_{max}\sigma^2}{\epsilon^2} \to 0$$

Inequality (1) also follows from Golub and Jackson (2010). The condition is also necessary for wisdom and the proof for this is discussed in Golub and Jackson (2010).

9.3 Speed

Proof of Lemma 3

Click to go back.

Proof for the 2 regular case First, consider a circle. The n agents in this circle can be organized in a sequence such that the i'th agent is connected to the $i-1$'th agent and $i+1$'th agent $\forall i \in N$. The rows and columns of Ω are arranged in the same order. Then, I partition the $2n$ current and past selves in this sequence into two sets M and M' defined as follows-

$$M = \{1, ..\frac{n}{2}\} \cup \{n+1, ..\frac{3n}{2}\}$$
$$M' = \{\frac{n}{2}+1, ..n\} \cup \{\frac{3n}{2}+1, ..2n\}$$

The lemma implies that an upper bound $\bar{c}$ for the Cheeger constant for a 2-regular network with under-reacting individuals and transition matrix Ω, obtained after partitioning the network into groups M and M' is as follows

$$\bar{c} = \frac{4}{n(3+2\alpha_2)}$$

Groups M and M' will have equal total influence since they contain the same number of agents of each type. In order to compute the upper bound, we need to find the number and type of links between the two groups. For simplicity, agents $k \in \{1, ...\frac{n}{2}\}$ will be referred to Current Selves Group (CSG) 1, agents $k' \in \{n+1...\frac{3n}{2}\}$ will be referred to as Past Selves Group (PSG) 1. Analogously, agents $k \in \{\frac{n}{2}+1, ...n\}$ will be referred to as CSG 2 and agents $k' \in \{\frac{3n}{2}+1, ...2n\}$ will be referred to as PSG 2.

The number of links between these different types of agents from one group to the other $\forall$ network sizes n are listed below-

1. Exactly two links between CSG 1 and CSG 2 (one at each border)
2. Exactly two links between CSG 1 and PSG 2 (one at each border)
3. 0 links between PSG 1 and CSG 2 and 0 links between PSG 1 and PSG 2.

The upper bound can then be derived by making the appropriate substitutions in the definition stated above. I will show that M and M' are better than some other potential partitions in order to establish how good the derived upper bound is. I discuss this below.

Why choose groups M and M'?

Consider the current selves of the agents i.e. CSG 1 and 2. I claim that any partition of agents which aims to minimize the number of inter-partition links should always have adjacent agents in the same partition if possible. The past selves (PSG 1 and PSG 2) are not linked to each other so this does not apply to them. If neighbouring current selves of the agents are not in the same partition, the inter-partition weight they place on each other will necessarily increase the value of the Cheeger candidate regardless of which group determines the Cheeger i.e. has an influence of at most half. This is because the links between CSG1 and 2 are links in the actual network and are undirected by assumption. So, replacing a non-adjacent current self in a partition with an adjacent one will reduce inter-partition links. The partitions with the lowest value of the Cheeger candidate will be such that the current selves who are linked to each other are kept in the same partition. This will always be true except at the border of the partition, so the inter-group links are 2.

Now, if the adjacent current selves belong to the same partition (except at the border), then I claim that their past selves should also belong in the corresponding partition as the unique current self they are linked to. Recall that the bottom left sub matrix of Ω is an identity matrix. This means that the past selves only weight a unique current self. Keeping them in a different partition will increase inter-partition links. Further, the current selves i and j adjacent to the current self k have directed links to the past self $n + k$. Since i, j, and k are prioritized to be in the same partition, then, adding $n + k$ to the other partition will create these extra inter-partition links. Thus, for any agent $i \in \{1, ..n\}$, if $i \in M$ then, $n + i \in M$ as well.

Finally, I claim that the number of current and past selves in each partition has to be the same. If adjacent agents are prioritised to be in the same partition, the inter-partition links between the current selves in both partitions is fixed regardless of the size of the partition. This is because the number of inter-partition links is only affected by the links of the agents around the border which does not change if the size of the partition is varied. Adding current selves into a partition will not change the inter-partition links but it will increase the total influence, lowering the Cheeger candidate. This influence can be

increased (and the Cheeger candidate values can be reduced) until the total influence of the group is equal to $\frac{1}{2}$. After this, the partition with less number of current selves will determine the Cheeger. Thus, the upper bound is obtained when the number of current and past selves in both the group is the same.

Competing Bounds

I show how the suggested partition for circles is better than some other partitions whose Cheeger candidates can be analytically computed. For example, if we choose M as the set containing the n current selves and M' as the set containing the n past selves and then remove k agents from M and add to M', then the Cheeger candidates for M and M' for different values of k can be written as follows-

$$c_{M(k)} = \frac{2(1-\alpha_2)}{3(n-k)} + \frac{2\alpha_2}{3}$$

$$c_{M'(k)} = \frac{2(1-\alpha_2) + 2(n-k)\alpha_2}{3k + 2n\alpha_2}$$

Agents are moved from M to M' in a way such that the number of inter-partition bounds between the current selves is always 2. The Cheeger upper bounds for all $k \in \{1, 2.., n\}$ are higher than the bound suggested above (see figure 1.13 below). The case where k agents are excluded from M' and added to M also doesn't provide better bounds.

Consider a deviation from M and M' where we exchange agents instead of moving them unilaterally. Consider the case where we move a current self at the border of M to M' and the past self they're connected to in M' to M. The Cheeger candidate is now going to be determined by M since M' has an influence greater than $\frac{1}{2}$. The number of links between CSG-1 and CSG-2 remain unchanged. The number of links between CSG-1 and PSG-2 decrease by 1 if the current self in M who placed a weight on this past self in M' is the one who has moved to M'. The number of links between PSG-1 and CSG-2 has increased from 0 to 1 since the new past self is connected to it's unique current self in M'. This means that the denominator of the Cheeger candidate has reduced (because the influence of M has reduced) and the numerator of the Cheeger candidate has increased (because the weight that the new past self in M places on their unique current self in M' is 1 and larger than the weight the current self, relocated from M to M' used to place on this past self, after taking their respective influences into account). Such a deviation isn't going to lower the upper bound suggesting that the original partition was better. This result doesn't change even if for instance k current selves from M are traded for k' past selves in M'. The influence of the suggested partition (the denominator of the upper bound) will necessarily be lower than $\frac{1}{2}$ and the inter-group weights will necessarily be higher.

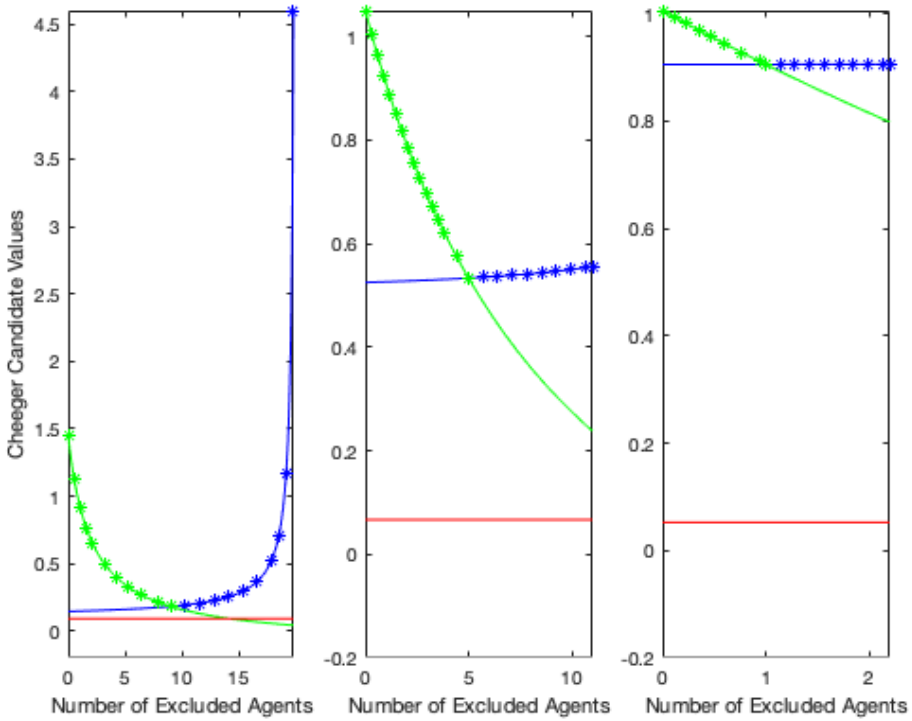


Figure 1.13: The graphs plot the alternative upper bounds for the Cheeger constant (starred*) for $\alpha_2 = 0.05, 0.45, 0.95$ respectively as current selves are excluded from the group containing all the current selves and added to the group containing all the past selves. The starred lines represent the potential candidates for the Cheeger values while ensuring that total group influence is at most half. The point at which the graphs intersect is the best upper bound among the alternatives. It is easy to show that the total influence of the two groups is equal at this point. Note that (a) the upper bounds computed from M (blue) and M' (green) are always higher than the chosen candidate shown in red and (b) the chosen candidate falls as α_2 rises- it takes values ≈ 0.1, 0.07, 0.05 respectively indicating that bottlenecks are likely to rise as under-reaction increases.

These arguments imply that a better upper bound for the Cheeger constant is obtained when agents are partitioned intro M and M' so that (a) current selves which are linked to each other are kept in the same partition, except at the border (b) past selves are kept in the same partition as the unique current self they are linked to and (c) the number of current and past selves in each partition are the same.

Proof for the general case

The proof for why the candidate evaluated from the suggested partition is a good upper bound for the Cheeger constant is an extension of the argument made for the 2-regular case.[29]

[29] A crucial difference between the arguments is that, for $d \geq 4$, the number of inter-group links between the current selves doesn't stay constant as the number of current selves in each group is varied. The computed candidate is still an upper bound for the Cheeger constant.

The Cheeger candidate for the suggested split can be derived by observing that the number of links between CSG 1 and CSG 2 and the number of links between CSG 1 and PSG 2 will be the same and that as before, the past agents are located in the same group as the unique current agent they place weight 1 on. This makes sure that the numerator does not depend on α_2 as the two terms cancel (i.e $\frac{\alpha_2}{d+1}$ and $\frac{1-\alpha_2}{d+1}$ cancel). While the number of inter-partition links was equal to 4 in the 2-regular case (2 between CSG-1 and CSG-2, and 2 between CSG-1 and PSG-2, giving a total inter-partition weight of $2(\frac{1-\alpha_2}{d+1}) + 2\frac{\alpha_2}{d+1} = \frac{2}{d+1}$), the number of inter-partition links for a generic d regular lattice is given by $k(d)$.

$k(d) = [\frac{(d)^2}{2} - \frac{(d-2)(d)}{4}]$ is the total number of cross-partition links between the current(past) selves in M and the current(past) selves in M'. $k(d)$ can be derived by noticing that for any even $d \geq 2$, the number of cross-partition links must be equal to $2 * \left[(\frac{d}{2})^2 - (\text{Sum of the first } \frac{d-2}{2} \text{natural numbers.})\right]$ For example, a 4 regular graph has 6 inter partition links while a 6 regular graph has 12 links and so on. The expression for the Cheeger upper bound can be derived by substituting the values relevant to this suggested partition in the definition.

This computation assumes that n is even, d is even, and that n is large enough i.e. it is greater than $2d$. If degree d is not even, then we can assume that the extra odd links of the agents at the border are in the same partition as the agent. If the extra link lies in the same partition, then the computation does not change. If not, then the bound derived above will still be the better upper bound for the Cheeger constant as it will overestimate how bottlenecked the network is. This will also not affect the dependence of the Cheeger constant on under-reaction since α_2 and $1 - \alpha_2$ will still get cancelled in the numerator for this extra link. This is because the past self of each agent is in the same partition as their current self so an extra odd link to an agent in the other partition also includes a link to their past self.

The lower bound on n is to ensure that $k(d)$ is correctly estimated. For example, if the network is 4 regular, then there need to be at least 4 nodes on each side of the partition so that $k(d) = (3 + 2 + 1)2$. In general, there need to be at least d nodes in each partition so $2d$ nodes in total. The $\frac{d}{2}$'th node from each of the two ends of the partition should both be distinct and have 1 link to the other partition. Any nodes lying between these two nodes will have 0 links to the other partition. This is only possible if each partition contains at least d nodes.

Complete Network

Substituting $d = n - 1$ in the previous case violates the condition on the size of n for any $n > 2$. The Cheeger bound for a complete network can be written as $\bar{c} = \frac{n}{2(n+(n-1)\alpha_2)}$. This is computed by partitioning the network as before i.e. into two groups with equal number of current and past selves and each past self belonging to the group containing its unique current self.

Chapter 2

Misperceptions about Interpersonal Dialogue in Social Networks [1] [2]

Ronak Jain [3] and Vatsal Khandelwal [4]

Misperceptions about peers can prevent individuals from seeking advice regarding personal decisions. We apply a theoretical model to illustrate how such misperceptions can arise within social networks and how they can push society towards an inferior equilibrium of low engagement with mental health. Then, we use existing data on networks from Indian villages to provide reduced-form evidence on the existence of strategic complementarities in disengagement. We structurally estimate the model using this dataset and find that majority of the villages have three equilibria of disengagement: a stable equilibrium of zero disengagement, a low non-zero unstable equilibrium, and a high stable equilibrium. We run policy counterfactuals to show that the success of belief-shifting interventions that aim to increase advice-taking by reducing misperceptions depends on the characteristics of the social network. Finally, we conduct a randomised control trial among low-income individuals affiliated with an NGO in New Delhi, India. We find that shifting individual beliefs about their community's willingness to engage in dialogue increases community engagement in terms of a higher willingness to participate in potential savings groups, to volunteer for a community mental health listening service, and higher financial contributions towards a public good. We also find positive spillover effects on willingness to have physical health-related dialogue and measure the treatment effect on longer-term outcomes collected during the peak of the COVID-19 crisis.

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[2] A few data anomalies were identified after examination. An updated version of the paper will be made available on the author's website. If not, please contact the authors for the latest version.

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1 Introduction

Lack of interpersonal dialogue and advice-seeking can exacerbate mental health problems such as stress and depression. This problem is especially a concern in developing country contexts due to the cyclical relationship between poverty and mental health (Ridley et al., 2019), high levels of stigma (Lauber and Rössler, 2007), and social norms that can cause isolation (Andrew et al., 2020). Poverty-induced shame may also induce individuals to isolate themselves and this can negatively affect their social capital (Walker and Bantebya-Kyomuhendo, 2014). In this paper, we study how an individual's misperceptions about their peers' willingness to have a dialogue about mental well-being can affect their decision to do so. For example, we find that roughly 54% of our baseline sample of low-income individuals in New Delhi, India report that they have 'rarely' or 'never' had a conversation about mental health-related concerns with their peers in the last two weeks. 64% of individuals reveal a willingness to do so and 68% underestimate the willingness of their community. Motivated by this, we first apply the models by Jackson and Yariv (2007); Jackson (2019) to show how misperceptions can naturally arise in social networks and push societies to sub-optimal levels of inter-personal dialogue. Then, we provide reduced form and structural estimates in support of the model using data from 75 villages in rural India collected by Banerjee et al. (2013). We run counterfactuals that show that credible belief-shifting interventions may not always succeed in increasing inter-personal dialogue and can have heterogeneous short-run and long-run impacts depending on the degree distribution of the networks. Finally, we present the results of a randomised controlled trial conducted with low-income individuals in New Delhi, India where we test if shifting beliefs about the community's willingness to engage can strengthen social ties by increasing engagement and dialogue around mental, physical, and financial health.

Our theoretical framework applies the models on network diffusion developed by Jackson and Yariv (2007) and the friendship paradox by Feld (1991); Jackson (2019) to study dialogue around mental health. Individuals in the model 'engage' if they choose to take an action that is visibly pro-mental well-being or mental health.[5] We apply the model to explain why individuals embedded in a social network, may, on average, underestimate engagement and choose not to have a dialogue about personal problems if they form incorrect expectations about the behaviour of the network by observing the level of dialogue among their peers. Given that there is considerable stigma attached to this in various societies, we assume that there are positive complementarities between decisions to disengage. These can take the form of various social benefits that an individual can obtain, for example, by signalling that they are of high ability (Chandrasekhar et al., 2018). An individual who believes that their peers will not engage can potentially disengage if they want to portray a certain social image, as Bursztyn and Jensen (2017) show in various other contexts. They may also fear discrimination in the labour market

[5]We borrow the term "engagement" from Jackson (2019) who describe the formation of misperceptions about behaviours that involve positive peer-effects.

(Sharac et al., 2010; Ridley et al., 2019). Hence, they may signal that they do not need support and are not eager to entertain a conversation about their personal problems. The model shows that societies can be stuck at an inferior symmetric Bayes Nash equilibrium of low engagement (i.e. high 'disengagement') and can benefit from a welfare-enhancing intervention if the personal benefits of engagement are high and individuals overestimate the social costs of engaging. Crucially, the level of engagement in equilibrium can affect the advice networks we observe in the real world. We use data on multiple networks in 75 Indian villages from Banerjee et al. (2013), including networks used for taking advice regarding personal decisions, to construct two network-based proxies for lack of engagement. These proxies are computed by comparing an individual's overall and advice-taking interactions. Then, we use the method proposed by Bramoullé et al. (2009); De Giorgi et al. (2010) to estimate a linear-in-means peer effects model and find evidence of positive strategic complementarities in disengagement.[6]

Next, we structurally estimate the strength of strategic complementarities in disengagement allowing for complete flexibility by identifying the parameters at the village level. The results from structural estimation demonstrate that there is network-level heterogeneity in the number, type, and magnitude of equilibrium disengagement. The majority of the villages have three equilibrium values of disengagement- a stable equilibrium at zero, and two strictly positive unstable and stable equilibria respectively. We subsequently run a policy-relevant counterfactual of a belief-shifting intervention intended to encourage advice-taking and find that the villages differ in the speed with which they either converge to a new equilibrium (i.e. positive short and long-run effects) or return to the old equilibrium (i.e. positive short-run effects and no long-run effects) emphasising the importance of timing in the detection of treatment effects. We also find that correcting individual beliefs by giving true information may not have any long-run effects in cases where the intervention is not sufficient to shift beliefs beyond the tipping point. We thereby demonstrate a link between social networks, advice-taking, and the potential short-run and long-run effects of credible belief-shifting interventions.

Finally, we present the results of an experiment with low-income individuals working with an NGO in New Delhi, India, conducted from mid-November 2020 to May 2021. We conducted a baseline survey with $\sim$ 360 individuals and measured individual demographic outcomes, first order beliefs about community members, attitudes, well-being, advice networks, and overall networks. We also measured beliefs and attitudes around mental, physical, and financial health. We find that (a) our sample exhibits high levels of disengagement with mental health inferred both via the degree-gaps between overall and advice networks and self-reported dialogue intensity, (b)

[6]We also document significant correlations between the beliefs about community's willingness to engage and self reported frequency of dialogue around mental health among the participants in the RCT. Further, individuals who severely underestimate community engagement have larger differences in the number of links in their overall and advice networks.

$\sim$ 68% of our sample for which we measure beliefs underestimates willingness to engage in a dialogue around mental health (with a similarly high level of underestimators for physical and financial health) and (c) individual disengagement (inferred using the network) is negatively correlated with both the intensity of dialogue around mental health and are higher for those who severely underestimate community-level engagement. These results, together with our theoretical framework, motivate a belief-correction intervention to increase dialogue and raise take-up for useful resources and training. We also measured the impact of the intervention on workplace safety practices, inclination to participate in savings groups, and cognitive load. Due to the inherent difficulty in contacting this sample and the additional impact of the COVID-19 crisis, we were only able to conduct the experiment with $\sim$180 individuals of our baseline sample.[7]

As a part of the experiment, we provided the treatment group with accurate information about the sample's willingness to engage in a dialogue about mental and financial health to individuals and then measured immediate outcomes. We find that the intervention significantly increases an individual's willingness to sign up for a potential savings group with their community members. Provision of information solely about willingness to converse about mental health-related increases an individual's willingness to sign up to train to become a listening volunteer in a potential listening service where they could be asked to hear the concerns of the members in their community. We also find that individuals in the treated group are likely to make a 28% higher financial contribution towards the public good of financing the training for this. Interestingly, conditional on agreeing to contribute, we find that individuals who were prejudiced against mental health in the baseline were significantly more likely to contribute when treated. Individuals in the treatment group are also more likely to report eagerness to visit a doctor for mental health-related concerns and to discuss physical health-related concerns with friends and family. We also document negative effects on an individual's willingness to listen to helpline numbers suggesting that seeking help from outside and within the community may be substitutes. We do not find any impacts on stigma-related outcomes, cognitive load, or self-efficacy. The high treatment effect on the demand for savings groups and negligible effect on financial self-efficacy, together, also provide suggestive evidence indicating that informal channels of borrowing may be currently weak or non-existent, there is sufficient demand for this, and beliefs may be a binding constraint.

We also conducted a follow-up survey more than 2 weeks after the individuals received the treatment. Our follow-up survey was conducted during the peak of the COVID-19 crisis in India as a result of which we could contact fewer individuals and had to work with a very small sub-sample of 113 individuals. We find a higher self-reported dialogue about mental and financial health and high levels of altruism among the treatment group as indicated by monetary donations made to community members in a hypothetical dictator

[7]Individuals in these communities are difficult to track due to changing phone numbers, old phone-number records, and network issues. We address the impacts on covariate balance between treatment and control groups in the analysis.

game. We also document lower well being in terms of self-reported happiness, stress, and life satisfaction among the treated participants. We discuss and rationalise our follow-up results both in terms of possible mechanisms and the potential effect of COVID-19 on the design of the study.

The rest of the paper proceeds as follows. In Section 2, we discuss how our paper contributes to existing literature. In section 3, we discuss the theoretical model, predictions on the speed of convergence, and results on welfare. In Section 4, we describe the sample, empirical specification, and reduced form results using secondary data. Structural estimation strategy and results are discussed in Section 5. We present the design and results of the RCT in Sections 6 and 7. Section 8 concludes.

2 Contribution

Individuals often overestimate the prevalence of certain behaviors such as alcohol or drug consumption as they form inferences based on a biased sample (Perkins et al., 1999, 2005; Jackson, 2019). This can be due to the friendship paradox (Feld, 1991) i.e. an individual's peers, on average, are more connected than they are. As Jackson (2019) shows, this may cause individuals to overestimate behaviour that involves complementarities. They may also misperceive social norms due to a lack of conversation about certain issues as in Bursztyn et al. (2018).[8] These misperceptions can sustain sub-optimal social norms and stifle productive and/or useful behavior, especially when individuals are concerned about their social image. This includes norms that, for example, prevent female participation in the labor force (Bursztyn et al., 2018), lead to the persistence of female genital mutation (Novak, 2020), or over-consumption of alcohol among students (Perkins et al., 2005). This creates scope for information interventions that correct individual misperceptions and consequently alter their behavior. Haaland et al. (2020) provide a review of the literature on belief-shifting experiments and suggest ways to conduct these experiments effectively.

We complement this literature on misperceptions, social norms, and belief correction by (a) applying existing models by Jackson and Yariv (2007); Jackson (2019) to provide a theoretical motivation for how misperceptions about the community can lead to low levels of engagement, (b) providing reduced-form evidence to support the theoretical predictions, (c) demonstrating via structural estimation how network-level heterogeneity can affect the success of misperception-correcting interventions, and (d) implementing an experiment to test this in the context of dialogue around mental health. Our structural estimation results on village level heterogeneity are most similar to those found by Novak (2020) in the context of female genital mutilation. Individuals in our setup have heterogeneous thresholds much like the households modelled in Novak (2020) except that these differences

[8] Bursztyn and Jensen (2017) review the growing literature on how social image concerns can affect decisions about education, voting, and consumption. They also discuss how an individual's concerns regarding their social image can be affected by their potentially incorrect beliefs about what is socially acceptable.

arise in our model due to differential costs and network positions. Unlike Novak (2020), we study norms around advice-taking at the level of the individual by explicitly taking account of the peer networks. The experimental part of our paper is most similar to Bursztyn et al. (2018) who also shift beliefs in a setting where individuals do not converse about an issue.

Existing research finds a bi-directional association between poverty and mental health (Kuruvilla et al., 2007; Ridley et al., 2019) and a strong link between poverty and cognitive load (Mani et al., 2013; Dean et al., 2017). Our experimental work aims to increase dialogue around mental health among the community to potentially tackle some of these issues. The role played by the community in improving mental health has also been considered by psychologists who, for example, aim to improve community well-being by appointing listeners from the community itself (Cavanaugh, 2017; Shidhaye et al., 2017). Chibanda et al. (2015) find a positive impact of "friendship bench" sessions with lay-health workers on the mental health outcomes of individuals in Zimbabwe. We elicit and shift the demand for such community-led activities. We find that our intervention increases demand for potential community-led listening groups where individuals choose to sign up to act as listening volunteers for the concerns of their community members and agree to be trained for the same. We also find that individuals in the treatment group are willing to contribute more towards the training for this. Unlike other studies which gauge the impact of community-led programs on mental health outcomes, we check if shifting beliefs increases the demand for such programs in the first place.

Finally, while social networks and their applications to development are being increasingly studied across many contexts, there is little existing literature that studies how it can affect one's decision to engage in a dialogue and seek advice.[9] An exception to this is Chandrasekhar et al. (2018), who study advice-taking decisions of individuals in villages in India and find that they can be ashamed to seek advice and worry how this decision might generate signals about their ability. We differ from this paper in two ways. First, we focus on an individual's decision to seek advice regarding personal decisions and primarily dialogue around mental health. Second, we adopt a structural approach to study how equilibrium engagement is determined and an experimental approach to test if correcting misperceptions is useful. The data does not allow us to disentangle between the various mechanisms discussed in Chandrasekhar et al. (2018), all of which could be plausible reasons why an individual does not choose to take advice and manifest as strategic complementarities to disengage. Instead, we focus on estimating these complementarities and use our structural model to predict the impact of hypothetical interventions under their presence.

[9]See Breza et al. (2019) for a review on exiting work on the applications of networks to development economics.

3 Theory

The setup, lemmas, and propositions discussed here follow from the results of Jackson and Yariv (2007) and Jackson (2019) whose models have been applied to our setting to study engagement with mental health. Let N be the set of all individuals in a society represented by the matrix G where $g_{ij} = 1$ if a link exists between i and j and 0 otherwise. Individuals in society choose whether they wish to 'engage' which is modelled as a discrete action $e_i \in \{0, 1\}$. Engagement can have personal benefits b_i drawn from an atomless distribution function H.

Engagement, in this model, can be interpreted as an individual's choice to take a visible, discrete action that is pro-mental well-being or mental health. This can include, for example, the choice to train and participate as a listening volunteer to hear the concerns of other community members or the choice to participate in a mental health related information session. We do not model the signalling mechanism that can affect these decisions. [10] The decision to engage can be interpreted as the release of a signal that can, as we discuss, negatively affect an individual's prospects. Critically, the link-by-link discrete choice to take advice or give advice to a specific peer is not interpreted as engagement —it must be a decision taken at the level of the peer-neighbourhood and is assumed to be observed by all an individual's peers.[11]

The individual also faces a cost of engagement $c(d_i, 1 - E[e_{j:j\in N}])$ proportional to the expected disengagement in society i.e. $1 - E[e_{j:j\in N}]$ and their network degree i.e. $d_i = \sum g_{ij}$. We assume that c is weakly increasing in both its arguments.

The dependence of costs of engagement on expected disengagement can be justified as follows. Consider social image concerns, for example, due to which an individual is concerned about being perceived as a certain type if they choose to engage. Bursztyn and Jensen (2017) extend the standard framework of Bénabou and Tirole (2006) and discuss how social image concerns can affect the choice of a discrete action depending on (a) what the action conveys about the individual's type and (b) the "social desirability" of being perceived as that type. In our case, an individual will be more concerned about engaging if the majority of the network is not doing so. While we do not model the cost function to illustrate these mechanisms, it can be argued that violating the norm increases their concerns of being perceived as a socially undesirable type. Further, in our experimental data in New Delhi, we observe the relationship between an individual's beliefs about their community's opinions and their own choice to engage. We find correlations between an individual's beliefs about the community's willingness to engage

[10] Chandrasekhar et al. (2018), for example, find that empirical evidence that signalling concerns can affect advice-taking.

[11] However, we develop a continuous network-based proxy for engagement in the reduced form estimation. The proxy assumes that an individual who chooses to take advice from most of their peers (whom they interact with otherwise) engages more. Taking advice from many peers can be assumed to generate a similar discrete signal of being pro mental-health. We discuss the definition and assumptions underlying this measure in Section 4.

with mental health-related conversations and their self-reported frequency of dialogue around these issues.

The assumption that costs are rising in network degrees is a simplifying assumption. It proxies for the case where an individual i interacts with each of their d_i neighbours in every time period and faces a cost of engaging in each of these interactions. These can include from costs borne due to social stigma (Lauber and Rössler, 2007), social image concerns (Bursztyn and Jensen, 2017), fewer potential work opportunities (Sharac et al., 2010), shame (Chandrasekhar et al., 2018) and are assumed to be incurred for each interaction that the individual has with each of their friends. Consider the simple case where costs are linear and multiplicative in its arguments so $c(d_i, 1-E[e_{j:j\in N}]) = d_i(1-E[e_{j:j\in N}])$.[12] This implies that an individual who engages in a society with positive expected disengagement (i.e. $1 - E[e_{j:j\in N}] > 0$) faces a cost proportional to the number of people they interact with (their degree) and the extent to which they violate the expected behaviour. This cost is at its maximum if they choose to engage in a society where everyone else is disengaging i.e. when $E[e_{j:j\in N}] = 0$.

It can be argued that the costs of engagement can be proportional to other measures of centrality that can affect the spread of information about the individual. For example, an individual with a high diffusion centrality (Banerjee et al., 2013) may face high costs of engagement because, in any given time-frame, news about their decision might be heard more number of times in the network. We do not consider such cases for simplicity. This simplifying assumption is also in line with existing literature on "semi-anonymous" games in which utility depends on the number of neighbours who take an action (Jackson, 2010).

Given these assumptions, agent i's utility can be written as follows:

$$U(e_i, d_i; e_{j:j\in N_i}) = [b_i - c(d_i, 1 - E[e_{j:j\in N}])]e_i \tag{2.1}$$

An agent i should engage if $c(d_i, 1 - E[e_{j:j\in N}]) < b_i$ i.e. the probability that an agent i engages should be equal to $1 - H(c(d_i, 1 - E[e_{j:j\in N}]))$. Assume that degrees d_i are distributed as per the probability mass function $P(d)$ and that agents know their degree d_i, benefits of engagement b_i, $H(b)$, and $P(d)$.

Analogous to Jackson and Yariv (2007) where agent types are determined by their costs and degrees, agent types here are determined by their benefits and degrees. We can solve for a symmetric Bayesian Nash equilibrium so that the proportion of agents choosing to engage in every neighbourhood is the same i.e. $E[e_{j:j\in N}] = \hat{e}\ \forall i$.[13] Hence, in equilibrium,

$$\hat{e} = \sum_d P(d)(1 - H(c(d, 1 - \hat{e}))) \tag{2.2}$$

[12] This is the same as the example of the benefit function $u(d, x) = u(dx)$ discussed in Jackson and Yariv (2007).

[13] This is a simplification which means that the network only affects the equilibrium outcome via its degree distribution.

Now, as in Jackson (2019), we assume that agents naively use the expected proportion of their friends in their network neighbourhood $N(i)$ who do not engage i.e. $1 - E[e_{j:j\in N(i)}]$ to proxy for the society-wide average $1 - E[e_{j:j\in N}]$. The distribution of the degree of their neighbours is equal to $\widetilde{P}(d) = \frac{d}{E[d]}P(d)$ as per the friendship paradox Feld (1991); Jackson (2019). Then, in the symmetric equilibrium

$$\widetilde{e} = \sum_d \widetilde{P}(d)(1 - H(c(d, 1 - \widetilde{e}))) \tag{2.3}$$

Where $\tilde{e}$ denotes the equilibrium engagement when individuals use $\widetilde{P}(d)$ instead of $P(d)$. To avoid having to write the difference terms (i.e. terms that subtract the probabilities and expected actions from 1), and for ease of interpretation of the interaction effects, we rewrite the equilibrium as follows.

$$\widetilde{e} = \sum_d \widetilde{P}(d)(1 - H(c(d, 1 - \widetilde{e}))) = 1 - \sum_d \widetilde{P}(d)(H(c(d, 1 - \widetilde{e})))$$

Let us denote the probability that a randomly chosen peer disengages by a. Clearly $a+\tilde{e} = 1$. Then, the above equation implies that

$$\widetilde{e} = 1 - \sum_d \widetilde{P}(d)(H(c(d, 1 - \widetilde{e}))) = 1 - a \implies a = \sum_d \widetilde{P}(d)(H(c(d, a)))$$

Note that this is the exact equilibrium configuration that would result from a model where an individual chooses to disengage, her benefits are proportional to the expected disengagement in the network, and her costs are heterogeneously drawn from a distribution H.

We know from Jackson (2019) that $\widetilde{P}(d)$ first order stochastically dominates $P(d)$. Further, the costs of engagement (or equivalently, the benefits from disengagement) are weakly rising in the agent's degree. This implies that the probability that a randomly chosen peer disengages is always higher than the probability that a randomly chosen person from the network does. This is because individuals overestimate the costs of engagement when they proxy disengagement using their peers. The following Lemma highlights this result.

Lemma 1 $E[H(c(d, a)] \leq \widetilde{E}[H(c(d, a)] \ \forall a \in [0, 1]$

The proof for Lemma 1 is provided in the appendix in Section A. What would happen if individuals observed the society-wide average and used it to make their choice? How does this compare with the case where individuals get utility as per equation (2.1) but play as per equation (2.3)? This problem (referred to as individuals playing the "naive game") is considered in Jackson (2019).

The following proposition states the case where there exist three equilibria of disengagement out of which one is unstable. We discuss this case since it is only meaningful to implement a belief shifting intervention under this equilibrium configuration. We will check if this equilibrium configuration exists in the villages in Banerjee et al. (2013) when we proceed with structural estimation.

Proposition 1 *Let $E[a_{j:j\in N}]$ be the society-wide expected disengagement and a_h and a_l be the non-zero symmetric Bayes Nash equilibrium disengagement that solve equation 2.2 such that $a_h > a_l$. Let $E[a_{j:j\in N(i)}]$ be the expected disengagement among the agent's friends and let $\widetilde{a}_l$ and $\widetilde{a}_h$ be the symmetric Bayes Nash equilibria that solve equation 2.3 such that $\widetilde{a}_l < \widetilde{a}_h$. Then,*

1. *$\widetilde{a}_l < a_l$ and $\widetilde{a}_h > a_h$ if H is strictly increasing in degree d.*
2. *$\widetilde{a}_l \leq a_l$ and $\widetilde{a}_h \geq a_h$ if H is weakly increasing in degree d.*

This directly follows from Lemma 1 and the assumption that there exist three equilibria out of which one is unstable. The proof is provided in Section A in the Appendix. Figure 2.1 illustrates this result.

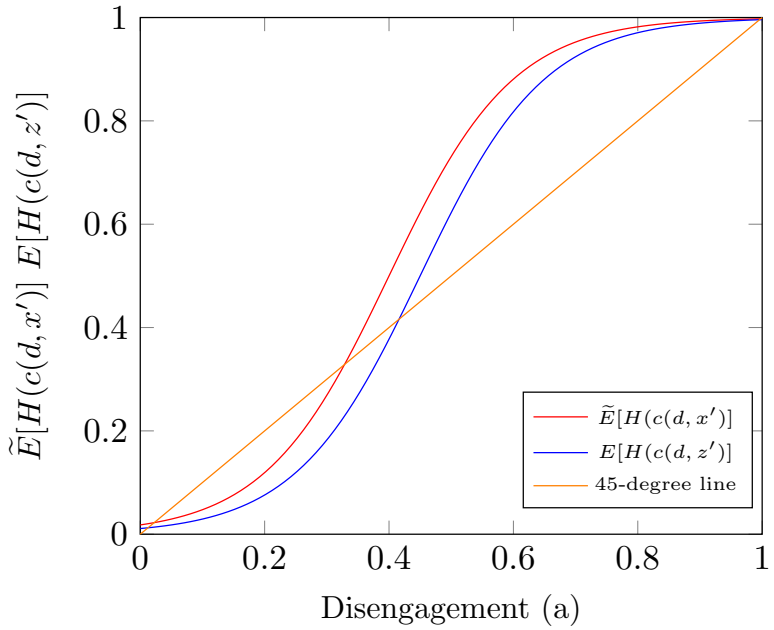


Figure 2.1: Illustrating Proposition 1 for H weakly increasing in degree d

This implies that in a society where there are three possible equilibrium values of disengagement out of which two are non zero, one stable, and one unstable, the highest stable equilibrium disengagement is even higher when individuals observe the actions of their peers and not the entire society.The lower unstable equilibrium is even lower implying that a larger shift in beliefs is required to cross the tipping point and reach the zero equilibrium disengagement. Provision of society-level beliefs will be useful in the case where individuals overestimate the costs of engagement and are stuck at the high

stable equilibrium disengagement. This will be true if they receive utility as per Equation 2.1 but proxy the society level expectation $\hat{e}$ with that among their peers $\tilde{e}$, as in Jackson (2019). The presence of substantial underestimation of the community's willingness to engage with mental health-related dialogue in our experimental sample suggests that this is indeed the case.

3.1 Speed of Convergence

We know from existing literature on diffusion that the speed with which beliefs converge to one of the two stable equilibria is a function of the distance between $E[H(c(d,a')]$ and the 45 degree line $\forall a' \in [0,1]$. When $0 < a_l < a' < a_h$, then speed of convergence S is a function f which is rising in its argument and can be written as follows-

$$\begin{aligned} S &= f(\int_0^{a_l} a' - \widetilde{E}[H(c(d,a')])\ da' \text{ if } 0 < a' < a_l \\ &= f(\int_{a_l}^{a_h} \widetilde{E}[H(c(d,a')] - a')\ da' \text{ if } a_l < a' < a_h. \end{aligned} \tag{2.4}$$

The following proposition compares the speed of convergence for the two cases considered above- (a) where the individual observes the society level disengagement and (b) where the individual guesses it using their friends' actions.

Proposition 2 *Convergence to a_h ($a = 0$) is faster (slower) when individuals guess the society average of disengagement using their friends' actions.*

This is clear from the definition of the speed of convergence. An increase in $\widetilde{E}[H(c(d,a')]$ increases the speed of convergence $\forall\ a_l < a' < a_h$ and reduces the speed of convergence $\forall\ 0 < a' < a_l$. The proposition implies that beliefs will converge to a_h faster when individuals guess the society average using their friends' actions. This is because friends with a higher degree are more likely to choose a higher action and there is a higher chance that an agent has a friend with a high degree under $\widetilde{P}$. This means that networks will converge quickly to the high disengagement equilibrium when individuals incorrectly proxy the societal disengagement using their friendship networks. Vice versa, networks will converge slowly to the zero disengagement equilibrium when individuals proxy societal disengagement using their friendship network.

Now we discuss the potential welfare impacts of an intervention that shifts individual beliefs by providing accurate information about expected engagement in the network.

3.2 Welfare

We only consider the configuration with 3 equilibria as before.

How would social welfare change if one considers an intervention that shifts beliefs to below the unstable non-zero equilibrium such that society converges to zero disengagement?

Recall that individuals overestimate the costs of engagement since they naively use their friend's average disengagement instead of the society-level average while choosing whether to engage. However, they still receive utility in accordance with the expected disengagement at the society level (since they are playing the "society game" as in Jackson (2019)). An intervention that shifts beliefs such that individuals converge to zero equilibrium disengagement should affect individuals differently depending on their benefit from engagement (b_i), ex-post costs of engagement in the actual game, $c(d_i, E[a_{j:j\in N}])$ and the ex-ante expected costs $c_i^{FP} = c(d_i, E[a_{j:j\in N(i)}])$. Note that $c_i^{FP} > c_i$ because of the friendship paradox, for any given vector of engagement $\hat{e}$.

Consider the following types of individuals: (a) Individuals for whom $c_i < c_i^{FP} < b_i$: These individuals have high benefits from engagement. Their decisions will not be affected by the intervention as they would have chosen to engage even before the intervention. (b) Individuals for whom $c_i < b_i < c_i^{FP}$: These individuals have moderate benefits of engagement. They will benefit from the intervention because they choose to disengage before the intervention. This is because they incorrectly anticipate negative utility if they engage due to an overestimation of costs. Therefore, their realized utility was zero. These individuals will now get positive utility when they engage. (c) Individuals for whom $b_i < c_i < c_i^{FP}$: These individuals have very low benefits of engagement. They will remain unaffected by the intervention as they continue to disengage before and after the intervention.

While the effects are heterogeneous, the total change in welfare will be unambiguously positive.

3.3 Pessimistic Beliefs

Individuals suffering from depression can be pessimistic and have "negative expectations" (Beck, 1967) . Since engagement with mental health may not be a perfectly visible action, we now allow for individuals to be pessimistic in their beliefs about their friends with some probability. Alternatively, we can interpret the actions of individuals in the previous section as their attitudes which may not be observed by those in their networks. We additionally assume that if the engagement e_j for any $j \in N(i)$ is not observed, then i assumes the worst about e_j and sets it equal to 0. This means that when an individual doesn't observe whether or not their friend wishes to have a conversation about mental health, they assume that their friend wishes to disengage. Therefore, we augment the existing model by allowing individuals to be of two types- 'observable' and 'unobservable' with a commonly known probability α and $1-\alpha$ respectively with $\alpha \in [0,1]$. The model in the previous section is nested in this model. The utility of agent i can be written as-

$$U(e_i, d; e_{j:j\in N_i}) = b_i - [c(d, (\alpha(1 - E[e_{j:j\in N}]) + (1-\alpha)1))]e_i \tag{2.5}$$

When individuals proxy for the societal disengagement using their friend's choices and do

not perfectly observe their actions, then, in equilibrium

$$a = \sum_{d} \widetilde{P}(d) H(c(d, \alpha a + (1-\alpha)1)) \tag{2.6}$$

where a, as before, is the probability that a randomly chosen friend disengages in equilibrium.

For any positive value of α, this implies that the expected disengagement curve in Figure 2.1 will shift to the left. This is analogous to the effect of the individual responding according to their friend's average disengagement instead of the societal average i.e. similar to the shift of the blue curve to the red in Figure 2.1. Pessimism implies that the lower unstable equilibrium will be lower, thereby implying a higher equilibrium gap and a larger required change in beliefs to cross the tipping point. Further, the stable equilibrium will be even higher. The speed with which society converges to the zero equilibrium disengagement will be slower.

4 Reduced-Form Evidence

4.1 Data

We use data from 75 villages, drawn from 5 districts in the Indian state of Karnataka. This data was collected as part of an earlier study by Banerjee et al. (2013). Individuals were asked to report different types of networks, including whom they go to advice for, whom they visit in their free time, whom they would call if they had a physical health-related emergency, and their borrowing and lending networks. We utilize this network data to construct proxies for disengagement with mental health. In particular, we use the question on advice networks in which the individual is asked: '*If you had to make a difficult personal decision, whom would you ask for advice?*' and compare the number of individuals reported here with that in one's overall network which is constructed by taking the union of the links reported in all of various kinds of elicited networks. Existing work shows the role played by stigma, shame, and signalling in individuals not wanting to seek advice (Chandrasekhar et al., 2018). The choice to disengage, in terms of the measure we use here, can be influenced by any of these mechanisms and we do not disentangle which of these effects are at play. Further, since our measure focuses on advice that is taken specifically for personal decisions, it is well aligned to proxy for disengagement pertaining to mental well-being.

Main Measure

Let A be the adjacency matrix of the advice network and G be the adjacency matrix of the overall network where the graph induced by A is a subgraph of the graph induced by G. Disengagement of individual i in our analysis can then be written as follows.

$$y_i = 1 - \frac{\sum_j A_{ij}}{\sum_j G_{ij}}.$$

This measure corresponds to the fraction of an individual's network that one would not take advice from for a personal decision i.e. it is a proxy of the extent to which an individual might face stigma about talking about one's problems. We use this ratio instead of simply using the degree distribution of an individual's advice network to account for the fact that people with a higher degree are likely to also have more people in one's advice network. Peer averages of this measure are computed across all peers of an individual listed in the overall network.

Alternative Measure

We also report our reduced form results using an alternative measure of disengagement. This measure can be defined as follows:

$$y_{alt1} = \sum_j V_{ij} - \sum_j A_{ij}.$$

where V is the adjacency matrix of the network where a link between i and j exists if i takes advice from j, borrows money from j, borrows kerosine/rice from j, contacts j for medical help, or visits j's house. This measure captures the extent to which i expects a favour from j but does not choose to take advice about their problems. This measure is more conservative in treating an individual as disengaging compared to the main measure. Recall that the overall network is less conservative in assuming the existence of a link between two individuals since it is the union of all the measured networks in the data. The alternative measure of disengagement aims to address the concern of classifying the individual as disengaging if they do not seek advice from their peers in the overall network. This is done by only comparing degrees in the advice network to degrees in the favour-taking network. Despite this, it can be argued that individuals who take advice from a small proportion of their peers are not necessarily disengaging if, for example, the frequency of interaction is high. We do not observe weighted-networks in the data which is why we cannot proxy for disengagement using a more refined measure. Peer averages of this measure are taken over the social graph as defined in Ambrus et al. (2014) where a link exists if either i or j visit each other's houses. We expect individuals to observe and be influenced by the disengagement of their close peers i.e. whose houses they visit or who visit them. We will run the structural estimation exercise using both these measures of disengagement.

The measures of disengagement introduced here assume that an individual's need to take advice from their peers is not related to their position in the network. For example, it can be argued that an individual with a high degree in the overall network is likely to need more advice in the first place presumably because these higher number of interactions involve

a higher number of personal decisions. Constructing the main measure by computing the proportion of the overall network that one does not take advice from (as opposed to only considering the difference between the overall and advice networks) deals with this concern to some extent. However, this is a simplifying assumption that we make to be able to use these network-based measures as proxies in the absence of a measure specifically measuring engagement with mental health.

Also, note that we do not control for degree or network position in the reduced-form regressions presented in this section despite the modelling assumption that the costs of engagement are rising in network degree. This is because the main measure used to proxy disengagement makes use of network degrees. However, we will control for degree centrality in the 'social' network (that assumes a link if people visit each other's houses) in an alternative specification that uses the alternative measure of disengagement. This will allow us to provide some correlational evidence pointing towards whether individuals who are more connected are more disengaged due to higher costs.

4.2 Sample Description

We pool the network data from all 75 villages. Table B.1 in the Appendix gives the summary statistics for the sample. Figure B.1 plots the cumulative mass distribution functions of the different degree distributions associated with the advice, borrowing, visit and medical-help networks.

As is evident from the figure, the CDFs of the other networks first order stochastically dominate that of the advice network. That is, the probability that an individual has at most a given number of people in one's advice network is higher for one's advice network compared to other networks implying that individuals tend to have lower degrees in their advice networks. This is also seen in Figure B.2 in the appendix that shows the discrete degree distributions for these four types of networks.

4.3 Results

While stochastic dominance is suggestive about an individual's reluctance to discuss their personal problems, it does not show if there may be complementarities or peer effects in disengagement about mental health. To check this, we report the reduced form regression of an individual's disengagement on the average disengagement among their peers. We conduct this exercise for both the main and alternative measures.[14] We cluster the standard errors at the village level.

Our main estimation equation is:

$$y_{iv} = \alpha_v + \alpha_2 \frac{\sum_{j \in N(i)} y_{jv}}{|N(i)|} + \gamma_{\mathbf{1}} \mathbf{x_{iv}} + \gamma_{\mathbf{2}} \frac{\sum_{j \in N(i)} \mathbf{x_{jv}}}{|N(i)|} + \epsilon_{iv}, \tag{2.7}$$

[14] The measure of disengagement is set missing for those whose degree in the overall network is zero.

where y_{iv} is the disengagement of an individual from village network v, $N(i)$ is the set of individual i's peers, $|N(i)|$ is their degree. α_2 is the coefficient of interest as it measures the endogenous peer effect. The vector $\mathbf{x_{iv}}$ controls for other individual-level characteristics which may affect disengagement. This includes demographic variables such as age, gender, education, religion, caste and an indicator for whether the individual is a village native and economic variables such as roof type, number of rooms, whether the individual works outside the village and has a savings account. We also measure exogenous peer effects by controlling for peer averages of these individual-level characteristics. We use the estimation strategy suggested by Bramoullé et al. (2009); De Giorgi et al. (2010) and instrument for peer disengagement using the characteristics of an individual's peers' peers who are not their peers. These characteristics include their average gender and level of education. We treat the network structure (adjacency matrix G) as exogenous and use village fixed effects. We do not use the estimated coefficient for further analysis and only use it to motivate the hypothesis of interest.

The main results using this estimation strategy are reported in Columns 3 and 6 in Table 2.1 for our main disengagement measure i.e. fraction of people in an individual's network they would not take advice from, and the alternative disengagement measure i.e. the fraction of people whom an individual may take favours from but does not contact for advice. Columns 1, 2 and 4, 5 in the table report the OLS results which do not correct for the endogeneity of peer effects. Columns 1 and 4 do not control for the village fixed effects. Columns 3 and 6 use Two stage least squares using the average gender and education as instruments for the average disengagement of an individual's peers. All specifications control for the exogenous peer-level averages of any individual-level controls.

Table 2.1: Reduced Form Results for Disengagement

	Disengagement (Main)			Disengagement (Alternative)		
	(1)	(2)	(3)	(4)	(5)	(6)
Peer Average	1.005***	1.032***	0.808***	0.901***	0.885***	0.493
	(0.015)	(0.017)	(0.275)	(0.016)	(0.017)	(0.485)
Observations	10,509	10,509	10,509	10,253	10,253	10,253
R-squared	0.511	0.519	0.378	0.428	0.437	0.246
FS F Stat			5.636			2.323
Kleibergen-Paap Statistic			0.00695			0.103
Anderson-Rubin P Value			0.119			0.480

Note: All regressions control for demographic variables such as gender, age, whether the individual is a native, head of household, religion etc and economic variables such as number of rooms, beds, type of electricity, latrine type, roof type etc. Regressions also control for these characteristics averaged across an individual's peer group. Column 2 additionally controls for village fixed effects and Column 3 shows the results from a 2SLS regression where peer average is instrumented using the average gender and education of the friends of an individual's friends who are not the individual's friends. Columns 4-6 similarly repeat these regression specifications for our alternative measure of disengagement. Standard errors are clustered at the village level.

The model predicts that an individual with a higher proportion of disengaging peers will disengage more. These predictions are confirmed by the reduced form results. The positive

peer effects of disengagement persist even after the endogeneity is taken into consideration (Table 2.1 Column 3). The first stage results, for both the main and alternative measure, confirm the existence of a statistically significant positive relationship between the average disengagement of an individual's friends and the average proportion of women among their friend's friends who are not their friends. The positive relationship between the proportion of women in one's peer group and own disengagement observed here is also in line with existing literature that shows how gender-norms can adversely affect female social networks (Andrew et al., 2020). The first stage F statistics are low which is why we additionally report the Anderson-Rubin statistic for inference robust to weak instruments.

The results of the main measure (Column 3) suggest that a 1 standard deviation increase in the average disengagement among one's peers leads to a 12 percentage point increase in their own disengagement i.e. they are less likely to take advice from their peers. The IV results using the alternative measure imply slightly weaker effects and are not significant. It is important to note that the alternative measure is constructed using a more conservative favour-taking network as the main network that is then compared with the advice network.

Recall that the model predicts that individuals with a higher degree will disengage more. We do not include degree in the overall network in the regressions in Columns 1-3 since degree in the overall network is used to construct the measure of disengagement in the first place and there is a positive correlation between disengagement and degree by construction. However, we conduct an additional exercise to check if degree in the 'social' network (that assumes a link if people visit each other's houses) is correlated with the alternative measure of disengagement. We control for degree in the specifications in Columns 4-6 and find that this is indeed the case. We find a positive correlation between an individual's degree and their disengagement but the coefficient is not significant in the main IV specification. The results are reported in Table B.2 in the appendix.

5 Structural Estimation

We now proceed with structural estimation of the above model using the data from Banerjee et al. (2013). We intend to recover structural estimates of (a) our main parameter of interest, the extent of complementarities θ in disengagement[15] and (b) the parameter κ which affects the shape of the distribution H of the benefit of engagement. As we will see, the shape of the distribution affects the magnitude, type, and number of equilibria. Structural estimation allows us to first compute and categorize stable and unstable equilibria for each village. Then, we compute how much a hypothesized intervention has to shift beliefs to set the village on a path towards zero disengagement. The gap between the stable and unstable equilibrium provides an estimate of how difficult it is to change beliefs and move to a welfare-improving social norm. Finally, we

[15]Recall that higher strategic complementarities in disengagement imply higher costs of engagement.

undertake a counterfactual exercise to consider an intervention that shifts beliefs in each village beyond the tipping point, in case such a tipping point exists. We do this to compute the time (iterations of belief updating) taken by individuals in each village to converge to the zero disengagement equilibrium.

Assumption 1 (Structural Estimation Assumptions) *We make the following simplifying parametric assumptions to proceed with structural estimation:*

1. *We assume that the cost of engagement takes the form* $c(d, 1 - E[e_{j:j\in N}]) = \theta * d * E[a_{j:j\in N}]$ *and analogously* $c(d, 1 - E[e_{j:j\in N(i)}]) = \theta * d * E[a_{j:j\in N(i)}]$ *where* $a_i = 1 - e_i$ *is the choice to disengage. This implies that the expected cost from engaging is multiplicative in the extent to which others disengage and one's degree, and is therefore rising in the expected number of neighbours who will disengage.*

2. *The benefit of engagement* b *is drawn from a log logistic distribution* H*. Recall that the probability that a randomly chosen peer of degree* d *disengages under equilibrium disengagement* x *is given by* $H(c(d, x))$*. That is,* $H(c(d, x)) = (1 + (\theta dx/\alpha)^{-\kappa})^{-1}$*. We do this in line with our model assumptions outlined in the theory section. Without loss of generality, we set* $\alpha = 1$*. The log logistic distribution has fatter tails compared to the log normal distribution. We use this instead of a log-normal distribution since its cumulative distribution function can be written in closed form and this helps with accuracy and speed in our simulations. This distribution is also a better choice than the logistic distribution since it has a positive domain and* $H(0) = 0$ *in this case. The parameter of the logistic distribution only allow* $H(0) = 0$ *in the limiting case.*

3. *Based on evidence from the reduced form estimation and because the log logistic distribution only allows a non-negative domain, we restrict both* θ *and* κ *to be non negative.*

Given that each of these villages constitutes a different network, may have different strength of peer complementarities, and potentially different benefit distributions, we allow for heterogeneity in θ and κ across villages. This also allows for ex-ante heterogeneity in the number, type, and magnitude of equilibria in different villages.

5.1 Estimation Strategy

We estimate θ_v and κ_v for each village $v \in \{1, 2, ..75\}$ by using the maximum likelihood method outlined in Bisin et al. (2011); De Paula (2013) for structural estimation. We later consider the robustness of the estimate of the strength of complementarities by (a) using an alternative method of moments estimation strategy and (b) estimating the model using the alternative measure of disengagement.

Our estimation strategy proceeds in the following steps:

1. We empirically compute the degree distribution $P(d)$ for each village using the adjacency matrix of the overall network. The overall network contains a link

between two agents if they interact in any capacity. We do not restrict these interactions only to advice-taking or advice-giving since the strategic complementarities from disengagement are potentially obtained from the neighbours whom one interacts with for lending, borrowing, visiting etc and not just for sharing advice. Then, we construct the degree distribution $\widetilde{P}(d)$ of an individual's friends as follows-

$$\widetilde{P}(d) = P(d) * (d/E(d)).$$

2. For a given initial choice of θ and κ, we numerically solve for the Bayes Nash equilibria which would arise when agents use their friend's disengagement to infer the society-wide norm. The equilibria solve the following equation:

$$x(\theta, \kappa) = \sum \widetilde{P}(d) H(c(d, x(\theta, \kappa)).$$

3. We compute the probability that each individual disengages depending on the computed equilibrium, their degree, and the proposed value of θ and κ. Then, we compute the likelihood of each equilibrium x^* in the village:

$$L(x^*) = \sum_i \{1\{a_i = 1\} ln[H(c(d_i, x^*(\theta, \kappa)] + 1\{a_i = 0\} ln[1 - H(c(d_i, x^*(\theta, \kappa)]\}.$$

   We assume that an individual disengages i.e. chooses $a_i = 1$, if they do not take advice from over 50% of their friends.

4. Then, we pick the equilibrium which maximizes the likelihood of that village.

5. The algorithm iterates to find θ and κ until convergence is reached. We use the *pattern search* solver in MATLAB to run these iterations and find the optimal θ and κ.

We repeat this for every village to obtain the set of optimal parameters for the entire population.

Identification

Now, we discuss the properties of the estimated parameters and the challenges faced in identification. The patternsearch solver employed in the main estimation starts with an initial starting point of $\{1, 1\}$. The solver continues exploring points evenly positioned around the starting point like a rhombus and switches to a new point if the estimated equilibria at that point generates a higher likelihood. Every successful iteration leads to an expansion in the size of the rhombus and every failure (i.e. where none of the four new points improve the likelihood) is met with a reduction in the size of the rhombus. However, the solver only ensures that we find a local optimum. While we cannot prove that the optimum we have found is global, we can comment on the number and types of

alternative equilibria that would exist if the computed optimum was indeed only a local one.

Consider the equilibrium equation-

$$x(\theta, \kappa) = \sum_{d} \widetilde{P}(d)(1 + (\theta dx)^{-\kappa})^{-1}.$$

Note that $\widetilde{P}(d)$ is a probability distribution function so the summation is equivalent to taking the weighted average of the function $(1 + (\theta dx)^{-\kappa})^{-1}$. Weighting the function by $\widetilde{P}(d)$ preserves the number and type of equilibria. The magnitude of the equilibria will change with the degree distribution.

We argue that there exists a threshold $t > 0$ such that for $\theta > t$ and $\kappa > t$, the equation above is solved for either three distinct values of $x \in [0, 1]$ including 0 as a stable equilibrium, and one unstable and stable positive equilibrium. As $\theta \to \infty$, it is solved at $x^* = 1$ regardless of the value of κ. We can ignore the second case since an equilibrium of zero disengagement i.e. $x^* = 0$, intuitively must be a solution of the model. Thus, above the threshold t, there always exist three equilibria out of which there is one non-zero stable equilibrium. We do not proceed with computing the threshold but can show, by graphical observation, that these conditions hold for $t = 3$. Cases 1 and 2 in Figure B.3 in the appendix shows the shapes of this function with two examples where $\{\theta, \kappa\} > 3$ and $d = 1$. So, for any pair $\{\theta, \kappa\} > 3$ we have one stable equilibrium at 0, one strictly positive stable equilibrium, and one unstable equilibrium. There only exists a stable equilibrium at 1 if θ is extremely large such that no matter what disengagement an individual expects in their neighborhood, their response is always to disengage with probability one. This is intuitive in that if the strategic complementarities of disengagement (or the costs of engagement) are extremely large. Excluding this extreme case, the above observation implies that if we find a local optimum θ^*, κ^* such that there are 3 equilibrium values of disengagement (of the type specified above), then if there exists a global optima θ^{**}, κ^{**} such that $\{\theta^{**}, \kappa^{**}\} > t = 3$, then the society must also have three equilibrium values of disengagement. The results from the counterfactual exercises we conduct in this section would still continue to hold qualitatively. This does not detract from the primary result of this section that (a) heterogeneity in advice taking equilibria depends on the network structure, (b) societies can be stuck at a inferior equilibrium of high disengagement, and (c) belief shifting interventions can push the society across the tipping point. These results only rely on the existence of 3 distinct solutions to the equilibrium equations.

Now, consider the case where $\theta^{**} < t, \kappa^{**} > t$. It is plausible that pattern search explores these values since, as we mentioned, it computes four mesh points around the value of $\{\theta, \kappa\}$ in each direction in each iteration and computes likelihood at these points. However, to be thorough, we also run exercises to check that this is indeed the case. If the global

optima were indeed one where the parameters are such that $\theta^{**} < t, \kappa^{**} > t$, then there could exist one stable equilibrium at zero and no other equilibrium (Case 3), or one unstable equilibrium at zero and one positive stable equilibrium (Case 4). A belief shifting intervention will not be useful in such cases. These cases are illustrated in Figure B.3 in the appendix.

To check if either of these cases are the global optimum, we run identification checks that input different starting values into the pattern search solver where θ is very low (below the threshold) and κ is high (above the threshold) or vice versa. In particular, we start with two extreme cases where the equilibrium configuration at our starting values will be one stable equilibria at zero and no other equilibria and one unstable equilibria at zero and a stable equilibria elsewhere as shown in Figure B.5 in the appendix. If the resultant solution still contains three equilibria, then we can be confident that the global optimum will also have three equilibria.

5.2 Results

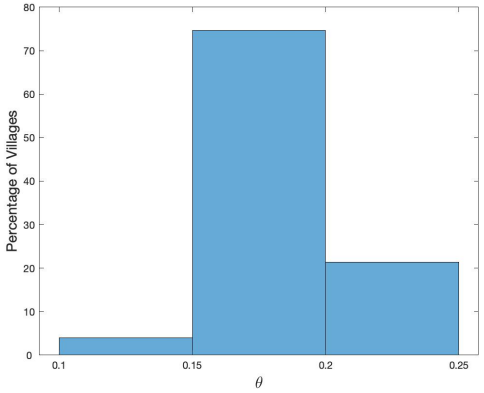
Figure 2.2 shows the results from the structural estimation. Figure 2.2(a) shows the distribution of θ_v^*, 2.2(b) shows the distribution of κ_v^*, and 2.2(c) plots the LHS and RHS of the equilibrium equation $x(\theta_v^*, \kappa_v^*) = \sum \widetilde{P}(d) H(v(d, x(\theta_v^*, \kappa_v^*))$ for each village $v \in \{1, 2, ...75\}$.

The mean value of θ is 0.18 and that of κ is 2.34 .We find that close to 75% of villages have an estimated θ which lies between 0.15 and 0.20, and close to 21% of the villages have an estimate larger than 0.20. These values of θ cannot be compared with the value of the strategic complementarities parameter obtained in the reduced form regressions. However, as we will discuss, these heterogeneous values of θ across different villages affect not just the magnitude of equilibria in these villages but also the shape of the curve that affects adjustment to equilibrium. The shape of the log logistic distribution is also determined by κ which lies between 1.3-3.4 for all the villages. The value of $\{\theta, \kappa\}$ and the village-specific degree distribution then provides us with heterogeneity in the number, type, and magnitude of equilibrium disengagement.

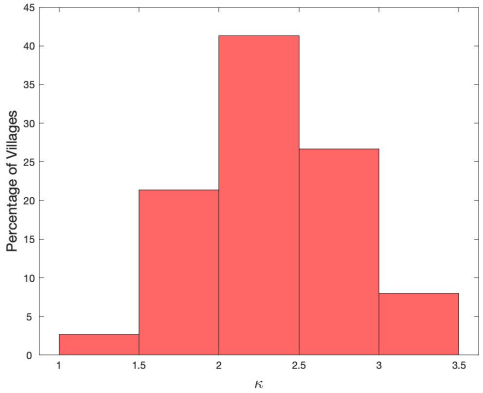
This heterogeneity is seen in Figure 2.2(c) where most villages ($\sim$90%) have three equilibria in line with the theory results- one stable equilibrium at zero, one unstable positive equilibrium, and one high stable positive equilibrium. However, the shapes of the equilibrium adjustment curves for each village are dependent on the village-specific degree distribution and estimated value of the strategic complementarities parameter. The remaining villages only have two equilibria- an unstable equilibrium at zero and an unstable strictly positive equilibrium. Our estimation strategy allows for such heterogeneity, highlighting that any intervention that seeks to alter beliefs and shift equilibria needs to take village specific network variations and differences in strategic complementarities into consideration.

Figure 2.2: Structural Estimation Results: Maximum Likelihood

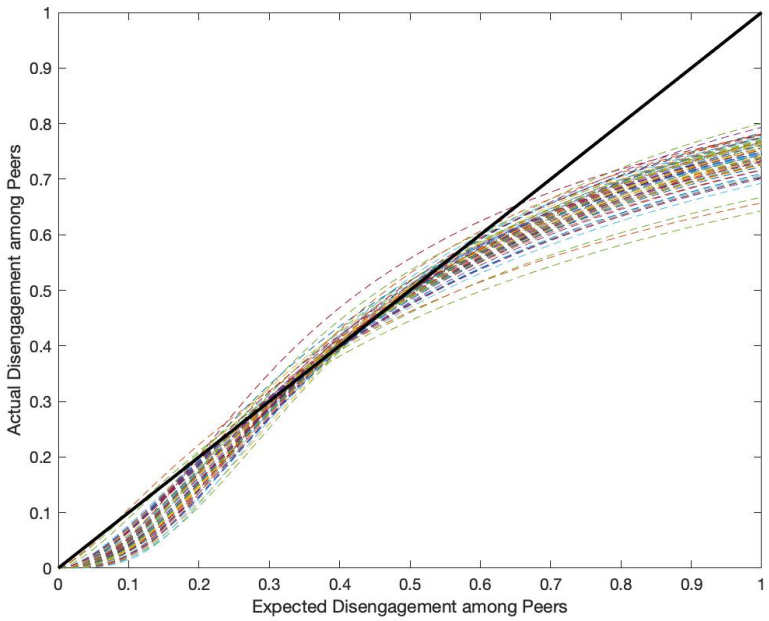
(a)



(b)



(c) Implied Expected Disengagement



Notes: Panels (a) and (b) illustrate the distribution of estimated θ (parameter for strength of peer complementarity) and κ (parameter of the log-logistic benefit distribution) across the 75 villages respectively. The estimated method used is Maximum Simulated Likelihood. Panel (c) plots the implied expected disengagement at the estimated θ and κ for each village.

Figure B.4 plots the stable and unstable non-zero equilibria for all the villages. We exclude the zero equilibrium from this graph since majority of the villages have a stable zero equilibrium. The figure shows that the stable non-zero equilibria are generally higher than the unstable ones. We find that in 63% of the cases where there are three equilibria (such that zero is stable and there is one other strictly positive stable and unstable equilibrium), the equilibrium which maximises the likelihood is the stable non-zero equilibrium. This means that out of all the villages, around 57% can be stuck at the stable, highest level of equilibrium disengagement.

The results for the method of moments procedure are provided in Section B in the appendix. The method of moments estimator proceeds analogously except that instead of the likelihood, the objective function to be minimized computes the quadratic distance between the mean and variance of disengagement implied by the model and the data. Since there can be multiple equilibria, we choose the objective function with the lowest value in each iteration analogous to the simulated maximum likelihood procedure. The results are similar although in this case, there are more outlier cases (in terms of the estimated θ and κ values) than before.

The results for the alternative measure of disengagement are also provided in the appendix in Figures B.9 and B.10. These results are also computed using the maximum likelihood method outlined above. We find that most villages have 3 equilibria but these equilibria are lower in the magnitude of disengagement. This is because this estimation uses a more conservative measure of disengagement. The results reported in this section correspond to those obtained from the main measure in which the overall network is compared with the advice network.

Identification Checks

Now, we discuss results that provide more evidence that the global optimum for the majority of villages is indeed one where there exist three equilibria- one stable equilibrium at zero, one positive stable equilibrium, and one positive unstable equilibrium. Recall from the discussion on identification that very high values of both θ and κ (above $\{3, 3\}$) will yield three equilibria. We run the estimation using two different starting values where θ is low and κ is high or vice versa to check if it still converges to a solution with three equilibria. We randomly pick villages and run the estimation using starting values for the θ, κ pair equal to $\{0.001, 5\}$ and $\{5, 0.001\}$. The expected and actual disengagement for these villages evaluated at these starting values of θ and κ are shown in Figure B.5. Crucially, at these starting values, there either does not exist any non-zero equilibrium (i.e. the curve is always below the 45 degree line) or there exists one stable non-zero equilibrium.

The estimation results are reported in figures B.6 and B.7. We increase the mesh-size of the patternsearch solver in these checks since otherwise in these cases, a small change in the starting values of θ or κ would not change the equilibrium or the likelihood and the

solver would converge to a local optima close to the starting value. By increasing the mesh size, we allow the solver to check for larger changes and to compare the likelihood around the starting values to likelihood estimated at points in the $\{\theta, \kappa\}$ space that lie further away.

We find that the difference between the estimated θ using these two alternative starting values and the starting value used in the main estimation is less than 0.02 in most cases. Similarly, the difference is less than 0.2 for κ in most cases. We additionally plot the expected and actual disengagement and find that these estimates still imply that villages have 3 equilibria as found in the main estimation. These plots are also presented in Figures B.6 and B.7. We exclude the cases where the original estimation resulted in an estimated $\kappa = 0$ since the log logistic distribution is not defined in this case.

In addition to this, we also obtain estimation results for starting points {0.01, 0.01} and {2,2} for a few randomly chosen villages from the dataset. We find that the results are similar to that obtained via the main estimation.

These identification checks cannot guarantee that we have found a global optima since a higher value of θ and κ could result in an alternative pair of estimated coefficients. However, as we discussed, there would still be three equilibria in those cases and these equilibria would depend on the degree distribution of the villages unless θ is infinitely high and the RHS of the equilibrium condition is 1. We also chose a high mesh-size (i.e. size of rhombus) precisely because the likelihood did not change around the points surroundng the starting value. Using alternative starting points with high mesh sizes also gives the solver the opportunity to compare likelihoods with higher values. The fact that it still converges back to a solution close enough to the one estimated in our main estimation gives us confidence in our estimated parameters.

5.3 Counterfactuals

We now focus of the villages with three equilibria- one stable equilibrium at zero, one positive unstable equilibrium, and one positive stable equilibrium. 90% of the villages have three equilibria. We focus on these villages to run the following counterfactual: How much does a hypothetical intervention need to shift beliefs to put the village on the path to the stable equilibrium at zero? We also estimate how quickly a village reaches zero disengagement after beliefs are shifted beyond the unstable equilibrium.

We define the minimum shift in beliefs needed to cross the unstable equilibrium and reach zero as the equilibrium gap. This is computed as the difference between the positive stable and unstable equilibria. This can also be understood as the distance to reach the tipping point - the threshold beyond which the society will over time converge to the zero equilibrium. Figure 2.3 plots the histogram of the equilibrium gap for the villages which have 3 equilibria. We find that there is a large gap between the unstable and stable non-zero equilibrium indicating that there has to be a substantial change in individual

beliefs to shift the norm to zero disengagement. Only 15 out of the 68 villages, can reach the zero equilibrium just by shifting their beliefs about disengagement by less than 5 percentage points, assuming that such a shift would be possible by revealing the true mean disengagement in the village. Other villages require a much larger change in beliefs to be pushed beyond the unstable equilibrium.

However, an intervention which *credibly* shifts beliefs about disengagement is one which corrects misperceptions about society-level disengagement by informing individuals about the true disengagement at the society level. We check whether the actual society-level disengagement lies below the estimated tipping point to see whether such an intervention which corrects misperceptions in these villages would be successful to set the village on a path to reach the zero-disengagement equilibrium. We find that revealing the true society level average disengagement would shift the beliefs beyond the unstable equilibrium for 53 out of the 68 villages with tipping points. There will, however, be no long run effects in the remaining 15 villages. In other words, the equilibrium gap for these villages is larger than the gap between the stable equilibrium and the true village-level average.

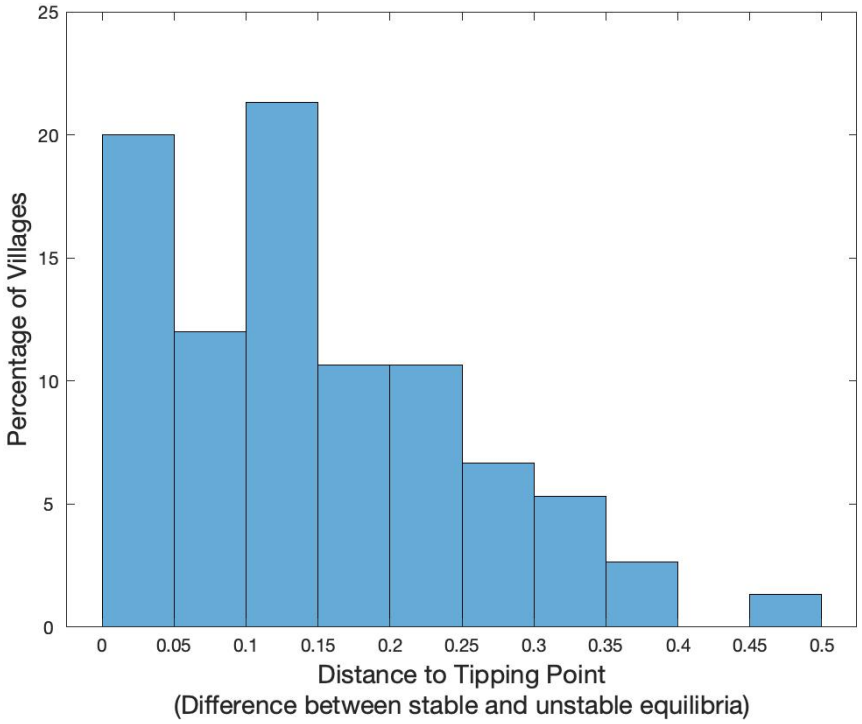
Long-Run Effects

We estimate how much time it will take villages to reach the zero disengagement equilibrium once the beliefs are pushed beyond the tipping point. We measure this in terms of the number of belief-updating iterations it takes for the villages to converge to the zero equilibrium.

To do so, we undertake the following exercise: Villages start from the positive stable equilibrium at time $t = 0$. The intervention shifts beliefs slightly below the unstable equilibrium at time $t = 1$. In each period, the average disengagement in the individual's neighbourhood responds to the beliefs of the individual. We record the expected and actual disengagement in each period and say that the beliefs have converged to zero when the expected disengagement is the same as the actual and both equal zero. The inverse of the time t at which this happens is a proxy for the speed with which villages converge to zero. Figure 2.4 Panel (a) plots the evolution of expected and actual disengagement in the neighbourhood against time for the first ten villages as an example. Each village starts at the high stable equilibrium at $t = 0$, the equilibrium gap is evident from the jump at time $t = 1$ and the evolution takes place until beliefs reach zero.

We find considerable heterogeneity among these villages in the time they take to reach the zero equilibrium. This heterogeneity is clearly visible in Figure 2.4 Panel (b) which plots the time taken to reach the zero equilibrium once pushed beyond the tipping point for every village. The heterogeneity arises because of the differences in the village specific value of θ and κ, and the village specific degree distribution. We correlate the time taken with average village-level characteristics. We find that this correlation is positive, albeit small, ($\rho = 0.02$) for share of females in the village, negative with average education ($\rho = -.11$), positive for share of the other backward castes in the village ($\rho = 0.19$) and

Figure 2.3: Counterfactual: Distance to Tipping Points



Notes: Figure shows the shifts in beliefs needed to converge to the zero equilibrium if we perturb beliefs from the highest stable equilibrium such that they just pass the threshold tipping point for all the villages (N=68) which have a tipping point (i.e. a non-zero stable and unstable equilibrium along with the zero stable equilibrium.).

negative for the proportion of those belonging to the higher General caste (ρ= -0.19). The correlation is small and positive with share of natives in a village (0.06) and with the average age in the village (0.03). These correlations, while purely descriptive, point towards the importance of village level characteristics in determining the long run impacts of a belief-shifting intervention.

Short-Run Effects

What will happen in the short run if the villages are at the upper stable equilibrium and an intervention shifts beliefs but does not manage to push the village beyond the unstable equilibrium? This will be the case if beliefs are shifted by a lower magnitude than the equilibrium gap. In this case, beliefs will return back to the upper stable equilibrium in the long run but there will be positive short run effects. We continue to maintain the assumption that individuals still proxy the social norm using the average behaviour within their peer neighbourhood.

An intervention such as this will be more useful to the beneficiaries if it takes more time for the villages to come back to the upper stable equilibrium. Figure 2.5 plots the time taken by these villages to reach the upper stable equilibrium. As is evident, there is considerable heterogeneity in the time taken by villages to reach the upper stable equilibrium indicating that there are positive short run effects but these differ depending on the degree distribution of the village. This heterogeneity also points towards the importance of timing in the measurement of treatment effects of a belief-correction intervention and how the magnitude of the measured treatment effects depends on the timing and the underlying network structure.

6 Experiment

Our baseline sample comprises of 362 low-income individuals affiliated to a NGO from 14 localities in New Delhi, India.[16] The individuals in this sample live in slum-like conditions and primarily work in waste-picking and waste-sorting related activities. The NGO works for their advocacy and promotes awareness for health and safety, and their rights. Our collaboration with the NGO seeks to encourage dialogue around mental-health related issues. Individuals in our baseline sample were contacted from a list of $\sim$ 800 phone numbers of individuals who expressed an interest to participate in the study, shared with us by the NGO. We were able to contact around 400 individuals out of these.[17] Approximately 10% of these individuals refused to participate.

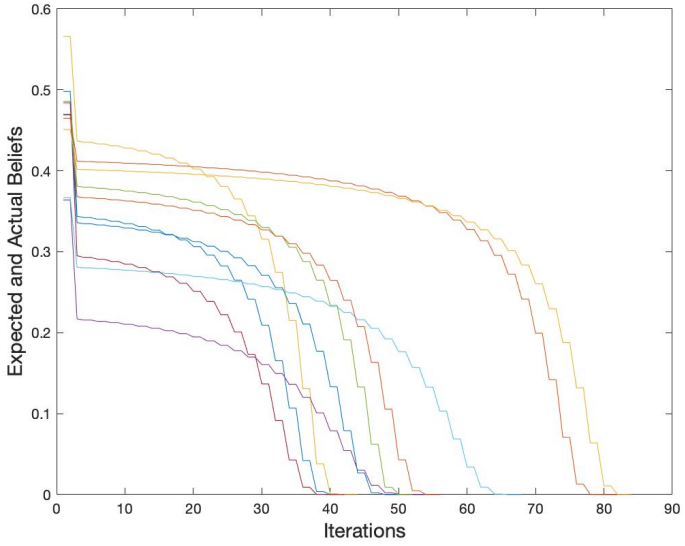
The baseline survey is in Section K in the appendix and the relevant graphs and tables for

[16] We do not have complete baseline data for *all* of these individuals since some of them left the phone survey midway or rescheduled the call for later but were not available. Any percentages expressed here are a proportion of the sub-sample for whom we have non-missing values of the relevant variable.

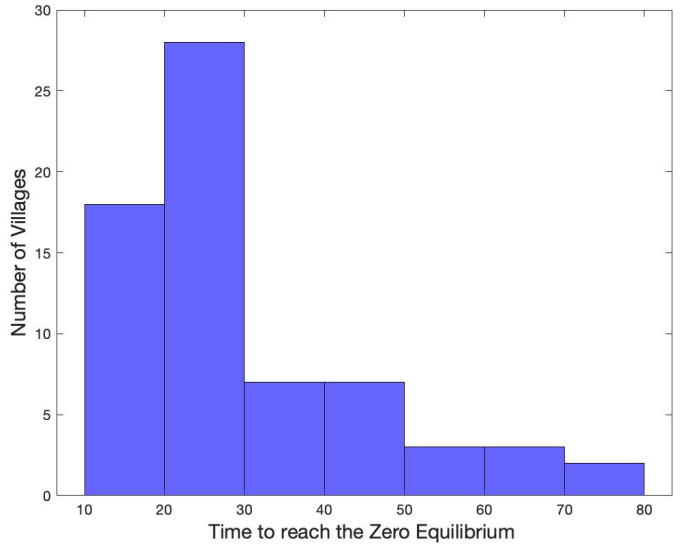
[17] We could not contact the remaining individuals since their phone numbers were invalid, switched off, out of network coverage, or not reachable.

Figure 2.4: Counterfactual: Shift in Beliefs and Long-run effects

(a) First 10 villages



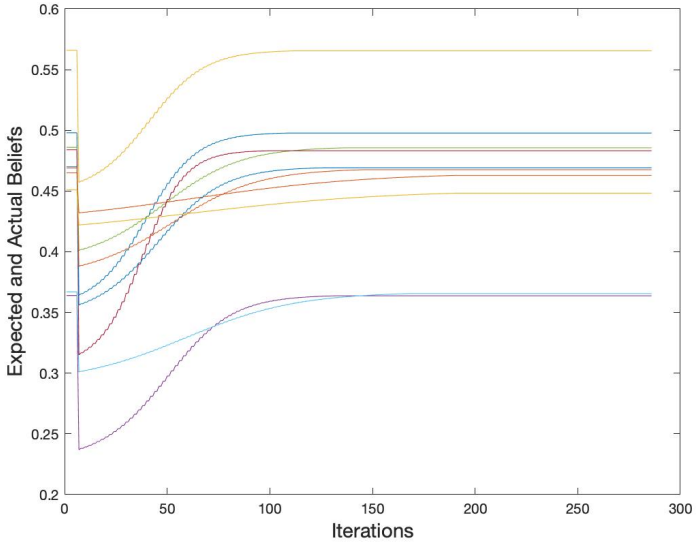
(b) All villages



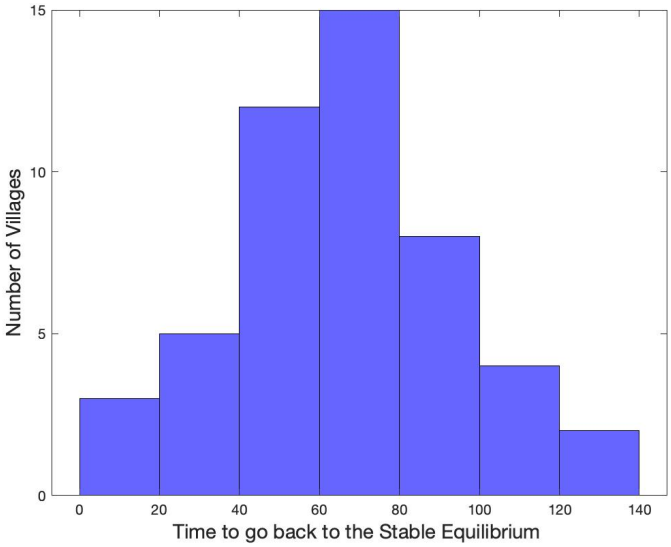
Notes: Figure shows the iterations (steps) needed to converge to the zero equilibrium if we perturb beliefs from the highest stable equilibrium such that they just pass the threshold tipping point. Panel (a) illustrates this for the first 10 villages. Panel (b) plots the histogram of the time taken for each village to reach the zero equilibrium after beliefs are shifted just pass the tipping point. We restrict to those villages (N=68) which have a tipping point (i.e. a non-zero stable and unstable equilibrium along with the zero stable equilibrium.).

Figure 2.5: Counterfactual: Shift in Beliefs and Short run effects

(a) First 10 villages



(b) All villages



Notes: Figure shows the iterations (steps) needed to converge back to the stable equilibrium if we perturb beliefs from the highest stable equilibrium such that they just miss the threshold tipping point. Panel (a) illustrates this for the first 10 villages. Panel (b) plots the histogram of the time taken for each village to reach the stable equilibrium after beliefs are shifted such that they just miss the tipping point. We restrict to those villages (N=68) which have a tipping point (i.e. a non-zero stable and unstable equilibrium along with the zero stable equilibrium.).

this section are in Section C. Tables C.1 and C.2 in the appendix show descriptive baseline statistics for demographic outcomes, baseline dialogue, stigma, beliefs, and networks for the experimental sample. The average age of participants is around 34 and 35% are female. Around 66% are currently employed and just under 50% earn between $\$2.5 - 5$ a day and $\sim 34\%$ earn less than \$2 a day. Individuals take advice from around 3 peers on average - this is the average degree of the 'advice network'. They interact with around 4 peers on average in other capacities including advice-taking, borrowing, lending, working together- this is the average degree in the 'overall network'. Now, we first discuss how we measured beliefs and then discuss baseline evidence that relates self-reported intensity of dialogues, with gaps between these networks, and beliefs about community's willingness to engage.

6.1 Belief Elicitation

Before measuring beliefs, we informed individuals about what we mean by physical and mental health. This is because individuals could interpret these in different ways and we wanted to standardise the measurement to the extent possible. Then, we asked them about their own willingness to engage and their attitude towards those with physical and mental health issues. After this, we elicited their beliefs about their community's willingness to engage and community attitudes. We defined a community in terms of geographic location i.e. those living the same NGO centre were interpreted to be from the same community. These beliefs were elicited in an incentive compatible way. Individuals were informed that they would receive a prize of Rs. 50 (a third of their total participation incentive) in case their guess was accurate within +/- 1 (on a range of 0-10).

So, for example, to get beliefs on mental health related engagement, we first asked:

"Would you be willing to share and discuss mental health related concerns with your friends, discuss ways to overcome them, and how these problems might be preventing you from achieving your goals ?"

Then, we asked them how many individuals among any 10 participants in their community associated with the NGO would be willing to share and discuss their mental health related concerns with their friends, discuss ways to overcome them, and how these problems might be preventing them from achieving their goals? Based on the sample responses to these two questions, we can infer if an individual underestimates engagement. Similarly, to get at stigma, we asked if the individual agrees with the statement: *"People should stay away from individuals who have mental health issues"* and then asked them how many individuals among any 10 individuals in their community associated with the NGO would agree with the statement. This exercise is repeated for engagement with physical health, financial health, stigma pertaining to physical heath, and a measure of stress.

The choice to measure beliefs by asking about any 10 individuals rather than ask in terms of percentages was made to ensure simplicity and ease of understanding. We found from the pilot conducted in January 2020 that many individuals did not understand what a

percentage meant unless it was translated in these words.

Table C.2 provides information on these elicited beliefs. For example, on average, $\sim$ 64 % of individuals were willing to engage with conversations about mental health but the expected engagement from the community was roughly equal to 5 out of any 10 individuals.

6.2 Baseline Findings

We document two stylistic facts about the engagement with mental health among these communities.

First, we find that the communities have low engagement with mental health. We find (a) gaps between overall and advice network degrees and (b) lower dialogue intensity associated with talking about issues related to emotional well-being compared to employment/financial issues. Figure C.1 plots the degree distributions of the advice and overall networks and we can see that the overall network degree distribution first order stochastically dominates to advice network degree distribution. Figure C.2 plots the dialogue intensity on mental and financial health related topics since the last two weeks. Dialogue intensity is significantly lower for mental health. We also construct the network-based measure of an individual's disengagement using differences in degrees in overall and advice networks as done in the structural analysis. We find that this measure is negatively correlated with the actual (coarse) frequency of dialogue individuals report to have had about mental health in the last two weeks. This suggests that individuals who engage in less dialogue about mental health are also those who are likely to have more gaps between their advice and overall networks.

Second, we compare beliefs about community willingness to engage and actual willingness in the sample. This is used to compute the number of underestimators and the magnitude of the wedge. Figure C.3 plots individual beliefs about their community's willingness to engage in dialogue and the sample averages. We find evidence of substantial misperceptions in individual beliefs about the other individual's willingness to engage in a dialogue about mental health concerns. Around 68% of the individuals for whom we have data on baseline beliefs, underestimate the percentage of individuals in their community who wish to discuss mental health related issues. The proportion of underestimators by type of dialogue (mental health, physical health, financial health) and by stress is shown in Figure C.4. We find that proportion of individuals who underestimate mental health related engagement are significantly higher than those who underestimate financial health related engagement. The magnitude by which beliefs differ from the community-level average engagement is plotted in Figure C.5.

In addition, we find suggestive evidence that supports two additional claims. *First*, individual beliefs about their community's willingness to engage are correlated with their own willingness to engage, their dialogue intensity, and the gaps we observe between the two networks. *Second*, individual beliefs about their community's stigma against mental

and physical health affect their willingness to engage. These correlations are reported in Table C.5, C.6, and C.7.

Table C.5 shows positive correlations between an individual's beliefs about their community's willingness to engage and their own self-reported dialogue frequency with respect to mental and financial health. This suggests that optimistic beliefs about peers can be associated with higher dialogue. We also document negative correlations between these beliefs and the gaps between individual overall and advice network degrees suggesting that pessimistic beliefs are associated with larger network gaps. These degree gaps are measured in exactly the same way as the "disengagement" measure used in our structural analysis with the data from Banerjee et al. (2013). These results are further substantiated in C.6 where we find that individuals who underestimate the sample-average engagement in their community are less willing to engage in dialogue around mental health. We also find that degree gaps are larger for individuals who are categorised as severe underestimators i.e. those for whom the difference between their belief and the sample average lies in the bottom 25th percentile. *Finally*, Table C.7 shows negative correlations between an individual's beliefs about how stigmatised their community is regarding mental and physical health and their own willingness to engage in dialogue around these issues.[18]

6.3 Design

We randomised individuals into a Control and Treatment Group. The treatment group received two types of information (i) true average sample willingness to engage in a dialogue about mental health and (ii) qualitative information about community willingness to engage in a dialogue about financial/work related concerns. Note that we did not provide information about community-level averages but provided information about sample-level averages. We did this because some communities had very low response rates, are similar in characteristics, and we did not wish to make individuals pessimistic or optimistic about their community on the basis of information obtained from very small samples.

The information provided to the treatment group was as follows-

Information 1: *"Just like we surveyed you, we also surveyed other people and we have found from their responses that out of any 10 individuals in your community and communities similar to yours (affiliated with the NGO), X individuals are willing to discuss their mental health concerns with their peers, how they can be preventing them from achieving their goals, and how they can be overcome."*

[18]We find high levels of stigma against mental health. Around 50% of our sample agrees with the statement "People should stay away from individuals suffering from mental health issues". This contrasts with 64% of them being willing to share mental health related concerns with their peers. After having spoken to the NGO staff and a psychologist, we realized that the phrasing and translation of the question may have have led participants to think of more severe kinds of mental health related illness.

Information 2: *"Just like we surveyed you, we also surveyed other people and we have found from their responses that the proportion of individuals willing to discuss their financial/work related concerns with their peers, how they can be preventing them from achieving their goals, and how they can be overcome is high."*[19]

The second piece of the information was provided closer to the end of the survey (with only a few questions remaining) before the questions related to financial outcomes. The control group received no information on sample beliefs.

Experiment Timeline

We had conducted a small in-person pilot in one of the NGO centres in January, 2020. We adapted the design and survey to avoid any in-person interactions due to COVID-19. As a result, we launched our baseline phone survey (i.e. the first phone call) in November 2020. The survey continued until January 2021. The endline surveys (i.e. the second phone call) for the control group started in February 2021 while the delivery of the intervention statement and endline surveys (i.e. the second phone call) for the treatment group started in mid-March. The surveys for both groups continued until April 2021. The individuals who responded to the second call are the sample for the experiment.

We staggered the treatment delivery and survey to avoid any potentially positive spillover effects from the treated to control groups that could downward bias the measured treatment effects. This is because the randomization is conducted at the individual-level and communities have individuals in both the treatment and control group. About 86% of the control group was surveyed before the first intervention call was made to the treatment group. We also collected additional data on follow-up outcomes (i.e. in the third phone call) after the endline survey. $\sim$ 90% of the follow up survey calls were launched in April and May 2021 after all the calls for the endline had been made. All follow up calls were made atleast 2 weeks after the endline survey for the individual was completed. We discuss the impact of the COVID-19 crisis on our study design and analysis wherever applicable. This is a particular concern for the follow up survey and is discussed in detail when we discuss those results.

Randomisation and Baseline Balance

We used re-randomisation to randomly allocated treatment status to individuals in the baseline sample for the experiment so as to ensure that we achieve balance on baseline covariates. Tables C.3 and C.4 show baseline balance across baseline covariates among treated and control groups along demographic outcomes, well being related outcomes, stigma, first and second order beliefs about mental, physical, and financial health, frequency of dialogue about these issues and their degree in the overall and advice

[19]Note that we do not provide a precise estimate here (the precise estimate of the proportion of individuals willing to share these concerns is 71%) because unlike mental health, where there is high proportion of underestimators, in this case, only 59% underestimate and we do not wish to make them pessimistic.

networks.

7 Results

The endline and follow up surveys are provided in the appendix in Section K and the list of outcomes collected during the endline and follow up are provided in Section D. Before discussing the endline and follow up results, we first discuss and address concerns of balance and attrition.

7.1 Balance and Attrition

We were not able to contact the entire baseline sample intended for the experiment due to phone numbers being switched off, not available, out of network service, or because individuals did not participate in the survey despite repeat attempts. We were only able to reach roughly 50% of our baseline sample for the second call i.e. to administer the treatment and continue with collecting immediate outcomes in the endline survey. Then, we could only contact 62% of this intervention and endline sample in the third call: i.e. to collect follow up outcomes. Our endline sample consists of 181 individuals out of which 92 are in the control group and 89 in the treatment group. Our follow up sample consists of 113 individuals out of which 59 are in the treatment group. Note that attrition between our baseline and endline samples cannot be correlated with treatment status since we only administered the treatment and endline survey on the same (second) call. Individuals were not aware of their treatment status before the second call so there is no reason for systematic dropouts by treatment status. In this section, we outline (a) balance checks to ensure that our endline sample is not systematically different among treated and control participants and (b) balance and attrition checks for the follow-up survey. In addition, we also conduct a sample representativeness check where we test if those who did not pick up our second call (for administration of the treatment and endline outcomes) are different in terms of baseline characteristics from those who did. This is to see if the sample on which the experiment is conducted is different in characteristics from the intended baseline sample. A brief discussion on this is presented in the appendix in Section E.

Balance

First, we run balance tests for the entire endline and follow up samples. We check if the samples are balanced across control and treatment for an exhaustive list of baseline variables including demographic information, information on networks, dialogue intensity, beliefs about mental health, physical health, and financial health, participant, well being, and own willingness to engage. We test balance on 44 variables and find that the sample is unbalanced for 3-5 variables. [20] These results are presented in Tables E.4 and E.5 for the endline sample and Tables E.6 and E.7 for the follow up sample. However, participants

[20]These include lack of balance on the categories of the dialogue intensity variables (eg: "Never", "Rarely" etc) even though the categorical variable mean is balanced.

may not have completed the entire survey as a result of which some outcomes may have received more responses than others. To address this, we adopt the following strategy. We run balance tests for *each* sub-sample for which the outcome variable is non-missing. Then, we include the unbalanced controls (at 5% significance) in the main specification. This robustness exercise is conducted and discussed in the relevant subsections for both endline and follow up results. As we will discuss in the section on follow-up survey results, we suspect that there may be COVID-19 related unobservables that may be unbalanced between our treatment and control group sample in the follow up survey. We discuss the rationale for this and the resulting implications on our follow-up results.

Attrition

Next, we check if attrition in the follow up survey is correlated with treatment status. We compute an indicator of whether an individual who participated in the second phone call (for treatment administration and collection of immediate outcomes) participated in the third phone call (for the follow up survey) and then regress this indicator on their treatment status. We do not find any evidence to suggest differential attrition rates across the treatment and control groups. In addition to the follow-up survey balance checks presented in Tables E.6 and E.7, we also check balance on baseline covariates for the attrited sample and the results are presented in Tables E.2 and E.3. We find that there is balance across 42 out of 44 variables. We also regress attrition status on baseline covariates, treatment, and the interaction terms between the two and find that the F statistic is 1.17 and the corresponding $p - value$ is 0.27. As a result, we do not proceed to address this further.

7.2 Endline Results

Our pre-registered detailed outcomes list, grouped in families for multiple hypothesis correction, is attached in the Appendix Section D. We conduct correction for tests of multiple hypothesis as per Benjamini et al. (2006); Anderson (2008). These q values are computed at the level of the outcome-families (discussed in the outcomes list) since we assume that the hypotheses under which the treatment affects the outcomes in different families are inherently different. The q-values are reported in each table for the respective family of outcomes. We also run an additional robustness exercise where we take a very conservative approach and treat all the outcomes as one family before computing the q values.

First, we find that the treatment statements increase the participant's willingness to engage with their community. These results are presented in Table 2.2. We find that there is a 14 % increase in community engagement (significant at 5%), which is the mean of three binary variables: (a) willingness to train as a listening volunteer for their community, (b) willingness to contribute for this volunteer training program (even if they aren't willing to participate) and (c) willingness to participate in a potential savings group with their

Table 2.2: Treatment Effect on Community Engagement

	(1) Savings Group	(2) Listening Volunteer	(3) Listening Contribution	(4) Contribution (in Rupees)	(5) Community Engagement
Treatment	0.149**	0.153*	0.124**	6.525**	0.136**
	(0.0568)	(0.0697)	(0.0502)	(2.798)	(0.0442)
q-values	0.053	0.053	0.053	0.053	0.053
Constant	0.667***	0.540***	0.738***	22.72***	0.662***
	(0.0406)	(0.0736)	(0.0737)	(2.925)	(0.0532)
Observations	151	175	171	164	151
R-squared	0.029	0.025	0.024	0.029	0.045

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.3: Treatment Effect on Own Health Outcomes

VARIABLES	Speaking to the Doctor (MH)	Depression Scoring (Immediate)	Depression Scoring	Listening to Helpline Numbers
Treatment	0.109	-0.263***	-0.131	-0.188**
	(0.0631)	(0.0711)	(0.118)	(0.0810)
q-values	0.125	0.011	0.199	
Constant	0.118**	0.606***	0.789***	0.591***
	(0.0399)	(0.0684)	(0.0643)	(0.0762)
Observations	155	144	144	138
R-squared	0.021	0.069	0.021	0.035

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.4: Treatment Effect on Other Outcomes

VARIABLES	(1) Memory (Numbers Remembered)	(2) Physical Health Dialogue (with Family)
Treatment	-0.231	0.203***
	(0.333)	(0.0502)
Constant	1.053***	0.184***
	(0.128)	(0.0453)
Observations	154	156
R-squared	0.008	0.050

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The regression specifications use clustered standard errors with NGO centres being the cluster unit. The q-values reported in each table treat the outcomes in the table as multiple hypotheses being tested together.

community. For (a) and (b), we asked individuals if they would be willing to sign up to potentially train and become a 'mental-health buddy' where they would listen to the worries of other members in their community.

Providing community level beliefs about mental health increases the probability of being willing to enlist as a listening volunteer by $\sim$ 15 percentage points. (significant at 10%) While this is a self-reported measure of willingness to volunteer, we also find that participants in the treatment group are $\sim$12 % more likely to wish to financially contribute to the training sessions for this, and donate roughly Rs 6.5 more (a 28% increase compared to control) for this public good for their community (significant at 5%). Individuals were informed that this money would be deducted from their prize of Rs. 50, if they won based on their guesses and would be informed about it at the end of the endline survey. Participant beliefs about their community are balanced across treated and control groups so their is no reason to anticipate that the treatment group would be selectively more pessimistic about their chances of winning this prize. The robustness exercise in Table G.1 shows that the effect of the treatment on this contribution at the intensive and extensive margin is still significant (at 5 and 10 % significance) when the unbalanced controls are included.

We find that $\sim$ 67% of the control group sample is willing to participate in savings groups. We find that the treatment increases this by an additional $\sim$ 15%. (significant at 5%). This question, unlike the other measures of community engagement, was asked *after* the participants received the two treatment statements about mental health and financial health. We will check for heterogeneity in individual baseline beliefs about their community's mental health and financial health related willingness to engage in dialogue to gauge whether this effect is driven by those who underestimated the former. This is discussed in the section on heterogeneity.

Second, we find that the treatment does not affect a participant's demand for additional information about mental health. It does not have any effect on the participant's willingness to participate in a potential mental health related information session and their willingness to listen to good practices about having mental health related conversations. Our ability to detect effects on the information session is low as $\sim$67%) of the control group participants agree to participate in the information session anyway. This is despite the time costs involved in this in future and potential costs in terms of stigma. Individuals may have interpreted this session as one of the regular training sessions (unrelated to mental health) that the NGO organises with them which is why the stigma associated with this may have been low. The results are presented in Table F.1.

Third, we find that the treatment has no effect on the participant's investment in their own health in terms of self-reported hesitation to speak to a doctor and participation in the depression scoring. However, there are two important caveats. One, as we show in the robustness exercise in Table G.3, the effect on their willingness to speak to a

doctor, which is not significant in Table 2.3 (t-statistic =1.73) becomes significant at 5% once the unbalanced controls (for the sub-sample that answered this question) are taken into account. This implies that correction of beliefs about their community may either affect the importance they attach to their own mental health or reduce the stigma around the issue. It raises their willingness to speak to a doctor *and* also their willingness to report to an enumerator that they are willing to do so. As per table G.3, there is a 12 percentage point increase in participant willingness to want to speak to a doctor. Second, while there is no significant difference between the treatment and control group on whether individuals agreed to participate in the depression scoring (immediately or later), individuals in the treatment group are less likely to participate in it immediately. This could be due to two reasons. On the one hand, unlike the self-reported lack of hesitation to visit a doctor, participating in the depression scoring has substantial time costs that are mechanically higher for the treatment group since they attend the call for longer to receive the treatment information. Alternatively, these results may be reflecting that being informed about their community's higher willingness to engage reduces their need to demand more information about their health. An individual's own investments may be a substitute for their community's willingness to engage. We find that the negative effect on participation in depression scoring immediately is also robust to the addition of unbalanced controls. The hypothesis that own investments and community engagement can be substitutes is also corroborated by the finding that the treated group is less likely to listen to helpline numbers at the end of the call.

Fourth, we find that being informed about their community's willingness to engage has positive spillover effects on dialogue pertaining to physical health. The treated group is 20% more likely to report a willingness to talk to their friends and family about physical health related issues. We know from the baseline survey that individuals have high levels of stigma associated with talking about physical health related concerns. We find that the treatment effect is robust to the addition of unbalanced controls as well as shown in Table G.6. This result suggests that correcting beliefs about a community's stance on mental health related dialogue can have positive impacts on individual's beliefs about their friends and family and on their willingness to engage in dialogue on other stigmatised topics. We do not find any significant effect on memory recall.

Finally, we find no impacts on outcomes measuring stigma, self efficacy, and interaction preferences. These results are reported in the appendix in tables F.2, F.3, F.4. Contrary to our prior, 92% of the individuals in the control group were willing to allow their name to be revealed to encourage others to participate in the information session by mentioning that they agreed. Given the baseline finding of considerable stigma around mental health, it is likely that this was not a good measure of stigma. This could have occurred because individuals may have interpreted the information session as one of the usual trainings held by the NGO that will be attended by other community members anyway so has no costs (in terms of stigma) attached to it. We also do not find any effect on an individual's belief in their ability to manage their finances, afford their children's education (if applicable), or

start a business if they wanted to. Our prior was that correction of beliefs about community willingness to engage with *both* financial and mental health would have improved financial self efficacy as it was asked after the two statements. However, the finding provides suggestive evidence that traditional mechanisms of risk-sharing may not already be in place within the community so being more optimistic about them in terms of dialogue doesn't necessarily mean that one can borrow from them in times of need. That individuals wish to engage in such risk-sharing is also evident from a significant increase in the willingness to participate in a savings group following the treatment.

The q-values for all the main regressions are reported in the relevant tables. We also take a more conservative approach by combining all outcomes together and compute the q values. We find that average community engagement (q-value= 0.084), immediate participation in the depression scoring (q-value= 0.044), and willingness to speak to family and friends about physical health are still significant (q-value= 0.044).

Heterogeneity

We analyse heterogeneous effects by baseline stigma, baseline beliefs, and social networks. The results are shown in Tables H.1-H.4. Table H.1 shows that conditional on saying 'Yes' to donating towards the public good, individuals who are stigmatised against mental health (who report they wish to "stay away" from those suffering from mental health concerns) donate Rs. 12 less compared to those who didn't explicitly report stigma at baseline. This is expected since the public good is directly associated with mental health as it is a listening service. Interestingly, we find that stigmatised individuals in the treatment group donate Rs 12 more than stigmatised individuals in the control group. This suggests that while receiving optimistic beliefs about community engagement may not eradicate stigma, it significantly increases altruism towards the community. We also find, as shown in Table H.2 that while the treatment on average increases self-reported willingness to talk to a doctor about mental health, this effect is lower (but still positive) for those who are stigmatised against mental health during the baseline. Note that these regressions additionally control for any unbalanced baseline variables in the sub-sample with non-missing values of the outcome and the variable of interest to test heterogeneity.

We also find some evidence of heterogeneity by an individual's degree in their overall network as shown in Table H.3. Individuals who are more connected in the network are more likely to respond to the treatment by reporting to be willing to participate in the savings group. In fact, the treatment effect is zero for those who have no peers in the network and every additional peer increases the probability that a treated individual says 'Yes' to participation by 5%. Individuals who have more peers are less likely to make positive contributions for the training for the listening service in the community but the treatment increases this probability. Aside from this, we do not find any evidence of heterogeneity by advice or overall network degrees or whether the individuals were underestimators for mental health or employment related beliefs during the baseline.

We do not find any evidence of heterogeneity by whether the individuals were under-estimators of mental health related engagement as per the information about the sample average provided to them. Under-estimators do not have higher treatment effects as one would expect. We also do not find any evidence of heterogeneous effects of being an underestimator of financial health related engagement during the baseline.

Impact of COVID-19

The treatment and endline calls were made from 23rd February to 11th April, 2021. The control group was called before the treatment group to ensure that spillovers do not contaminate the treatment effect. Unlike the follow up survey, the endline survey was not conducted during the peak of the COVID-19 crisis. It is important to note that the rise in cases during the period when the endline survey was conducted was not the first time our sample was exposed to COVID-19 or rising cases. Similar episodes were recorded in 2020. However, we report two robustness exercises that confirm that the rise in COVID-19 cases in Delhi during these months did not drive our findings on the endline outcomes.

First, we divide individuals in the treatment group into two equal groups based on whether they were called before or after 30th March, 2021. The date is chosen to ensure equal division of the treatment group. We then check if our outcomes systematically differ for the treatment group before and after this date. The salience of COVID-19 was rising during this period as cases increased. If it were the case that the outcomes we detect a positive effect on were increasing due to COVID-19, it would be the case that the latter half of the treatment group would have higher outcomes compared to the former half. We do not find this to be the case for any outcome for which we detect an effect, except the contributions to a public good in which we find that there is a reduction after 30th March. This suggests, that if anything, the treatment effect on the public good contribution would be higher in the absence of a growing crisis. These results are presented in Tables I.1 and I.2.

Next, we conduct the analysis only including half of the treatment and control groups. All individuals who were called before 7th March and after 30th March are removed from the sample. These dates are chosen to ensure that 50% of both the treatment and control groups are retained. We control for unbalanced baseline variables as before. The results are shown in Tables I.3 and I.4. Despite this conservative specification that removes half the sample and then controls for unbalanced baseline variables specifically chosen for the sub-sample for which the outcome is non-missing, we still find that there is a positive effect (significant at 10 %) on an individual's probability of signing up to be a listening volunteer and to be willing to contribute towards the public good i.e. the training for the listening service. We also find that the negative impact on willingness to engage in immediate depression scoring and to listen to helpline numbers persists despite the conservative specification.

7.3 Follow up Survey Results

Around 90% of our follow up surveys were conducted during or after April 2021. This was during the peak of the COVID crisis in India and we were informed that some of our study participants had moved to their villages and left Delhi. This affects our follow up survey results in two ways. One, it restricted the number of people we could contact both due to connectivity issues. The crisis also affected some of our enumerators' pace of making calls during this stressful period. We could only contact 113 people, 57 of which were in our treatment group. Second, while we check for balance along the entire set of baseline controls and include unbalanced controls in our robust regression specifications, we do not have information on the participant's or their peers' exposure to COVID-19 and more importantly, their location. Differential exposure to COVID risk, dependent on treatment status, can affect some of the outcomes we have measured during the follow up survey.

We discuss these as we proceed. Tables J.1 to J.3 show the follow up results without controlling for unbalanced controls. The tables also include q values which are computed by including all outcome variables. Tables J.4 to J.6 include unbalanced controls treating the sample for which the outcome is non-missing as the follow up sample.

First, we find in Table J.1 individuals who received the treatment are $13-22\%$ more likely to have reported that they made a call to their peers to discuss their own or their peers' mental health or employment related concerns respectively. We also document positive effects at the intensive margin since we also asked individuals how many peers they spoke to. The treated group has spoken to significantly more number of peers about both mental health and employment related concerns. The results are robust to the inclusion of unbalanced controls as seen in Table J.4. It is worth noting that the effect on dialogue is stronger, and in the case of mental health only present, when individuals in the treated sample are making the calls rather than receiving them. This could suggest that either (a) the treatment is at work here since it only impacts the participants and not their peers or (b) the treatment group is located in an area with low COVID-19 risk and is able to make these calls more than control group. If individuals in areas of high COVID-19 risk are more likely to be in the treatment group, then these one-sided effects on dialogue suggest that the treatment is driving them.

Next, we find in Table J.3 that individuals in the treatment group are likely to donate Rs 30 more than the control group in a hypothetical dictator game where they can split Rs 200 with a randomly chosen member of their community. This result is robust to the inclusion of unbalanced controls as well, as seen in Table J.6. However, we also document that individuals in the treatment group are more likely to report higher levels of unhappiness, stress, and lower life satisfaction. Given that we find an increase in dialogue, a potential mechanism explaining this could be that a conversation where employment/mental health related risk is shared becomes ineffective in the presence of correlated risks such as COVID-19. This can explain the low levels of well-being. Alternatively, it could also be the case

that either (a) the treatment group has lower well being because they have migrated to an area of low COVID risk and hear about the impact of the pandemic on their peers via increased dialogue or (b) the treatment group is located in an area of high COVID risk and well being is consequently lower. We believe that mechanism (a) seems to be more likely due to the increased amount of donations made by the individuals in the dictator game. This is also substantiated by the result in Tables J.2 and J.5 that the treatment group wears COVID-19 masks less often than the control group. 92% of our sample reports to have *always* worn a mask in the past two weeks before the call and the negative effect on the treatment only driven by the remaining 8%.[21] Individuals in low risk-areas may have been less likely to wear COVID-19 safety masks. We also find that the treatment group wears a work safety gear significantly more often than the control group, conditional on having worked. We also find that the proportion of individuals for whom the question on safety gear is missing, is higher for the treatment group after controlling for unbalanced baseline variables. This again suggests that they may have migrated from their place of work into an area of low risk and exposure to COVID-19. We find positive treatment effects on wearing safety gear among those who do answer the question.

Thus, while we document positive effects on dialogue, altruism, and safety gear adoption, we also document negative effects on happiness, life-satisfaction, stress, and wearing masks during COVID-19. The positive effect on safety gear adoption and the negative effect on masks contradict each other so it is difficult to conclusively establish if the treatment increased or reduced the attention individuals pay to their physical health. While we have discussed a potential explanation which rationalises the findings (namely, migration out of Delhi as reported by a number of our enumerators), we do not have conclusive evidence to substantiate this. As a result, it is difficult to make conclusive inferences from the follow up results.

8 Conclusion

In this paper, we show that misperceptions about engagement in the community can affect an individual's own advice-taking behavior. We structurally estimate a model that shows how beliefs are influenced by an individual's social network, present reduced form results using secondary data that validate this claim, and then present the results of a randomised controlled trial to measure the impact of correction of misperceptions around financial and mental health on an individual's choice to engage in interpersonal dialogue about mental health.

Our results make three contributions to the literature. First, we apply existing theory on the friendship paradox (Jackson, 2019) to (a) show that individuals can overestimate the costs of engaging in interpersonal dialogue and (b) illustrate the need for a belief correction intervention. Next, we construct and use a measure of an individual's engagement in

[21] We also reminded all our participants to follow COVID-19 guidelines implemented in their area at the end of the survey.

interpersonal dialogue- the differences in the links between different networks. We use this to structurally estimate the model to highlight the heterogeneity in the type and magnitude of equilibrium engagement depending on the structure of the network. This allows us to comment on the usefulness of belief-correction interventions. Our counterfactual exercises show that measurements of belief-correction interventions are sensitive to the time-period over which the results are collected and the degree distribution of the network determines the magnitude of observed treatment effects.

Finally, we conduct a RCT with a difficult to reach sample of low income workers in New Delhi, India during the COVID-19 crisis when advice-taking relationships can be of immense value. Our baseline results suggest that individual beliefs about sample willingness to engage in a conversation about mental health are correlated with dialogue intensity and the network measure of disengagement implying that network gaps can be used as a proxy for disengagement. We find that correction of beliefs about average community engagement with mental and financial health increase community engagement in terms of an individual's willingness to volunteer for a listening service, participation in a savings groups, and contribution to a public good. In addition, we find evidence for positive spillover effects on willingness to engage in dialogue pertaining to physical health.

Although most of our results capture immediate effects of the information, we find suggestive evidence of longer-term effects in our follow-up survey on self-reported dialogue and altruism towards the community. Our ability to disentangle these mechanisms is constrained by the effect of COVID-19 crisis on the implementation of our follow-up survey. Our findings of higher community engagement and contributions towards a public good suggest that belief-correcting interventions can be used to strengthen social ties. The long-run effect of such an intervention in the presence of correlated shocks remains to be explored further.

Appendix

A Theory

Proof for Lemma 1

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Consider the distribution function of the probability mass function $\widetilde{P}(d)$

$$\widetilde{\mathbf{P}}(\bar{\mathbf{d}}) = \sum_{d=1}^{d=\bar{d}} \widetilde{P}(d)$$

We first prove that the CDF corresponding to P is first order stochastically dominated by the CDF corresponding to $\widetilde{P}$. Consider $\bar{d} \leq E[d]$. In this case, $\sum_{d=1}^{d=\bar{d}} \widetilde{P}(d) = \sum_{d=1}^{d=\bar{d}} \frac{d}{E[d]} P(d) \leq \sum_{d=1}^{d=\bar{d}} P(d)$ since $\frac{d}{E(d)} \leq 1$.

When $\bar{d} > E[d]$, then $\sum_{d=1}^{d=\bar{d}} \widetilde{P}(d) = 1 - \sum_{\bar{d}}^{d=d_{max}} \widetilde{P}(d)$. The second term can be written as $\sum_{\bar{d}}^{d=d_{max}} \widetilde{P}(d) = \sum_{\bar{d}}^{d=d_{max}} \frac{d}{E(d)} P(d) > \sum_{\bar{d}}^{d=d_{max}} P(d)$ since $\frac{d}{E(d)} > 1$. So, $\sum_{d=1}^{d=\bar{d}} \widetilde{P}(d) < \sum_{d=1}^{d=\bar{d}} P(d)$ in this case as well. Hence, $\widetilde{\mathbf{P}}(\bar{\mathbf{d}})$ first order stochastically dominates $\mathbf{P}(\bar{\mathbf{d}})$.

We can rewrite

$$\sum_{d} \widetilde{P}(d) H(c(d,a)) = H(c(d_{max},a)) - \sum_{d=1}^{d=d_{max}-1} \widetilde{\mathbf{P}}(\mathbf{d})(H(c(d+1,a)) - H(c(d,a)))$$

and similarly rewrite

$$\sum_{d} P(d) H(c(d,a)) = H(c(d_{max},a)) - \sum_{d=1}^{d=d_{max}-1} \mathbf{P}(\mathbf{d})(H(c(d+1,a)) - H(c(d,a)))$$

Given that H is weakly increasing in degree d and$\widetilde{\mathbf{P}}(\mathbf{d}) < \mathbf{P}(\mathbf{d})$, this implies that-

$$\sum_d \widetilde{P}(d)H(c(d,a)) \geq \sum_d P(d)H(c(d,a))$$

.

Proof for Proposition 1

Click to go back.

If c and consequently H is strictly increasing in degree, Lemma 1 implies that $\widetilde{E}[H(c(d,z'))] > E[H(c(d,z')] \ \forall z' \in (0,1]$. This means that for any fixed point z that satisfies Equation 2.2, $\widetilde{E}[z] > z$. Given that we have assumed H to be such that there are three equilibria out of which 1 is unstable, this implies that the fixed points a_l and a_h solving equation 2.2 will not solve equation 2.3 and (b) the fixed points $\widetilde{a}_h$ and $\widetilde{a}_l$ that solve 2.3 will be such that $\widetilde{a}_l < a_l$ and $\widetilde{a}_h > a_h$.

The intuition for Case 2 is analogous.

B Secondary Data

Descriptives

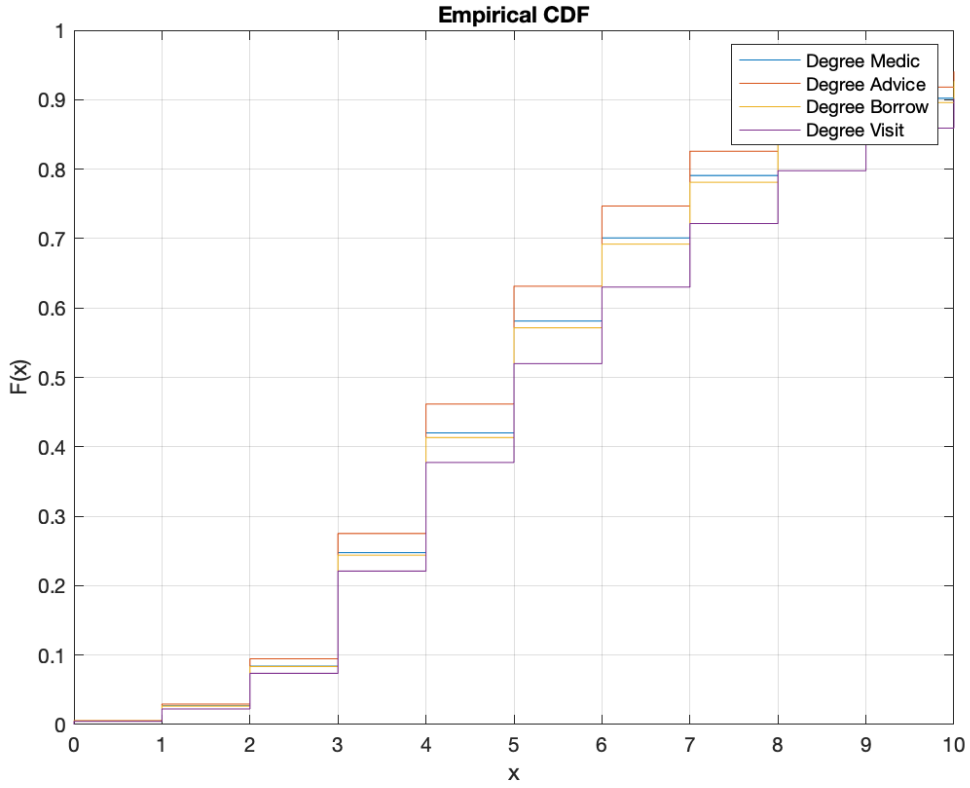
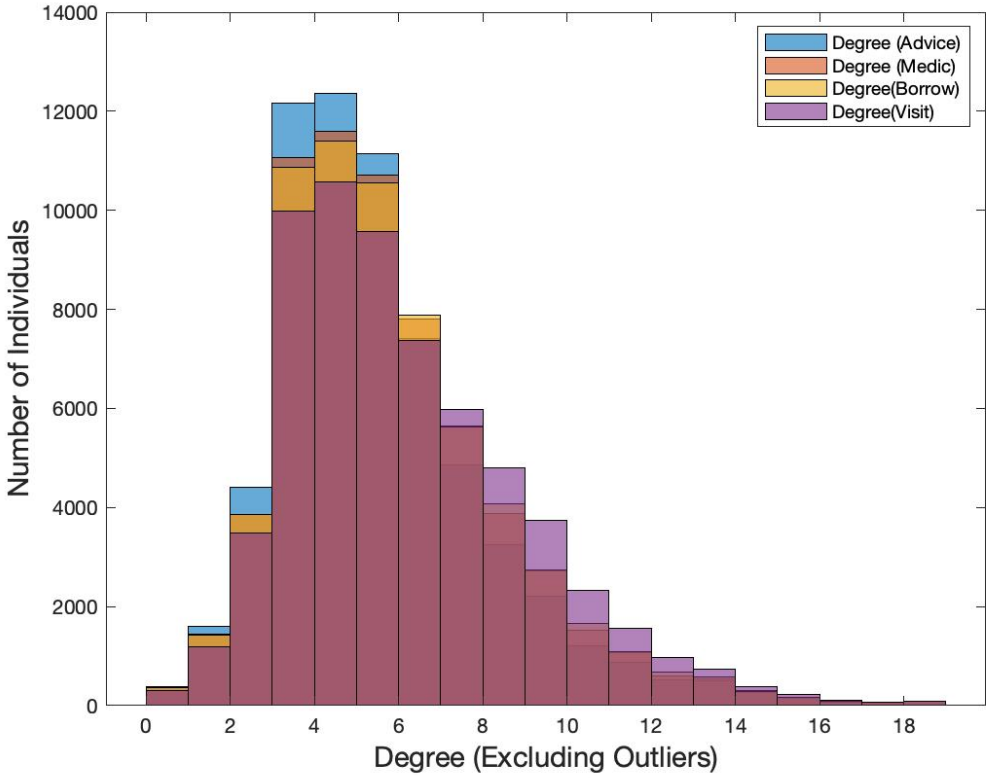


Figure B.1: Cumulative Distribution Functions of Degree in Advice, Borrowing, Visit and Medical-help networks from the data in Banerjee et al. (2013).

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Figure B.2: Histogram of Degree in Advice, Borrowing, Visit and Medical-help networks.



Notes: Histogram of individual degrees from four different networks collected in Banerjee et al. (2013). Frequency of degrees in the advice network are higher at lower values.

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Table B.1: Summary Statistics

	Means	Standard Deviation
Female	0.554	(0.497)
Age	39.00	(12.68)
Degree (Overall)	15.82	(6.012)
Education		
No Education	0.377	(0.485)
Primary	0.158	(0.365)
Secondary	0.359	(0.480)
Secondary+	0.0989	(0.299)
Religion		
Hinduism	0.958	(0.200)
Islam	0.0403	(0.197)
Christianity	0.00153	(0.0391)
Caste		
Scheduled Caste	0.251	(0.434)
Scheduled Tribe	0.0602	(0.238)
Other Backward Class	0.564	(0.496)
General	0.121	(0.327)
Native	0.559	(0.497)
Observations	16977	

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Reduced Form Results

Table B.2: Reduced Form Results for Disengagement

VARIABLES	(1)	(2)	(3)
	Disengagement (Alternative)		
Peer Average	0.902***	0.889***	0.625
	(0.016)	(0.017)	(0.393)
Degree (Social Network)	0.001*	0.001*	0.000
	(0.001)	(0.001)	(0.001)
Constant	0.507***	0.555***	
	(0.077)	(0.084)	
Observations	10,253	10,253	10,253
R-squared	0.429	0.437	0.280

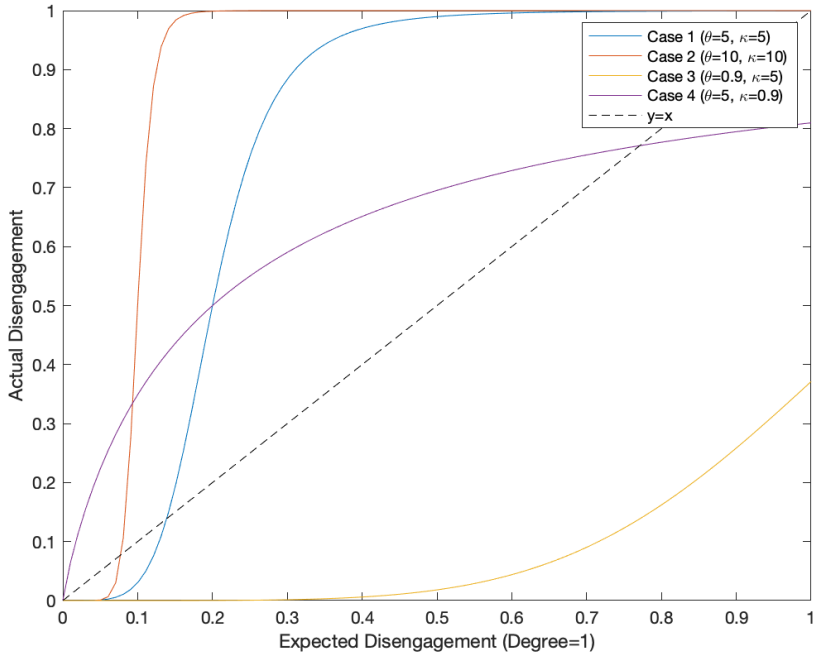
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: All regressions control for demographic variables such as gender, age, whether the individual is a native, head of household, religion etc and economic variables such as number of rooms, beds, type of electricity, latrine type, roof type etc. Regressions also control for these characteristics averaged across an individual's peer group. Column 2 additionally controls for village fixed effects and Column 3 shows the results from a 2SLS regression where peer average is instrumented using the average gender and education of the friends of an individual's friends who are not the individual's friends. Standard errors are clustered at the village level.

Click to go back.

Structural Estimation

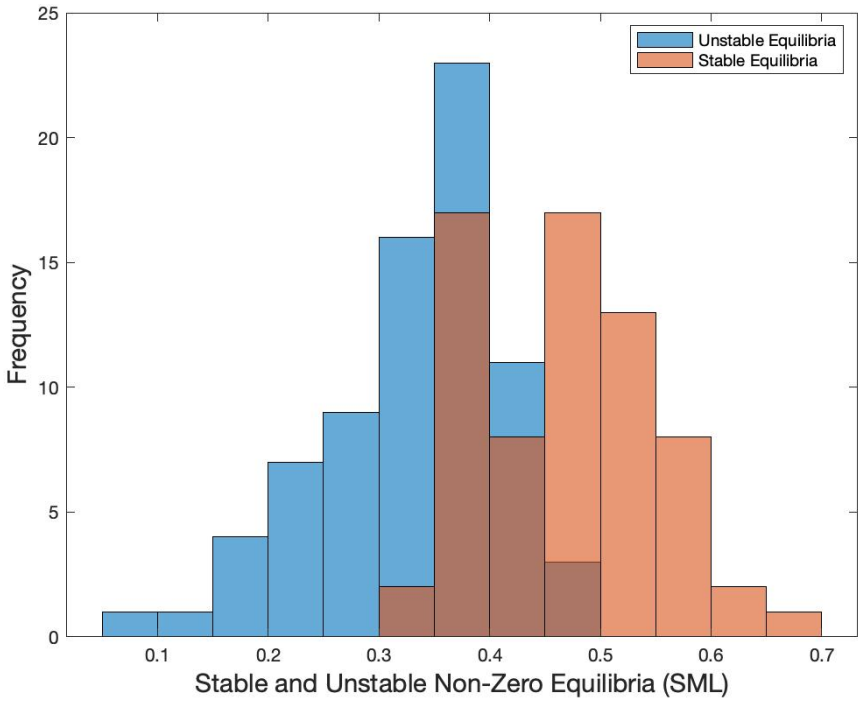
Figure B.3



Notes: The above figure shows the shape of the log logistic distribution function for different values of θ and κ in a society where agents have degree 1.

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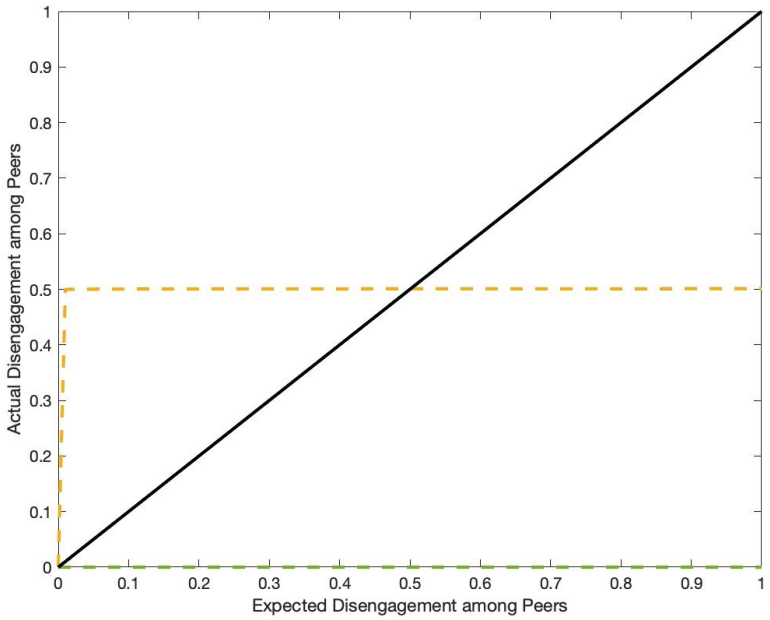
Figure B.4: Stable and Unstable Non-Zero Equilibria



Notes: Figure plots the histogram of the non-zero stable and unstable equilibria for all villages. Equilibria are determined using the estimated θ (parameter for strength of peer complementarity) and κ (parameter of the log-logistic cost distribution) estimated by the Maximum Likelihood Estimation Procedure using the main measure of disengagement. We determine whether they are stable or unstable by looking at the implied expected disengagement at the point close to to the left and right of the equilibrium and the 45-degree line.).

Click to go back.

Figure B.5: Expected and Actual Disengagement (evaluated for the two θ, κ starting value pairs)

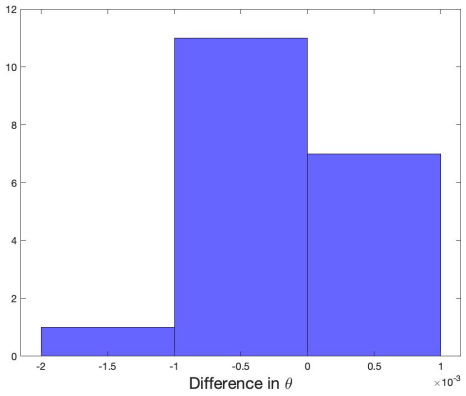


Notes: The curve in yellow is evaluated at $\theta = 5, \kappa = 0.001$ and vice-versa for the curve in green. These curves evaluated at these initial starting points are plotted for all the randomly chosen villages used for identification checks.

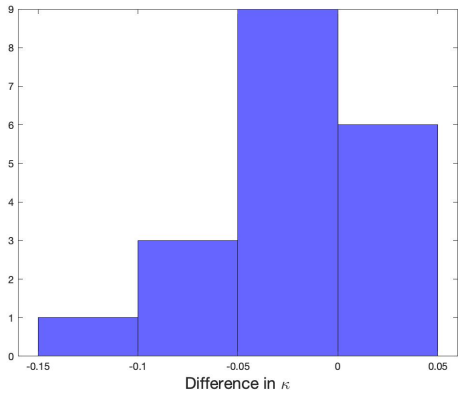
Click to go back.

Figure B.6: Structural Estimation Robustness Results (Starting Values: θ low, κ high)

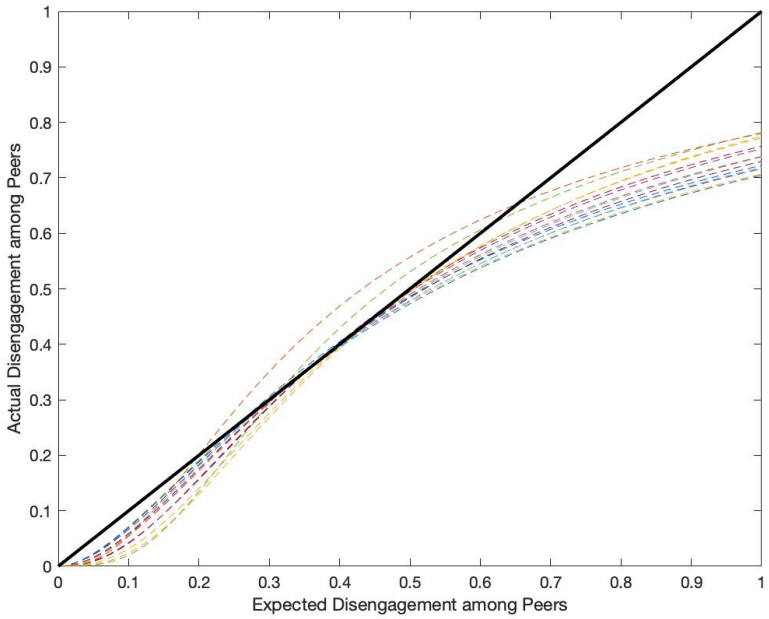
(a) θ (Main)- θ (Robust)



(b) κ (Main)- κ (Robust)



(c) Implied Expected Disengagement

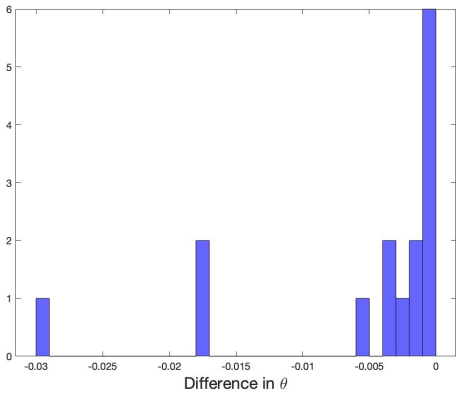


Notes: Panel (a) illustrates the difference in estimated θ for the main and robust estimation with starting parameters {1,1} and {0.001,5} respectively. Panel (b) illustrates this difference for κ. We conduct this exercise across randomly chosen villages. Panel (c) plots the expected and actual disengagement at the estimated θ and κ.

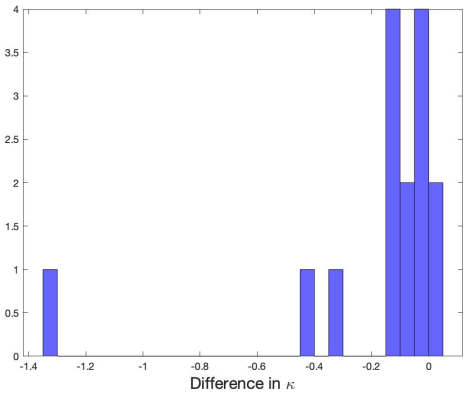
Click to go back.

Figure B.7: Structural Estimation Robustness Results (Starting Values: θ high, κ low)

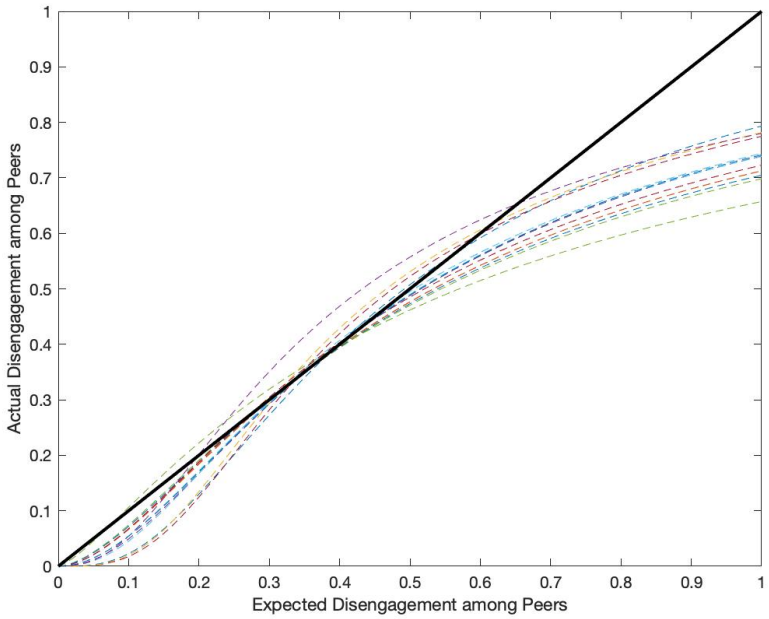
(a) θ (Main)- θ (Robust)



(b) κ (Main)- κ (Robust)



(c) Implied Expected Disengagement



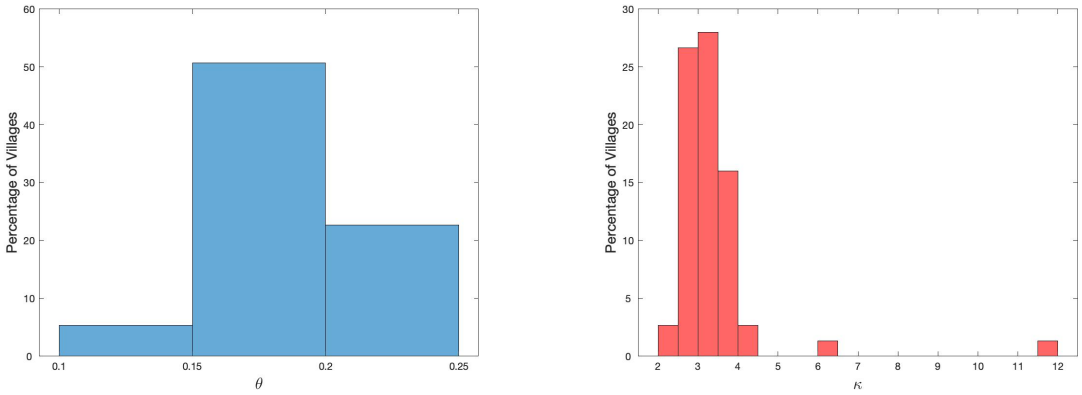
Notes: Panel (a) illustrates the difference in estimated θ for the main and robust estimation with starting parameters {1,1} and {5, 0.001} respectively. Panel (b) illustrates this difference for κ. We conduct this exercise across randomly chosen villages. Panel (c) plots the expected and actual disengagement at the estimated θ and κ (using the new starting values) for these villages.

Click to go back.

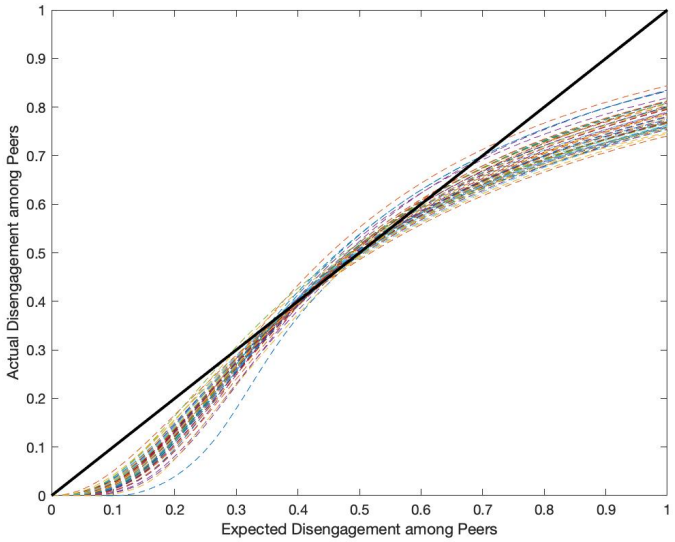
Structural Estimation using Method of Moments

Figure B.8: Structural Estimation Results: Method of Moments

(a) (b)



(c) Implied Expected Disengagement



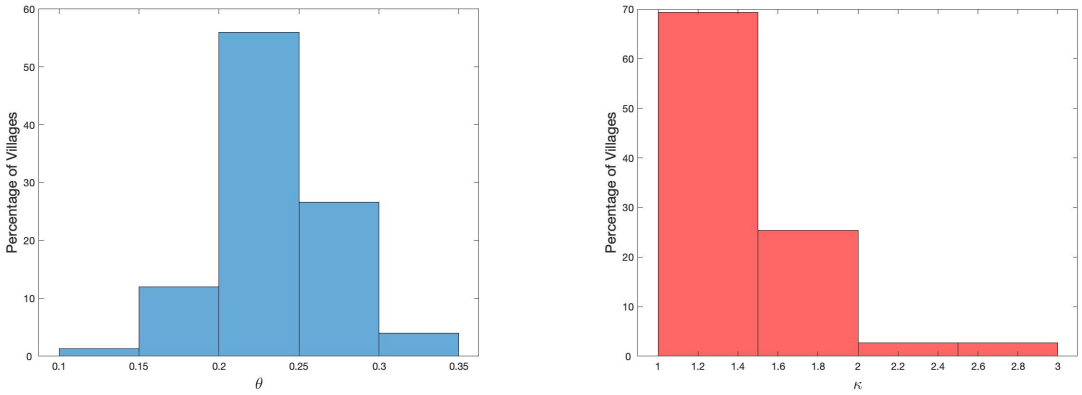
Notes: Panels (a) and (b) illustrate the distribution of estimated θ (parameter for strength of peer complementarity) and κ (parameter of the log-logistic cost distribution) across the 75 villages respectively. The estimated method used is Method of Moments using the mean disengagement and variance in disengagement in a village as the two moments. Panel (c) plots the implied expected disengagement at the estimated θ and κ for each village. The starting values of θ and κ are {1,10} respectively. We also run this estimation for starting values {1,1} and find that around 68% of villages reach a similar value of θ and κ resulting in three equilibria. Pattern-search does not converge to the correct optima for the remaining villages. The value of the objective function for the remaining 24 villages is more than 10^3 times higher and the estimation generates a very high value of κ greater than 100 for 21 villages out of these 24.

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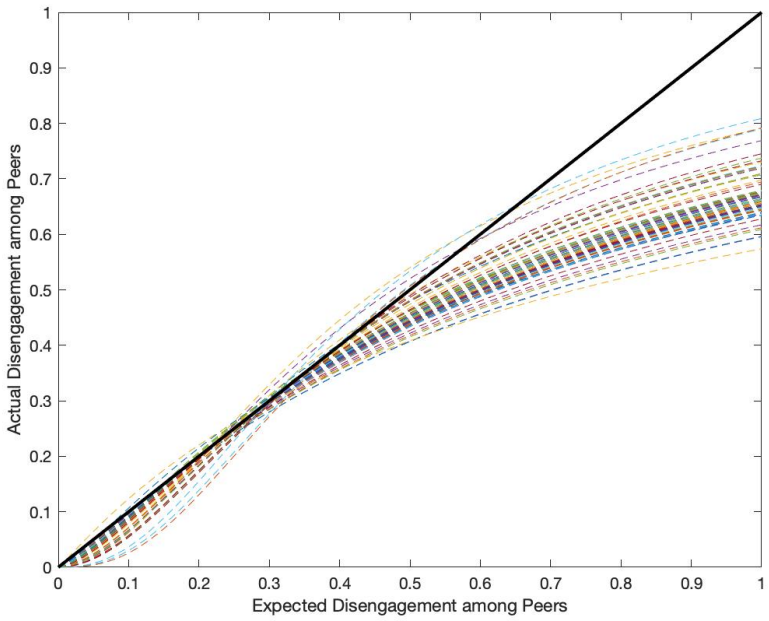
Structural Estimation using Alternative Measure

Figure B.9: Structural Estimation Results for Alternative Measure: Maximum Likelihood

(a) (b)



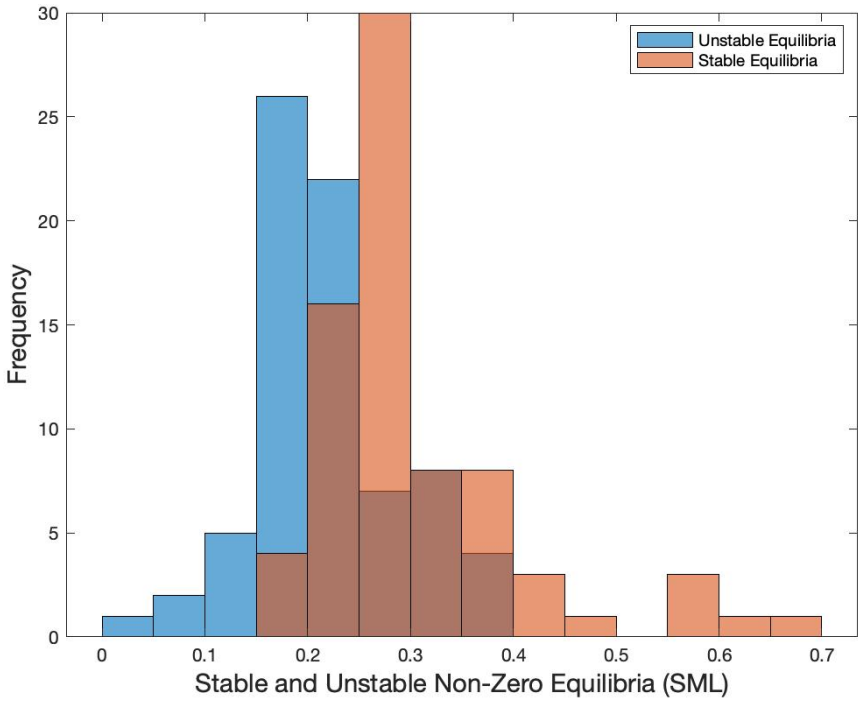
(c) Implied Expected Disengagement



Notes: Panels (a) and (b) illustrate the distribution of estimated θ (parameter for strength of peer complementarity) and κ (parameter of the log-logistic benefit distribution) across the 75 villages respectively using the alternative measure of disengagement using the favour-taking and advice networks. Panel (c) plots the implied expected disengagement at the estimated θ and κ for each village.

Click to go back.

Figure B.10: Stable and Unstable Non-Zero Equilibria



Notes: Figure plots the histogram of the non-zero stable and unstable equilibria for all villages. Equilibria are determined using the estimated θ (parameter for strength of peer complementarity) and κ (parameter of the log-logistic cost distribution) estimated by the Maximum Likelihood Estimation Procedure using the alternative measure of disengagement. We determine whether they are stable or unstable by looking at the implied expected disengagement at the point close to to the left and right of the equilibrium and the 45-degree line.).

Click to go back.

C Baseline Results

Baseline Tables and Figures

Table C.1: Summary Statistics

	Mean	SD
Age	33.67	(9.352)
Female	0.351	(0.478)
Monthly HH Income (< Rs 2,500)	0.152	(0.360)
Monthly HH Income (Rs 2,500-5,000)	0.195	(0.397)
Monthly HH Income (Rs 5,000-10,000)	0.443	(0.497)
Monthly HH Income (Rs 10,000+)	0.210	(0.408)
Employed	0.652	(0.477)
Degree (Advice)	2.793	(3.358)
Degree (Overall)	3.760	(3.653)
Stress (Index; Scale 1-4)	3.068	(0.862)
Satisfaction (Scale 1-4)	2.866	(0.946)
Happiness (Scale 1-4)	2.484	(0.983)
Difficulties- High (Binary)	0.495	(0.501)
Observations	362	

Click to go back.

Table C.2: Summary Statistics (Click to go back.)

	Mean	SD
Willingness to Talk (Employment)	0.711	(0.454)
Willingness to Talk (Mental Health)	0.636	(0.482)
Willingness to Talk (Physical Health)	0.627	(0.484)
Stigma (Physical Health)	0.556	(0.498)
Stigma (Mental Health)	0.505	(0.501)
Beliefs (Mental Health)	5.014	(3.027)
Beliefs (Physical Health)	5.127	(3.040)
Beliefs (Employment)	5.982	(3.195)
Beliefs -Stigma (Mental Health)	4.789	(3.298)
Beliefs -Stigma (Physical Health)	4.812	(3.276)
Beliefs -Stress (Mental Health)	5.648	(3.303)
Physical Health talk (Scale 1-5)	2.208	(1.313)
Physical Health talk (Never)	0.423	(0.495)
Physical Health talk (Rarely)	0.220	(0.415)
Physical Health talk (Sometimes)	0.164	(0.371)
Physical Health talk (Often)	0.113	(0.317)
Physical Health talk (Very Often)	0.0804	(0.272)
Mental Health talk (Scale 1-5)	2.529	(1.311)
Mental Health talk (Never)	0.288	(0.454)
Mental Health talk (Rarely)	0.252	(0.435)
Mental Health talk (Sometimes)	0.189	(0.392)
Mental Health talk (Often)	0.183	(0.387)
Mental Health talk (Very Often)	0.0871	(0.282)
Employment talk (Scale 1-5)	2.857	(1.468)
Employment talk (Never)	0.247	(0.432)
Employment talk (Rarely)	0.213	(0.410)
Employment talk (Sometimes)	0.177	(0.382)
Employment talk (Often)	0.162	(0.369)
Employment talk (Very Often)	0.201	(0.402)
Observations	342	

Click to go back.

Table C.3: Baseline Balance: Demographics and Health

	Control	Treatment	p-value
Age	34.04	33.24	0.43
Female	0.37	0.33	0.37
Monthly HH Income (< Rs 2,500)	0.13	0.16	0.51
Monthly HH Income (Rs 2,500-5,000)	0.19	0.21	0.65
Monthly HH Income (Rs 5,000-10,000)	0.47	0.42	0.38
Monthly HH Income (Rs 10,000+)	0.21	0.21	0.96
Employed	0.67	0.64	0.58
Stress (Index; Scale 1-4)	3.08	3.05	0.73
Satisfaction (Scale 1-4)	2.81	2.92	0.27
Happiness (Scale 1-4)	2.44	2.52	0.43
Difficulties- High (Binary)	0.51	0.48	0.62
Degree (Advice)	2.60	3.06	0.19
Degree (Overall)	3.67	4.29	0.14
N	178	178	

Notes: N=356 includes all individuals in the intended sample for the experiment.

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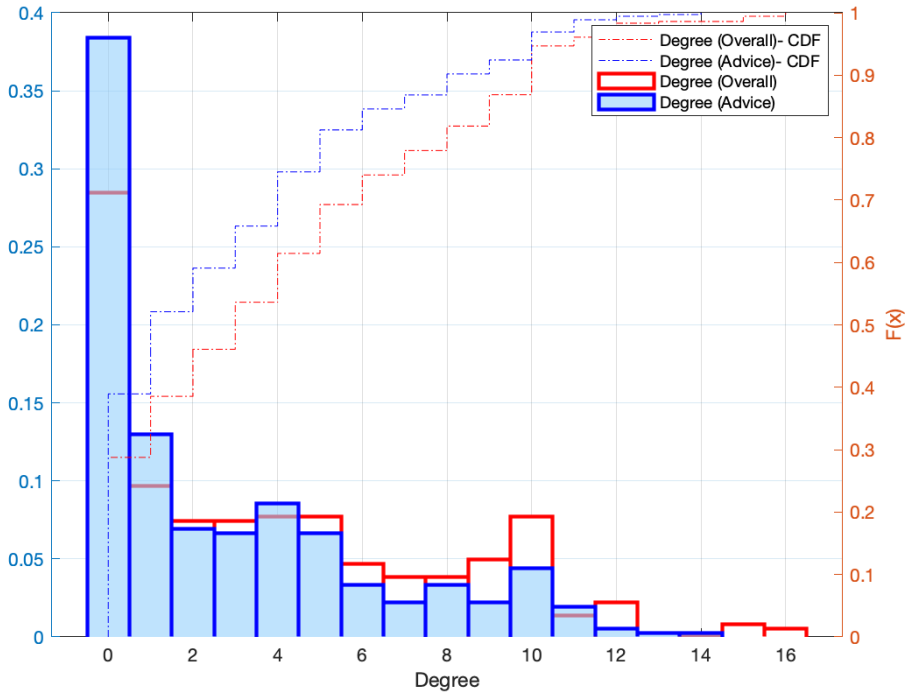
Table C.4: Baseline Balance Table: Willingness to Talk and Beliefs at Baseline

	Control	Treatment	p-value
Willingness to Talk (Employment)	0.73	0.69	0.51
Willingness to Talk (Mental Health)	0.66	0.61	0.33
Willingness to Talk (Physical Health)	0.65	0.60	0.32
Stigma (Physical Health)	0.59	0.52	0.25
Stigma (Mental Health)	0.53	0.48	0.43
Beliefs (Mental Health)	5.10	4.94	0.66
Beliefs (Physical Health)	5.29	4.92	0.31
Beliefs (Employment)	5.92	6.06	0.71
Beliefs -Stigma (Mental Health)	4.81	4.74	0.86
Beliefs -Stigma (Physical Health)	4.96	4.67	0.47
Beliefs -Stress (Mental Health)	5.66	5.64	0.96
Physical Health talk (Scale 1-5)	2.28	2.14	0.33
Physical Health talk (Never)	0.41	0.43	0.61
Physical Health talk (Rarely)	0.22	0.22	0.98
Physical Health talk (Sometimes)	0.15	0.17	0.47
Physical Health talk (Often)	0.13	0.10	0.48
Physical Health talk (Very Often)	0.10	0.07	0.31
Mental Health talk (Scale 1-5)	2.54	2.51	0.83
Mental Health talk (Never)	0.31	0.27	0.32
Mental Health talk (Rarely)	0.19	0.31	0.01
Mental Health talk (Sometimes)	0.20	0.17	0.50
Mental Health talk (Often)	0.22	0.14	0.07
Mental Health talk (Very Often)	0.07	0.10	0.26
Employment talk (Scale 1-5)	2.79	2.92	0.43
Employment talk (Never)	0.25	0.24	0.77
Employment talk (Rarely)	0.21	0.23	0.69
Employment talk (Sometimes)	0.19	0.16	0.39
Employment talk (Often)	0.19	0.13	0.18
Employment talk (Very Often)	0.16	0.24	0.05
N	178	178	

Notes: N=356 includes all individuals in the intended sample for the experiment.

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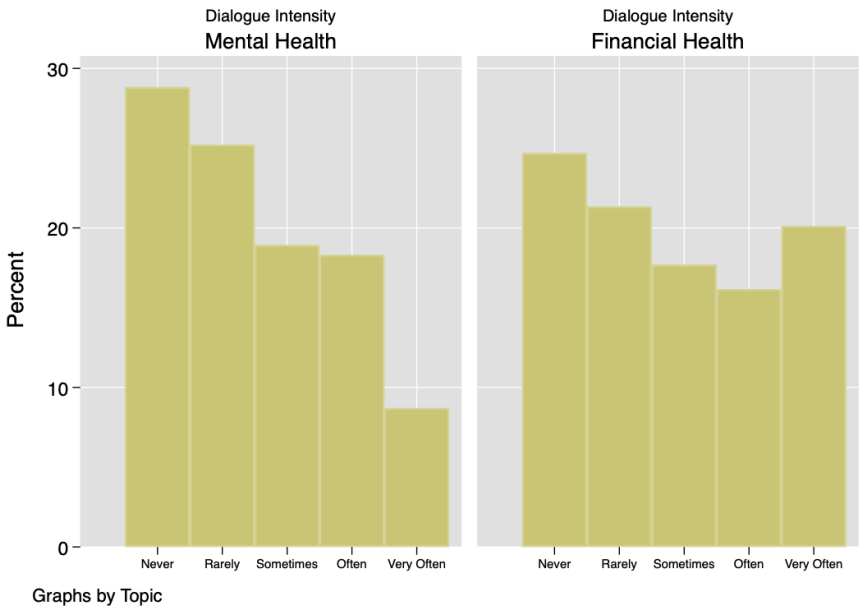
Figure C.1: Degree Distributions for Advice and Overall Networks



Notes: Individuals were asked to list up to ten other individuals in their community whom they interact with to borrow/lend, take/give advice, work with etc (overall networks) and whom they only take advice from regarding mental health issues (advice networks).

Click to go back.

Figure C.2: Intensity of Dialogue in the last two weeks

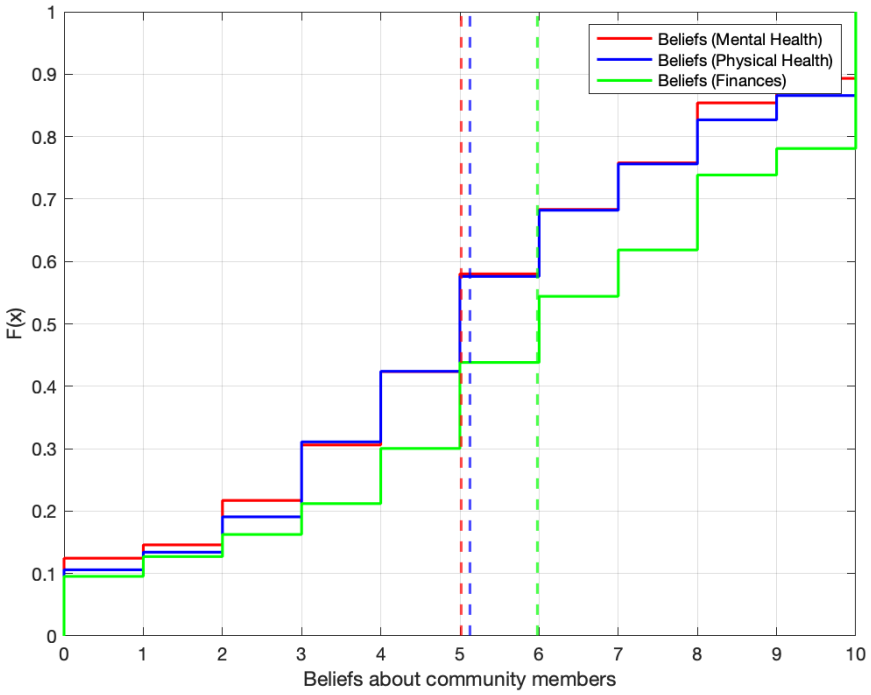


Notes: This measure of dialogue intensity is created by asking individuals to report the frequency of dialogue around these topics in the last two weeks. See Q16 in the baseline survey.

Click to go back.

Figure C.3: Second order Beliefs about Mental, Physical, and Financial Health

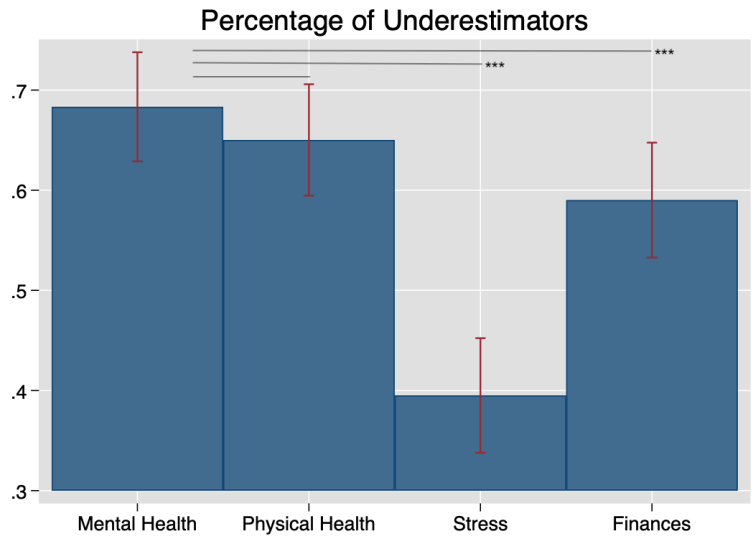
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Notes: Individuals were asked to guess how many community members (out of a randomly chosen 10) would be willing to engage in a dialogue about these issues. Individual guesses were monetarily incentivised to ensure truthful reporting. The dotted lines indicate sample averages. Beliefs about engagement with financial health stochastically dominate beliefs about engagement with mental health.

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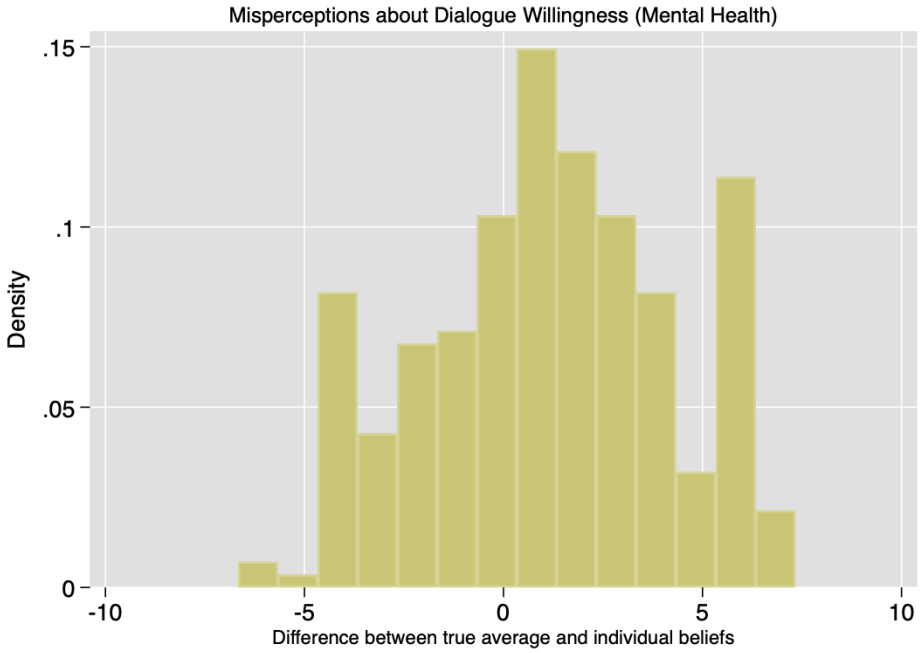
Figure C.4: Percentage of Underestimators



Notes: Stars indicate significance of two-sided t-tests comparing average number of underestimators with respect to mental health related dialogue with average underestimators with respect to other topics.

Click to go back.

Figure C.5: Distance between individual beliefs and community average (Mental Health)



Click to go back.

Table C.5: Correlations of Network Gaps and Dialogue Intensity with Beliefs about Community

VARIABLES	(1) Disengagement	(2) Dialogue (MH)	(3) Dialogue (PH)	(4) Dialogue (EMP)
Beliefs (Mental Health)	-0.015	0.061*		
	(0.010)	(0.032)		
Beliefs (Physical Health)			0.021	
			(0.022)	
Beliefs (Employment)				0.081***
				(0.019)
Observations	216	277	281	269
R-squared	0.016	0.020	0.002	0.031

Click to go back.

Table C.6: Correlations of Network Gaps and Dialogue Intensity with being an Underestimator

VARIABLES	(1) Disengagement	(2) Disengagement	(3) Dialogue (MH)	(4) Dialogue (MH)
Underestimator	0.030		-0.298	
	(0.064)		(0.170)	
Severe Underestimator		0.167**		-0.345*
		(0.071)		(0.169)
Observations	216	216	277	277
R-squared	0.002	0.040	0.011	0.013

Click to go back.

Table C.7: Correlations of Willingness to Engage with Beliefs about Community.

VARIABLES	(1) Willing to have MH Dialogue	(2) Willing to have MH Dialogue	(3) Willing to have PH Dialogue	(4) Willing to have PH Dialogue
Beliefs (Mental Health)	0.015			
	(0.009)			
Beliefs -Stigma (Mental Health)		-0.013**		
		(0.005)		
Beliefs (Physical Health)			0.016	
			(0.009)	
Beliefs -Stigma (Physical Health)				-0.023***
				(0.007)
Observations	280	283	281	281
R-squared	0.009	0.008	0.010	0.024

Click to go back.

D Outcomes

Click to go back.

We measure the following outcomes at the endline survey (as immediate outcomes) or via a follow up survey, more than 2 weeks after the delivery of the treatment statement. All outcomes listed below are regressed on a treatment indicator and standard errors are clustered at the level of the community.

Endline Outcomes

We discuss the endline outcomes below. The outcomes are listed with their outcome family. Multiple hypothesis correction tests are conducted at the level of the outcome family. The endline survey can be found in section K.

1. Community Engagement

    - Willingness to volunteer and train to become a sensitive listener in a potential system where individuals can talk to community members about mental health related concerns. Participants were informed that a training may be organised (depending on COVID) to train them for becoming volunteers.

    - Willing to contribute towards the costs of running volunteer trainings if they were to be held, even if they do not wish to participate themselves. Willingness to contribute is measured at both the intensive and extensive margin. Individuals were informed that the payment will be deducted from the Rs. 50 which they could receive as a prize based on their baseline guesses about their community's beliefs.

- Willingness to sign up for a savings group with other community members where they can collect funds and discuss concerns regarding finances.
- Average of the three community engagement measures listed above.

2. Demand for Information
    - Willingness to participate in a potential mental health information session.
    - Willingness to learn about good listening and talking practices about mental health. Participants were also given the option to listen to these practices at another time preferred by them.
3. Investment in Own Health
    - Willingness to share own mental health concerns with a doctor.
    - Willingness to participate in getting more information about their own mental health status by immediately participating in depression scoring conducted by the enumerator or scheduling a time to conduct this later. Participants were informed that their responses to the individual question and their score could be kept private from the enumerator as well if they chose to do so. This is to ensure that the choice measured here is not influenced by the participant's reluctance to share the score with the enumerator. We give them the choice to share the score later and measure this as an outcome to capture stigma.
4. Self Efficacy
    - Ability to manage financial troubles. Participants were asked how sure they are that they will be able to manage their financial/employment related troubles in the next few months.
    - Ability to manage child's education. Participants were asked how sure they are

that they will be able to organise money for children's education (if applicable)

- Ability to start a business. Participants were asked how sure they are that they will be able to start a small business.
- Self efficacy measure constructed by taking the average of the three self efficacy outcomes

5. Stigma
    - Willingness to reveal decision to sign up for an information session (if they agreed to attend) to other community members. Participants who agreed to attend the potential information session were asked if they would not mind if their name were shared with other community members to encourage them to attend.
    - Willingness to share depression score with the enumerator, conditional on participation in depression scoring.
    - List experiment. Participants were asked how many, out of 4 statements they agree with out of which one was about their willingness to interact with someone who has mental health concerns.
6. Assessment of their ability to remember a sequence of five numbers that are narrated to them during the survey and asked again after a few questions. We aim for this to be a measure of "working memory" which is associated with cognitive load (Diamond, 2013; Lichand and Mani, 2020). It is similar to the digit span test used by Lichand and Mani (2020).
7. Willingness to discuss physical health concerns with family members and friends.
8. Ranking of people whom they prefer to talk to about mental health concerns.

Options are- family member/relative, friend from the community, stranger from the community.

Follow-up Outcomes

The follow up survey outcomes are listed below.

1. Well-being
   (a) Happiness, Life-Satisfaction, Stress
2. Self Reported Dialogue
   (a) Indicator whether they have initiated a conversation with their peers to discuss matters relating to either of their mental and financial health.
   (b) Number of peers they have initiated conversations with to discuss matters relating to either of their mental and financial health.
   (c) Indicator whether their peers have initiated a conversation with them to discuss matters relating to their own mental and financial health.
3. Physical Health Safety
   (a) How often did they follow COVID rules (distancing, wearing masks)?
   (b) How often did they wear safety gear (masks, gloves, jacket) while working in hazardous conditions?
4. Altruism towards community members (Dictator Game)
5. Self-reported contact with a doctor/helpline for mental or physical health concerns

E Design

Attrition

Table E.1: Correlation of Follow-up Survey Attrition with Treatment Status

VARIABLES	(1) Attrition
Treatment	-0.0346
	(0.0613)
Constant	0.393***
	(0.0518)
Observations	181
R-squared	0.001

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Click to go back.

Table E.2: Attrited Sample in Follow up Survey: Demographics and Health

	Control	Treatment	(1) vs. (2), p-value
Age	33.94	35.67	0.48
Female	0.40	0.30	0.46
Income (Category)	2.86	2.84	0.96
Monthly HH Income (< Rs 2,500)	0.11	0.09	0.78
Monthly HH Income (Rs 2,500-5,000)	0.20	0.22	0.82
Monthly HH Income (Rs 5,000-10,000)	0.40	0.44	0.59
Monthly HH Income (Rs 10,000+)	0.29	0.25	0.75
Employed	0.63	0.70	0.53
Stress (Index; Scale 1-4)	3.00	3.11	0.59
Satisfaction (Scale 1-4)	2.65	2.96	0.24
Happiness (Scale 1-4)	2.47	2.43	0.82
Degree (Advice)	2.83	3.06	0.74
Degree (Overall)	4.14	4.24	0.90
Degree (Advice Network) >0	4.71	5.32	0.32
Degree (Overall Network)>0	5.58	6.09	0.51
N	35	33	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Click to go back.

Table E.3: Attrited Sample in Follow up Survey: Willingness to Talk and Beliefs

	Control	Treatment	p-value
Willingness to Talk (Employment)	0.71	0.79	0.34
Willingness to Talk (Mental Health)	0.60	0.57	0.80
Willingness to Talk (Physical Health)	0.70	0.79	0.43
Stigma (Physical Health)	0.62	0.61	0.91
Stigma (Mental Health)	0.60	0.54	0.23
Beliefs (Mental Health)	4.25	5.00	0.34
Beliefs (Physical Health)	5.37	5.04	0.56
Beliefs (Employment)	5.36	6.72	0.02
Beliefs -Stigma (Mental Health)	5.11	4.92	0.85
Beliefs -Stigma (Physical Health)	4.89	4.84	0.97
Beliefs -Stress (Mental Health)	5.64	6.60	0.23
Dialogue (PH)	2.48	2.21	0.40
Physical Health talk (Never)	0.33	0.39	0.74
Physical Health talk (Rarely)	0.21	0.21	0.99
Physical Health talk (Sometimes)	0.21	0.25	0.74
Physical Health talk (Often)	0.12	0.07	0.39
Physical Health talk (Very Often)	0.12	0.07	0.47
Dialogue (MH)	2.53	2.82	0.43
Mental Health talk (Never)	0.31	0.21	0.38
Mental Health talk (Rarely)	0.19	0.32	0.32
Mental Health talk (Sometimes)	0.25	0.14	0.17
Mental Health talk (Often)	0.16	0.07	0.23
Mental Health talk (Very Often)	0.09	0.25	0.12
Dialogue (EMP)	2.47	2.90	0.19
Employment talk (Never)	0.31	0.17	0.08
Employment talk (Rarely)	0.28	0.28	0.94
Employment talk (Sometimes)	0.16	0.24	0.48
Employment talk (Often)	0.12	0.10	0.78
Employment talk (Very Often)	0.12	0.21	0.43
N	35	33	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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Balance

Table E.4: Endline Balance: Demographics and Health

	Control	Treatment	p-value
Age	34.90	34.55	0.84
Female	0.30	0.35	0.58
Income (Category)	2.83	2.83	1.00
Monthly HH Income (< Rs 2,500)	0.13	0.11	0.70
Monthly HH Income (Rs 2,500-5,000)	0.17	0.21	0.51
Monthly HH Income (Rs 5,000-10,000)	0.43	0.42	0.75
Monthly HH Income (Rs 10,000+)	0.27	0.26	0.92
Employed	0.65	0.67	0.75
Stress (Index; Scale 1-4)	3.09	3.05	0.83
Satisfaction (Scale 1-4)	2.83	2.96	0.31
Happiness (Scale 1-4)	2.42	2.49	0.66
Degree (Advice)	2.68	3.08	0.30
Degree (Overall)	3.90	4.51	0.12
Degree (Advice Network) >0	4.75	4.67	0.83
Degree (Overall Network) >0	5.79	5.84	0.94
N	92	89	

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Table E.5: Endline Balance: Willingness to Talk and Beliefs

	Control	Treatment	p-value
Willingness to Talk (Employment)	0.72	0.74	0.74
Willingness to Talk (Mental Health)	0.68	0.56	0.23
Willingness to Talk (Physical Health)	0.62	0.65	0.68
Stigma (Physical Health)	0.64	0.51	0.03
Stigma (Mental Health)	0.51	0.47	0.41
Beliefs (Mental Health)	4.74	5.24	0.20
Beliefs (Physical Health)	5.04	5.29	0.54
Beliefs (Employment)	5.55	6.82	0.02
Beliefs -Stigma (Mental Health)	4.86	5.00	0.84
Beliefs -Stigma (Physical Health)	4.92	4.97	0.94
Beliefs -Stress (Mental Health)	5.70	6.30	0.11
Dialogue (PH)	2.30	2.14	0.51
Physical Health talk (Never)	0.43	0.46	0.77
Physical Health talk (Rarely)	0.19	0.17	0.85
Physical Health talk (Sometimes)	0.15	0.22	0.08
Physical Health talk (Often)	0.12	0.08	0.39
Physical Health talk (Very Often)	0.12	0.07	0.42
Dialogue (MH)	2.58	2.45	0.52
Mental Health talk (Never)	0.33	0.30	0.60
Mental Health talk (Rarely)	0.16	0.30	0.05
Mental Health talk (Sometimes)	0.20	0.14	0.50
Mental Health talk (Often)	0.21	0.16	0.48
Mental Health talk (Very Often)	0.09	0.10	0.96
Dialogue (EMP)	2.83	3.08	0.36
Employment talk (Never)	0.27	0.18	0.08
Employment talk (Rarely)	0.19	0.23	0.66
Employment talk (Sometimes)	0.17	0.18	0.87
Employment talk (Often)	0.19	0.17	0.66
Employment talk (Very Often)	0.18	0.25	0.38
N	92	89	

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Table E.6: Follow-up Balance: Demographics and Health

	Control	Treatment	p-value
Age	35.81	33.66	0.35
Female	0.24	0.37	0.12
Income (Category)	2.77	2.87	0.60
Monthly HH Income (< Rs 2,500)	0.15	0.11	0.58
Monthly HH Income (Rs 2,500-5,000)	0.15	0.20	0.59
Monthly HH Income (Rs 5,000-10,000)	0.46	0.40	0.43
Monthly HH Income (Rs 10,000+)	0.23	0.29	0.42
Employed	0.67	0.66	0.95
Stress (Index; Scale 1-4)	3.10	3.05	0.75
Satisfaction (Scale 1-4)	2.94	2.96	0.87
Happiness (Scale 1-4)	2.41	2.51	0.59
Degree (Advice)	2.50	3.16	0.33
Degree (Overall)	3.72	4.66	0.21
Degree (Advice Network) >0	4.66	4.46	0.72
Degree (Overall Network) >0	5.91	5.74	0.84
N	54	59	

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Table E.7: Follow-up Balance: Willingness to Talk and Beliefs

	Control	Treatment	p-value
Willingness to Talk (Employment)	0.71	0.73	0.79
Willingness to Talk (Mental Health)	0.71	0.58	0.22
Willingness to Talk (Physical Health)	0.58	0.56	0.85
Stigma (Physical Health)	0.69	0.44	0.01
Stigma (Mental Health)	0.49	0.41	0.24
Beliefs (Mental Health)	5.19	5.22	0.95
Beliefs (Physical Health)	4.76	5.46	0.24
Beliefs (Employment)	5.55	6.89	0.11
Beliefs -Stigma (Mental Health)	4.74	5.00	0.76
Beliefs -Stigma (Physical Health)	4.98	5.00	0.98
Beliefs -Stress (Mental Health)	5.80	6.07	0.63
Dialogue (PH)	2.24	2.07	0.56
Physical Health talk (Never)	0.48	0.50	0.86
Physical Health talk (Rarely)	0.16	0.16	0.96
Physical Health talk (Sometimes)	0.12	0.19	0.18
Physical Health talk (Often)	0.12	0.09	0.50
Physical Health talk (Very Often)	0.12	0.07	0.48
Dialogue (MH)	2.62	2.26	0.17
Mental Health talk (Never)	0.34	0.34	0.96
Mental Health talk (Rarely)	0.14	0.29	0.01
Mental Health talk (Sometimes)	0.18	0.14	0.70
Mental Health talk (Often)	0.24	0.21	0.71
Mental Health talk (Very Often)	0.10	0.02	0.09
Dialogue (EMP)	3.15	3.10	0.90
Employment talk (Never)	0.21	0.21	0.98
Employment talk (Rarely)	0.15	0.19	0.64
Employment talk (Sometimes)	0.17	0.16	0.87
Employment talk (Often)	0.25	0.19	0.51
Employment talk (Very Often)	0.23	0.26	0.71
N	54	59	

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Selection

We compare the baseline characteristics of those in our experimental sample (i.e. who picked up the second call) and those in our intended baseline sample who did not respond to our calls after. These checks are reported in Tables E.8 and E.9. We find that those who do not respond to our second call, and are consequently not a part of the experimental sample, are younger and have a lower income (only driven by those in the highest income bracket). They are also more optimistic about how stressed others are in their community, and are more likely to report that they have rarely had a conversation about physical health. We find balance between those who stayed and left after baseline on all other characteristics. Note that this analysis does not address the potentially larger concern that the baseline sample itself is comprised of engaged individuals who showed an initial interest in the study as per the initial calls made by the NGO. We do observe considerable heterogeneity in baseline measures including heterogeneity in dialogue frequency and engagement. However, we cannot comment on how representative this sample is of the larger NGO population. While we cannot address this concern now, we aim measure baseline characteristics and networks of individuals excluded from our baseline sample after the NGO updates its list and it is COVID-secure to do so.

Table E.8: Sample Selection Checks: Demographics and Health

	Stayed after Baseline	Left after Baseline	p-value
Age	34.72	32.60	0.00
Female	0.33	0.38	0.12
Income (Category)	2.83	2.59	0.04
Monthly HH Income (< Rs 2,500)	0.12	0.18	0.09
Monthly HH Income (Rs 2,500-5,000)	0.19	0.20	0.82
Monthly HH Income (Rs 5,000-10,000)	0.43	0.46	0.56
Monthly HH Income (Rs 10,000+)	0.26	0.16	0.04
Employed	0.66	0.64	0.73
Stress (Index; Scale 1-4)	3.07	3.06	0.90
Satisfaction (Scale 1-4)	2.90	2.83	0.52
Happiness (Scale 1-4)	2.46	2.53	0.57
Degree (Advice)	2.88	2.76	0.76
Degree (Overall)	4.20	3.71	0.25
N	181	181	

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Table E.9: Sample Selection Checks: Willingness to Talk and Beliefs

	Stayed after Baseline	Left after Baseline	p-value
Willingness to Talk (Employment)	0.73	0.69	0.40
Willingness to Talk (Mental Health)	0.62	0.66	0.49
Willingness to Talk (Physical Health)	0.63	0.63	0.78
Stigma (Physical Health)	0.57	0.54	0.48
Stigma (Mental Health)	0.49	0.52	0.59
Beliefs (Mental Health)	4.99	5.02	0.95
Beliefs (Physical Health)	5.16	5.10	0.83
Beliefs (Employment)	6.19	5.73	0.15
Beliefs -Stigma (Mental Health)	4.93	4.65	0.46
Beliefs -Stigma (Physical Health)	4.95	4.66	0.16
Beliefs -Stress (Mental Health)	6.00	5.24	0.03
Dialogue (PH)	2.22	2.19	0.82
Physical Health talk (Never)	0.44	0.40	0.39
Physical Health talk (Rarely)	0.18	0.26	0.08
Physical Health talk (Sometimes)	0.18	0.14	0.31
Physical Health talk (Often)	0.10	0.13	0.33
Physical Health talk (Very Often)	0.09	0.07	0.19
Dialogue (MH)	2.51	2.53	0.89
Mental Health talk (Never)	0.32	0.26	0.23
Mental Health talk (Rarely)	0.23	0.28	0.26
Mental Health talk (Sometimes)	0.17	0.21	0.25
Mental Health talk (Often)	0.18	0.18	0.81
Mental Health talk (Very Often)	0.10	0.08	0.51
Dialogue (EMP)	2.96	2.75	0.19
Employment talk (Never)	0.22	0.27	0.33
Employment talk (Rarely)	0.21	0.22	0.91
Employment talk (Sometimes)	0.17	0.18	0.86
Employment talk (Often)	0.18	0.14	0.30
Employment talk (Very Often)	0.22	0.19	0.54
N	181	181	

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F Endline Results

Table F.1: Demand for Information

	(1) Information Session	(2) Listening to Good Practices (Immediate)	(3) Listening to Good Practices
Treatment	0.0452	-0.0439	0.0284
	(0.0712)	(0.0749)	(0.0614)
q-values	1	1	1
Constant	0.674***	0.551***	0.821***
	(0.0570)	(0.0626)	(0.0462)
Observations	181	142	140
R-squared	0.002	0.002	0.001

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table F.2: Self Efficacy

VARIABLES	Goals (Finance)	Goals (Education)	Goals (Business)	Self Efficacy
Treatment	0.136	-0.207	0.0493	-0.0333
	(0.304)	(0.270)	(0.248)	(0.206)
q-values	1	1	1	1
Constant	2.219***	2.729***	2.548***	2.481***
	(0.136)	(0.234)	(0.161)	(0.150)
Observations	149	141	145	140
R-squared	0.002	0.005	0.000	0.000

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table F.3: Stigma

VARIABLES	Stigma (Information Session)	List Experiment	Depression Score Revelation
Treatment	0.0313	-0.0567	-0.125
	(0.0340)	(0.240)	(0.127)
q-values	1	1	1
Constant	0.922***	3.507***	0.925***
	(0.0240)	(0.146)	(0.0353)
Observations	128	155	65
R-squared	0.004	0.000	0.034

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table F.4: Interaction Preferences

Interaction Preference	(1) Stranger	(2) Friend	(3) Family	(4) Preference for Community
Treatment	0.0556	-0.0687	-0.0423	0.0627
	(0.242)	(0.110)	(0.104)	(0.0738)
q-values	1	1	1	1
Constant	2.778***	1.905***	1.185***	0.115
	(0.159)	(0.103)	(0.0902)	(0.0674)
Observations	33	82	97	99
R-squared	0.003	0.004	0.002	0.006

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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G Robustness Checks

Table G.1: Community Engagement (Robust)

	(1) Savings Group	(2) Listening Volunteer	(3) Listening Contribution	(4) Contribution (in Rupees)	(5) Community Engagement
Stigma (PH)	0.0598	0.0247	0.0260	0.503	0.00150
	(0.0711)	(0.0549)	(0.0779)	(4.032)	(0.0514)
Beliefs (MH)		0.0319*		-0.657	
		(0.0176)		(0.732)	
Beliefs (EMP)		-0.0190	0.00298	0.503	
		(0.0142)	(0.00937)	(0.846)	
Beliefs -Stress (MH)		0.0153		0.329	
		(0.0139)		(0.393)	
Degree (Overall)			-0.00440		
			(0.00793)		
Treatment	0.166**	0.206*	0.119**	5.780*	0.140**
	(0.0671)	(0.103)	(0.0412)	(2.819)	(0.0485)
Constant	0.644***	0.376***	0.736***	21.55***	0.671***
	(0.0703)	(0.0966)	(0.0827)	(3.071)	(0.0466)
Observations	135	142	143	134	135
R-squared	0.040	0.090	0.026	0.042	0.052

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: "MH" refers to Mental Health, "PH" refers to Physical Health, and "EMP" refers to Financial Health (i.e. employment or money related concerns). Degree (Overall) is the number of reported connections in the overall network that includes all interactions.

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Table G.2: Demand for Information (Robust)

	(1) Information Session	(2) Listening to Good Practices (Immediate)	(3) Listening to Good Practices
Stigma (PH)	0.0825	-0.108	-0.109*
	(0.0798)	(0.0625)	(0.0580)
Beliefs-Stress		-0.00369	0.0105
		(0.0184)	(0.0127)
Dialogue (EMP)		-0.0150	
		(0.0184)	
Beliefs (EMP)	-0.0146		
	(0.0145)		
Treatment	0.105	-0.0565	0.0118
	(0.0831)	(0.0923)	(0.0658)
Constant	0.704***	0.668***	0.823***
	(0.0906)	(0.0592)	(0.0754)
Observations	150	120	123
R-squared	0.024	0.017	0.027

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: "MH" refers to Mental Health, "PH" refers to Physical Health, and "EMP" refers to Financial Health (i.e. employment or money related concerns). Degree (Overall) is the number of reported connections in the overall network that includes all interactions.

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Table G.3: Own Health Outcomes (Robust)

VARIABLES	Speaking to the Doctor (MH)	Depression Scoring (Immediate)	Depression Scoring	Listening to Helpline Numbers
Stigma (PH)	0.0472	-0.147***	-0.0698	
	(0.0825)	(0.0472)	(0.0619)	
Beliefs -Stress	0.0116	0.000705	0.00111	-0.0137
	(0.00661)	(0.0114)	(0.00665)	(0.0133)
Dialogue (EMP)		0.00207	-0.00367	0.0665**
		(0.0247)	(0.0175)	(0.0236)
Treatment	0.120**	-0.283***	-0.122	-0.187**
	(0.0508)	(0.0706)	(0.131)	(0.0839)
Constant	0.000929	0.689***	0.834***	0.481***
	(0.0596)	(0.0982)	(0.0761)	(0.107)
Observations	131	120	120	118
R-squared	0.044	0.090	0.022	0.069

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: "MH" refers to Mental Health, "PH" refers to Physical Health, and "EMP" refers to Financial Health (i.e. employment or money related concerns). Degree (Overall) is the number of reported connections in the overall network that includes all interactions.

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Table G.4: Self Efficacy (Robust)

VARIABLES	Goals (Finance)	Goals (Education)	Goals (Business)	Self Efficacy
Stigma (PH)	-0.181	-0.129	-0.318	-0.250
	(0.208)	(0.246)	(0.359)	(0.231)
Beliefs -Stress	0.00708		-0.0437	-0.00247
	(0.0487)		(0.0449)	(0.0380)
Dialogue (EMP)	0.0565		0.0219	
	(0.0924)		(0.121)	
Treatment	0.238	-0.0682	0.0184	0.00930
	(0.316)	(0.304)	(0.281)	(0.212)
Constant	2.084***	2.701***	3.022***	2.644***
	(0.324)	(0.317)	(0.565)	(0.256)
Observations	122	128	121	122
R-squared	0.013	0.002	0.019	0.010

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: "MH" refers to Mental Health, "PH" refers to Physical Health, and "EMP" refers to Financial Health (i.e. employment or money related concerns). Degree (Overall) is the number of reported connections in the overall network that includes all interactions.

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Table G.5: Stigma (Robust)

VARIABLES	Stigma (Information Session)	List Experiment	Depression Score Revelation
Income (Category)	0.0177		-0.0190
	(0.0155)		(0.0495)
Willingness to Talk (MH)	0.00715		
	(0.0513)		
Beliefs (EMP)	0.0100	-0.0170	
	(0.00860)	(0.0349)	
Beliefs -Stress (MH)	-0.00699	0.0376	
	(0.00406)	(0.0300)	
Treatment	-0.0172	-0.121	-0.0850
	(0.0246)	(0.259)	(0.112)
Stigma (PH)		-0.261	-0.0197
		(0.149)	(0.0590)
Beliefs (MH)		-0.0691	
		(0.0442)	
Female			-0.122
			(0.0847)
Degree (Overall)			0.00859
			(0.00690)
Constant	0.885***	4.085***	0.984***
	(0.115)	(0.243)	(0.165)
Observations	104	127	57
R-squared	0.026	0.043	0.050

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: "MH" refers to Mental Health, "PH" refers to Physical Health, and "EMP" refers to Financial Health (i.e. employment or money related concerns). Degree (Overall) is the number of reported connections in the overall network that includes all interactions.

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Table G.6: Other Outcomes (Robust)

VARIABLES	Memory (Numbers Remembered)	Physical Health Dialogue (with Family)
Stigma (PH)	-0.537**	0.0160
	(0.207)	(0.0724)
Beliefs -Stress		0.00869
		(0.0107)
Treatment	-0.264	0.182***
	(0.289)	(0.0571)
Constant	1.303***	0.118*
	(0.170)	(0.0622)
Observations	137	131
R-squared	0.054	0.048

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: "MH" refers to Mental Health, "PH" refers to Physical Health, and "EMP" refers to Financial Health (i.e. employment or money related concerns). Degree (Overall) is the number of reported connections in the overall network that includes all interactions.

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Table G.7: Interaction Preferences (Robust)

Interaction Preference	(1) Stranger	(2) Friend	(3) Family	(4) Preference for Community
Satisfaction (Scale 1-4)	0.0331			
	(0.113)			
Beliefs (MH)	-0.0163	-0.00948	0.0145	0.00747
	(0.0176)	(0.0175)	(0.0112)	(0.0134)
Degree (Overall)		-0.00491		
		(0.0161)		
Treatment	-0.00515	-0.0653	-0.0702	0.0658
	(0.299)	(0.136)	(0.113)	(0.0805)
Constant	2.833***	1.996***	1.121***	0.0639
	(0.158)	(0.136)	(0.110)	(0.0956)
Observations	30	72	84	86
R-squared	0.013	0.013	0.018	0.012

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: "MH" refers to Mental Health, "PH" refers to Physical Health, and "EMP" refers to Financial Health (i.e. employment or money related concerns). Degree (Overall) is the number of reported connections in the overall network that includes all interactions.

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H Heterogeneity

Table H.1: Heterogeneous Treatment Effects by Stigma (Mental Health) -1

	(1) Savings Group	(2) Listening Volunteer	(3) Listening Contribution	(4) Contribution (in Rupees)	(5) Contribution (>0)	(6) Community Engagement
Treatment	0.259***	0.183	0.129	2.084	-2.979	0.181**
	(0.0820)	(0.141)	(0.0859)	(5.589)	(3.182)	(0.0643)
Stigma (MH)	0.166	-0.246	-0.0533	-11.58*	-10.16***	0.0256
	(0.136)	(0.140)	(0.153)	(5.942)	(2.044)	(0.109)
Interaction	-0.168	0.0465	-0.0169	7.933	11.91***	-0.0476
	(0.142)	(0.122)	(0.159)	(7.991)	(2.854)	(0.0792)
Constant	0.364***	0.389***	0.724***	23.85***	30.55***	0.490***
	(0.0861)	(0.119)	(0.115)	(3.575)	(5.948)	(0.0689)
Observations	134	142	143	134	112	134
R-squared	0.109	0.122	0.028	0.080	0.084	0.115

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Click to go back.

Table H.2: Heterogeneous Treatment Effects by Stigma (Mental Health) -2

VARIABLES	(1) Physical Health Dialogue (with Family)	(2) Depression Scoring (Immediate)	(3) Listening to Helpline Numbers	(4) Speaking to the Doctor(MH)
Treatment	0.103	-0.190	-0.207	0.211**
	(0.0709)	(0.128)	(0.147)	(0.0748)
Stigma (Mental Health)	-0.0547	-0.0259	-0.00712	0.0156
	(0.130)	(0.149)	(0.155)	(0.0694)
Interaction	0.211	-0.187	0.0442	-0.157
	(0.153)	(0.165)	(0.203)	(0.0980)
Constant	-0.0101	0.628***	0.489**	-0.116
	(0.0729)	(0.0861)	(0.169)	(0.115)
Observations	130	120	118	130
R-squared	0.110	0.106	0.070	0.071

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Click to go back.

Table H.3: Heterogeneous Treatment Effects by Degree (Overall) -1

	(1) Savings Group	(2) Listening Volunteer	(3) Listening Contribution	(4) Contribution (in Rupees)	(5) Contribution (>0)	(6) Community Engagement
Treatment	-0.0350	0.239	0.112	2.125	-3.141	0.0861
	(0.127)	(0.186)	(0.0750)	(3.159)	(2.627)	(0.0943)
Degree (Overall)	-0.0205	0.0114	-0.00520	-0.433	-0.748*	-0.00625
	(0.0179)	(0.0123)	(0.0147)	(0.496)	(0.405)	(0.0101)
Interaction	0.0442**	-0.00784	0.00151	0.782	1.355**	0.0119
	(0.0167)	(0.0210)	(0.0138)	(0.437)	(0.571)	(0.0120)
Constant	0.728***	0.324***	0.739***	23.30***	22.79***	0.697***
	(0.108)	(0.0947)	(0.0808)	(2.753)	(6.005)	(0.0642)
Observations	135	142	143	134	110	135
R-squared	0.083	0.095	0.026	0.049	0.081	0.058

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Click to go back.

Table H.4: Heterogeneous Treatment Effects by Degree (Overall) -2

VARIABLES	(1) Physical Health Dialogue (with Family)	(2) Depression Scoring (Immediate)	(3) Listening to Helpline Numbers	Speaking to the Doctor(MH)
Treatment	0.229	-0.348**	-0.169	0.162
	(0.131)	(0.113)	(0.102)	(0.0966)
Degree (Overall)	0.0191	0.0119	-0.00120	0.0209**
	(0.0123)	(0.0227)	(0.0120)	(0.00856)
Interaction	-0.0121	0.0117	-0.00368	-0.0157
	(0.0234)	(0.0216)	(0.0176)	(0.0190)
Constant	0.0254	0.638***	0.484***	-0.172
	(0.0840)	(0.0958)	(0.134)	(0.140)
Observations	131	120	118	127
R-squared	0.063	0.112	0.070	0.076

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Click to go back.

I Effect of COVID-19

Table I.1: Differences in Treatment Group Subsamples due to COVID-19 - 1

	(1) Savings Group	(2) Listening Volunteer	(3) Listening Contribution	(4) Contribution (in Rupees)	(5) Community Engagement
Surveyed after 30th March, 2021	0.00970	0.159	-0.135**	-9.413*	0.0633
	(0.0884)	(0.0877)	(0.0528)	(4.627)	(0.0387)
Constant	0.811***	0.614***	0.930***	34.23***	0.766***
	(0.0581)	(0.0489)	(0.0439)	(3.314)	(0.0421)
Observations	76	88	87	83	76
R-squared	0.000	0.030	0.038	0.063	0.012

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Click to go back.

Table I.2: Differences in Treatment Group Subsamples due to COVID-19 - 2

VARIABLES	(1) Physical Health Dialogue (with Family)	(2) Speaking to the Doctor(MH)	(3) Depression Scoring (Immediate)	(4) Listening to Helpline Numbers
Surveyed after 30th March, 2021	-0.0444	-0.00577	0.0180	0.0610
	(0.100)	(0.152)	(0.182)	(0.117)
Constant	0.410***	0.231***	0.333**	0.371***
	(0.0480)	(0.0668)	(0.109)	(0.0610)
Observations	80	79	73	72
R-squared	0.002	0.000	0.000	0.004

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Click to go back.

Table I.3: Treatment Effects on Restricted Sample - 1

	(1) Savings Group	(2) Listening Volunteer	(3) Listening Contribution	(4) Contribution (in Rupees)	(5) Community Engagement
Female	-0.139	-0.208		-18.51***	-0.143
	(0.147)	(0.139)		(3.073)	(0.0837)
Employed				-0.199	
				(4.359)	
Satisfaction (Scale 1-4)	0.00451		0.0385	0.845	0.0207
	(0.0493)		(0.0365)	(2.314)	(0.0430)
Willingness to Talk (EMP)				1.912	
				(6.866)	
Dialogue (EMP)	0.0865**			-1.032	0.0656**
	(0.0355)			(1.638)	(0.0250)
Treatment	0.0390	0.172*	0.161*	11.51	0.0773
	(0.0630)	(0.0914)	(0.0741)	(6.979)	(0.0797)
Constant	0.526***	0.531***	0.644***	29.28***	0.466**
	(0.169)	(0.0803)	(0.134)	(7.787)	(0.154)
Observations	61	81	71	61	61
R-squared	0.112	0.053	0.066	0.275	0.154

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table I.4: Treatment Effects on Restricted Sample - 2

VARIABLES	(1) Speaking to the Doctor(MH)	(2) Physical Health Dialogue (with Family)	(3) Depression Scoring (Immediate)	(4) Listening to Helpline Numbers
Satisfaction (Scale 1-4)	0.0132	-0.0345	0.0840	
	(0.0419)	(0.0819)	(0.0792)	
Willingness to Talk (EMP)			0.178	-0.141
			(0.146)	(0.212)
Beliefs -Stress			-0.00158	0.0123
			(0.0166)	(0.0144)
Dialogue (EMP)	0.00383	0.0723*	-0.0338	0.0972*
	(0.0489)	(0.0381)	(0.0426)	(0.0516)
Treatment	0.112	0.131	-0.412***	-0.297***
	(0.100)	(0.116)	(0.124)	(0.0841)
Constant	0.0622	0.114	0.450	0.341**
	(0.168)	(0.269)	(0.320)	(0.130)
Observations	63	63	55	54
R-squared	0.026	0.092	0.189	0.105

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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J Follow up Results

Table J.1: Dialogue

VARIABLES	(1) Employment (Made Call)	(2) Employment Calls (Frequency)	(3) Employment (Got Call)	(4) Mental Health (Made Call)	(5) Mental Health Calls (Frequency)	(6) Mental Health (Got Call)
Treatment	0.218**	1.321**	0.125*	0.133***	0.925***	0.0279
	(0.0943)	(0.452)	(0.0690)	(0.0373)	(0.177)	(0.0571)
q-values	0.034	0.023	0.068	0.018	0.005	0.172
Constant	0.308***	0.817***	0.288***	0.212***	0.471***	0.231***
	(0.0660)	(0.227)	(0.0483)	(0.0482)	(0.126)	(0.0341)
Observations	111	110	110	110	110	110
R-squared	0.048	0.081	0.017	0.022	0.050	0.001

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Click to go back.

Table J.2: Other Outcomes

VARIABLES	(1) Masks (How often)	(2) Safety Gear (How often)	(3) Maintain Distance (How often)	(4) Mental Health-Doctor (Made Call)
Treatment	-0.169***	0.713***	-0.0112	-0.0272
	(0.0543)	(0.172)	(0.109)	(0.0360)
q-values	0.021	0.014	0.246	0.172
Constant	3.942***	2.953***	3.596***	0.0962***
	(0.0406)	(0.110)	(0.0802)	(0.0293)
Observations	105	70	105	110
R-squared	0.024	0.098	0.000	0.002

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table J.3: Well Being

VARIABLES	(1) Happiness	(2) Life Satisfaction	(3) Stress	(4) Altruism (Dictator Game)
Treatment	-0.538***	-0.404**	0.229*	30.27**
	(0.173)	(0.132)	(0.128)	(12.87)
q-values	0.021	0.021	0.068	0.034
Constant	3.192***	3.423***	2.692***	54***
	(0.105)	(0.0660)	(0.0884)	(10.83)
Observations	104	104	103	105
R-squared	0.084	0.054	0.018	0.046

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Click to go back.

Robustness Checks

Table J.4: Dialogue (Robust)

VARIABLES	(1) Employment (Made Call)	(2) Employment Calls (Frequency)	(3) Employment (Got Call)	(4) Mental Health (Made Call)	(5) Mental Health Calls (Frequency)	(6) Mental Health (Got Call)
Treatment	0.232**	1.202**	0.169*	0.136**	0.741***	0.0374
	(0.104)	(0.391)	(0.0779)	(0.0487)	(0.216)	(0.0457)
Stigma (PH)	0.0385	0.0233	0.105	0.00722	-0.404	0.0697
	(0.0853)	(0.424)	(0.0675)	(0.0858)	(0.419)	(0.0956)
Constant	0.278***	0.843**	0.212***	0.213**	0.783*	0.192**
	(0.0891)	(0.307)	(0.0671)	(0.0857)	(0.368)	(0.0651)
Observations	101	100	100	100	100	100
R-squared	0.052	0.069	0.033	0.022	0.051	0.007

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: "MH" refers to Mental Health, "PH" refers to Physical Health, and "EMP" refers to Financial Health (i.e. employment or money related concerns). Degree (Overall) is the number of reported connections in the overall network that includes all interactions.

Click to go back.

Table J.5: Physical Health (Robust)

VARIABLES	(1) Masks (How often)	(2) Safety Gear (How often)	(3) Maintain Distance (How often)	(4) Mental Health-Doctor (Made Call)
Satisfaction (Scale 1-4)		-0.139		
		(0.104)		
Degree (Overall)		0.0155		
		(0.0331)		
Stigma (PH)	-0.128	-0.322	-0.0440	0.0398
	(0.0997)	(0.408)	(0.0785)	(0.0482)
Treatment	-0.211**	0.531**	-0.0494	-0.0248
	(0.0827)	(0.224)	(0.120)	(0.0384)
Constant	4.021***	3.610***	3.660***	0.0819***
	(0.0890)	(0.478)	(0.100)	(0.0261)
Observations	95	64	95	100
R-squared	0.037	0.098	0.002	0.008

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: "MH" refers to Mental Health, "PH" refers to Physical Health, and "EMP" refers to Financial Health (i.e. employment or money related concerns). Degree (Overall) is the number of reported connections in the overall network that includes all interactions.

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Table J.6: Well Being (Robust)

VARIABLES	(1) Happiness	(2) Life Satisfaction	(3) Stress	(4) Altruism (Dictator Game)
Stigma (PH)	-0.0521	-0.0509	0.279*	-4.573
	(0.136)	(0.129)	(0.148)	(10.85)
Treatment	-0.436**	-0.363**	0.208*	31.81**
	(0.165)	(0.130)	(0.100)	(14.34)
Constant	3.209***	3.447***	2.551***	58.70***
	(0.163)	(0.110)	(0.152)	(12.70)
Observations	94	94	93	95
R-squared	0.058	0.044	0.034	0.054

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: "MH" refers to Mental Health, "PH" refers to Physical Health, and "EMP" refers to Financial Health (i.e. employment or money related concerns). Degree (Overall) is the number of reported connections in the overall network that includes all interactions.

Click to go back.

K Surveys

Baseline Survey (Click to go back.)

1. Surveyor Name
2. Participant Name
3. Unique ID
4. Centre
5. You must have been called by the NGO where you expressed interest in participating in a study. Can you spare 15-20 minutes to speak privately where you will not be disturbed?
6. If not, can we call you later today? If not, then when?
7. Read the consent form. Do you consent to participate?
    - Yes
    - No
8. Confirm: Do you live in centre *centre name*? Instructions: If not, change the centre name to the correct one after asking the participant.
    - Yes
    - No
9. What is your gender?
    - Female
    - Male
10. What is your age?
11. What was your TOTAL household income last month?
    - Below 2500
    - 2500 - 5000
    - 5000-10000
    - Above 10,000
12. What is your current employment status?
    - Employed
    - Unemployed and looking for work
    - Unemployed and not looking for work
13. List up to 10 any individuals in your community associated with the NGO whom you interact with/used to interact with? These can include individuals with whom you work, ask advice, give advice, borrow/lend money or interact in any other capacity etc.
14. List up to 10 any individuals in your community associated with the NGO whom you discuss your own or their personal problems such as low mood, stress, worries, etc?

15. How much money do you use to topup your mobile phone for phone calls and/or data combined in a month? Round it off to the nearest 5.
16. In the last two weeks how often have you discussed the following issues with your friends? (a) Money or employment related issues, (b) Physical health related issues, (c) Personal problems (sadness, stress, worries).
    - Never
    - Rarely
    - Sometimes
    - Often
    - Very Often
17. In the last two weeks how often have you felt that you were unable to control the important things in your life?
    - Never
    - Rarely
    - Sometimes
    - Often
    - Very Often
18. In the last two weeks how often have you you felt confident about your ability to handle your personal problems?
    - Never
    - Rarely
    - Sometimes
    - Often
    - Very Often
19. In the last two weeks how often have you felt that things were going your way?
    - Never
    - Rarely
    - Sometimes
    - Often
    - Very Often
20. In the last two weeks how often have you felt difficulties were piling up so high that you could not overcome them?
    - Never
    - Rarely
    - Sometimes
    - Often
    - Very Often

21. All things considered, how satisfied are you with your life as a whole at the moment?
    - Very dissatisfied
    - Little dissatisfied
    - Little satisfied
    - Very satisfied
22. Taking all things together, how happy have you felt in the last two weeks? (with 1 being the lowest and 4 the highest)
    - Very unhappy
    - Little unhappy
    - Little happy
    - Very happy
23. We are now going to ask you about your beliefs about physical, mental, and economic, health and how much you and your community participate in conversations about these topics. By your community, we mean the individuals who are in your NGO centre- who live close to you. Mental health concerns include issues such stress, worry, or depression. Depression can include symptoms such as having little interest or pleasure in doing things, feeling tired or having little energy or having trouble falling or staying asleep or sleeping too much. We will contact you again to give you more information about this. Physical health concerns include anything that you would typically go to see a doctor for. Such as fever, diarrhea, cough, skin problems, and other such body-related illnesses.
    The order of the following questions is randomised.
24. Would you be willing to share and discuss finance/employment related concerns with your friends, discuss ways to overcome them, and how these problems might be preventing you from achieving your goals ?
    - Yes
    - No
25. Would you be willing to share and discuss mental health related concerns with your friends, discuss ways to overcome them, and how these problems might be preventing you from achieving your goals ?
    - Yes
    - No
26. Would you be willing to share and discuss physical health related concerns with your friends, discuss ways to overcome them, and how these problems might be preventing you from achieving your goals ?
    - Yes
    - No
27. Do you agree with the following statement? "People should stay away from individuals who have mental health issues"
    - Yes
    - No

28. Do you agree with the following statement? "People should stay away from individuals who have physical health issues."
    - Yes
    - No
29. Now, you will be presented with a series of 6 questions where we ask you to make a guess. Before we call you the next time, we will randomly pick one of these 6 questions and if your answer is correct to the nearest integer, you will receive Rs 50 as a reward.
30. How many individuals among any 10 participants in your community associated with the NGO do you think will agree with the statement that "People should stay away from individuals who have mental health issues".
31. How many individuals among any 10 participants in your community associated with the NGO do you think will agree with the statement that "People should stay away from individuals who have physical health issues."
32. How many individuals among any 10 participants in your community associated with the NGO would be willing to share and discuss their finance/employment related concerns with their friends, discuss ways to overcome them, and how these problems might be preventing them from achieving their goals?
33. How many individuals among any 10 participants in your community associated with the NGO would be willing to share and discuss their physical health related concerns with their friends, discuss ways to overcome them, and how these problems might be preventing them from achieving their goals ?
34. How many individuals among any 10 participants in your community associated with the NGO would be willing to share and discuss their mental health related concerns with their friends, discuss ways to overcome them, and how these problems might be preventing them from achieving their goals ?
35. How many individuals among any 100 participants in your community associated with the NGO feel that "difficulties were piling up so high that they could not overcome them" often or very often?
36. If you are a waste worker (i.e. you collect waste, sort through it, or do any task associated with waste) which of the following did you wear the last time you were handling waste? (Surveyor Instructions: You can select multiple options. Leave empty if participant is not a waste picker.)
    - Mask
    - Gloves
    - Jacket
    - None
37. According to you, how important is it to wear the safety gear while handling waste? (Surveyor Instructions: Leave empty if participant is not a waste picker)
    - Not at all
    - A little important
    - Very important
38. Was there someone listening to your responses during this survey?
    - Yes

- No

39. Thank you for your time! We will call you again in a few weeks. Is there any other phone number that you prefer we contact you on? If yes, which one?
40. Surveyor comments

Endline Survey (Click to go back.)

1. Centre
2. Surveyor Name
3. Unique ID
4. Is the participant in the control group or the treatment group
   - Control
   - Treatment
5. Introduction. Do you wish to continue with the second survey now?
   - Yes
   - No
6. If not, then when can we call you?
7. Intervention Statement 1 (Only for the Treatment Group) Read out the following statement.

   Just like we surveyed you, we also surveyed other individuals from your community or communities similar to yours who are affiliated with the NGO.

   "We have found from the responses, that out of these, 64% individuals, or 6 individuals out of any 10, are willing to discuss mental health related concerns with their peers, how they might be preventing them from achieving their goals, and ways to overcome them."

   Confirm below that you read the above statement(s) as it is to the respondent.
   - Yes
   - No
8. Is this above, below, or the same as what you had anticipated?
   - Below
   - Same
   - Above
9. If the participant asked you to repeat the statement, please enter how many times?
10. Surveyor comments about the intervention statement
11. Outcome: Information session about mental health

    We are thinking of organizing a 1-hour information session with the NGO and other participants to discuss mental health related concerns and give additional

information. You will be able to discuss these issues and how to deal with them in a safe environment in this session and it may be organized after the COVID-19 situation improves. Would you like to participate?

- Yes
- No

12. Outcome: Information session about mental health

    If yes, we want to list your name as a potential participant to other individuals to encourage them to participate. Can we forward your name with other names of participants who said yes to others to encourage them?

    - Yes
    - No

13. Now we will read out five numbers. Please try to remember them and we will ask you about this again in a few minutes. 365, 72, 745, 21, 98

    Enter any comments below.

14. We wish to have some members of the community to take out the time to listen to the worries of other members and become "mental health buddies". They will be trained before this but will not receive any money. Do you wish to become a mental health buddy? If yes, then we will call you again to inform you about the training.

    - Yes
    - No

15. At the end of the survey, we will inform you if you have won Rs 50 or not. If you win this prize, then would you be willing to donate some of this to organize the above training in your community?

    - Yes
    - No

16. If yes, then how much? This will be deducted from the amount if you get the prize.

17. Now we'll read out 4 statements. Please tell us how many of these 4 statements you agree with. You can tell us how many, i.e. 0,1,2,3, or 4, statements you agree with once we have read the statements.

    - People should only enter politics if they are educated.
    - The Delhi Government is doing enough to tackle air pollution.
    - People should remain friends with those suffering from mental health concerns.
    - Teachers should be paid more than film actors.

How many statements do you agree with?

18. Willingness/Comfort to have a dialogue

    Do you-

    - ·Feel comfortable discussing your mental health related problems with a doctor
        - Yes
        - No
        - Refuse to Answer
    - Feel comfortable discussing your physical health related problems with your friends and family
        - Yes
        - No
        - Refuse to Answer

19. Can you please tell us the numbers we asked you to remember. Mark how many they got right: 365, 72, 745, 21, 98.

20. Whom would you want to discuss your mental health concerns the most?

    - Family member/relative
    - Friend from the community
    - Stranger from the community

21. Intervention Statement 2 (Only for the Treatment Group)

    "Just like we surveyed you, we also surveyed other individuals from your community or communities similar to yours who are affiliated with the NGO.

    Through this, we have found that out that many individuals, are willing to discuss employment/work related concerns with their peers, how they might be preventing them from achieving their goals, and ways to overcome them."

    Confirm below that you read the above statement(s) as it is to the respondent.

    - Yes
    - No

22. Is this above, below, or the same as what you had anticipated?

    - Below
    - Same
    - Above

23. If the participant asked you to repeat the statement, please enter how many times?

24. Surveyor comments about the intervention statement

25. Savings group

    We are thinking of starting a savings group with the collaboration of the NGO in which you and your community members can discuss financial concerns openly and can assemble money to help each other in difficult times. Would you like to be a part of such a group?

    - Yes
    - No

26. Goals. Please select one of the following options-

    Not at all/Very little/Quite a lot/Almost certain/Not applicable

    (a) How confident are you about your ability to deal with financial/employment related concerns in the coming months

    (b) How confident are you that you will be able to arrange money for your child's education (if applicable)

    (c) How confident are you about your ability to start a small business if you wanted to?

27. Read out the introduction to depression scoring section. Would you like to answer these questions?

    - Yes
    - No

28. If not, do you want us to call you later for you to answer these questions?

    - Yes
    - No

29. Every question can have an answer from 0-3. In the past few weeks, if you've never felt that way, then it is 0. If often, then 1. If more than half the time, then 2. If almost every day then 3. Please remember your score or write it on a piece of paper and then add it in the end. The added score will be the final score. Please do not tell us the score at any point. Can we begin?

    Over the last 2 weeks, how often have you had any of the following problems? Not at all, Several days, More than half the days, Nearly every day?

    - Little interest or pleasure in doing things
    - Feeling down, depressed, or hopeless

- Trouble falling or staying asleep, or sleeping too much
- Feeling tired or having little energy
- Poor appetite or overeating
- Feeling bad about yourself — or that you are a failure or have let yourself down or your family down
- Trouble concentrating on things, such as reading the newspaper or watching television
- Moving or speaking so slowly that other people could have noticed? Or the opposite — being so fidgety or restless that you have been moving around a lot more than usual

30. Please add the scores but don't tell us the total. Your score can be interpreted in the following manner-
    1-4 Minimal depression
    5-9 Mild depression
    10-14 Moderate depression
    15-19 Moderately severe depression
    20-24 Severe depression

    Since the questionnaire relies on self-report, all responses should be verified by the clinician, and a definitive diagnosis is made on clinical grounds taking into account how well the patient understood the questionnaire, as well as other relevant information from the patient.

    We will also provide you with a list of resources (names of hospitals and facilities you can access locally to seek help) and the option to learn about more information about mental well-being towards the end of the session.

    Now you have two options. Do you want to share the total score with us?

    - Yes
    - No

31. Outcome: Listening to good practices

    Now we want to give you some suggestions about how to talk about mental health such as how to begin a conversation to discuss your worries and how to become a better listener. Do you want to listen to these suggestions now?

    - Yes [Read out these]
    - No

32. If no, do you want to listen to these at another time?

- Yes
- No

33. Prize based on their baseline response [surveyor reads out an announcement informing the participant if they have won prize money based on their baseline guess] Did you read this out?
    - Yes
    - No
34. COVID notice: We would also like to remind you to make sure you that follow the COVID guidelines in your area. We do not intend to promote any in-person interactions.
35. Helpline numbers: We have a resource list that contains a list of government hospitals and facilities provided by the Delhi Psychiatric Society. Most of these are free/inexpensive and do not require referral. You may ask the NGO for help in accessing these. Would you like us to read out the list to you? .
    - Yes
    - No
36. Surveyor comments

Follow up Survey

1. In the last two weeks, have you called or sent an SMS to any of your friends to discuss your own or their financial/employment related concerns? If yes, how many?
2. In the last two weeks, have any of your friends called or sent an SMS to you to discuss your own or their financial/employment related concerns?
3. In the last two weeks, have you called or sent an SMS to any of your friends to discuss your own or their mental health related concerns? If yes, how many?
4. In the last two weeks, have any of your friends called or sent an SMS to you to discuss your own or their mental health related concerns?
5. In the last two weeks, have you tried to call a mental health helpline or doctor?
6. If you were given Rs. 200 and you could share a portion of it with a randomly chosen person in your community (via a computer lottery), would you like to share it? If yes, how much would you like to give them?
7. In the last two weeks, have often did you
   (a) Wear a mask outside your house
   (b) Maintained distance from people outside your house
   (c) Wore safety gear while cleaning waste
8. Happiness, Life Satisfaction, and Stress (as in the baseline)

Chapter 3

Network Intermediaries and Network Rules [1]

Vatsal Khandelwal [2]

I study the effect of an agent's network position on the probability with which they break rules in their social network by taking actions that risk the loss of existing links. I test the hypothesis that agents lying on more shortest paths in their borrowing network are less likely to travel to work outside their village. I propose that this is because they receive higher payoffs from brokering transactions in the network. I modify, apply, and test an existing theoretical model to show that central agents who lie on more shortest paths among other agents (i.e. 'between' central agents) are more likely to follow network rules and credibly punish those whose actions impose a negative externality. I test these relationships using a cross-sectional dataset and adjacency matrices of networks in 75 villages in Karnataka, India and find that between-central agents make choices that signal a commitment to stay and preserve the status quo. I address the endogeneity of the network variables by using theoretically motivated instrumental variables. I find that the results are robust to the inclusion of competing centrality measures and the type of network. I also compute and control for both endogenous and exogenous peer effects and find that decisions to commute to work outside the village are strategic complements. Finally, I report correlational evidence to assess if individuals located around central peers or located in networks with agents endowed with disproportionately large market power are less likely to travel to work outside. The observed effect of network position can be used to complement policies that aim to increase rural-urban mobility.

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"The substantive richness of competition lies in its imperfections, the jostling of specific players against one another, each looking for a way to make a difference." (Burt, 1992)

1 Introduction

Social networks can prevent individuals from making optimal decisions and coerce them to follow rules that preserve the status quo. For example, caste networks prevent rural-urban migration in India leading to large wage gaps (Munshi and Rosenzweig, 2016) and prevent marriage across caste groups (Munshi and Rosenzweig, 2009). In this paper, I test if agents located in an advantageous network position can be lucrative intermediaries and consequently be less likely to make decisions that violate rules and lead to a loss of network links.[3] This is because they benefit from the network by charging positive prices to facilitate information flows and transactions among other agents who wish to trade with each other. Their role as brokers is particularly important in the presence of imperfect information, incomplete markets, and reliance on social capital. I highlight the relationships of interest by modifying and applying the model proposed by Choi et al. (2017) to study adherence to rules. Then, I test the relationships using secondary data of 75 rural Indian village networks collected by Banerjee et al. (2013). I find that agents who lie on many shortest paths in the network (i.e have a high 'betweenness centrality') are less likely to travel outside the village for work and more likely to open a savings account indicating an intention to stay.[4] I also find evidence of strategic complementarities in agents' decisions to travel to work outside the village and discuss the effects of their peer's network position on their decision. Given these results, I suggest that an increase in rural-urban mobility can be achieved by reducing the market power of the between-central brokers. Mobility can be increased if (a) there is free access to information, (b) there is access to complete markets that do not rely on network-based transaction facilitators, (c) competition among agents providing such access is increased, and more traditionally, if (d) the outside option is improved. [5]

Existing literature in sociology discusses how social capital can grant individuals access to information when individual attention is constrained (Coleman, 1988) and that agents who fill "structural holes" can benefit from doing so (Burt, 1992). Access to social capital also reduces transaction costs and increases productivity (Fafchamps and Minten, 2001, 2002). First, I apply the model by Choi et al. (2017) to demonstrate that some identifiable agents,

[3] I refrain from referring to rules as 'norms' because unlike norms, that solve coordination concerns (Young, 2007), rules specifically benefit certain agents and can be imposed in a top-down manner by caste networks. As Ambedkar (2014) wrote "Caste is another name for control. Caste puts a limit on enjoyment. Caste does not allow a person to transgress caste limits in pursuit of his enjoyment."

[4] The definitions of centrality used in the paper are as per Freeman (1977); Jackson (2010). I will discuss the definitions and justify the choices as we proceed.

[5] Baseler (2021), for example, find that providing accurate information about post-migration urban incomes increases mobility. I argue that free access to information *within* the village can reduce the reliance on between-central individuals and imporove mobility.

located in lucrative network positions, can facilitate the reduction of these transaction costs documented in the literature. They can do this by lying on the shortest network-path connecting two traders so that they need to be contacted if the traders wish to access each other. For example, consider agents s and t who can trade with each other via two network-paths- s contacts i_1 who contacts i_2 who contacts t, or s contacts j_1 who contacts j_2 who contacts t. i_1, i_2, j_1, and j_2 are brokers who can announce prices that they would like to charge s and t and s and t choose the path with the lowest cost. These transactions take place, in what I refer to, as the 'market for access'. Choi et al. (2017) show how an individual's network position in terms of the proportion of network-paths they lie on affects their benefits. I introduce extensions to the model to show that agents lying on many 'shortest' paths can find it in their interest to make rule-adhering choices that do not dilute or cause loss of network links. This generates the first empirically testable prediction.

Next, I discuss how the network position of an individual's peers can affect their decisions. I propose that between-central agents can credibly threaten others to prevent them from making rule-violating choices that reduce their payoffs. For example, i_1's decision to violate a rule can make the path containing i_1 and i_2 less visible or usable to s and t thereby inducing i_2 to punish i_1 to prevent them from breaking the rule. I use a standard signalling game as an example to illustrate that under certain conditions, there exists a fully separating Perfect Bayesian Equilibrium in which agents do not violate rules because between-central agents can credibly punish them. This generates the second empirically testable prediction.

I empirically test the predictions of the model using a large data-set containing individual characteristics and network matrices of 75 Indian villages collected by Banerjee et al. (2013). First, I check if between-central agents are less likely to travel for work outside the village. Even though whether an individual travels outside the village for work is a weak proxy for their intent to temporarily migrate, I use this variable to capture the intention of an individual to risk the loss of network relationships by commuting to a place of work outside their location of residence. I also capture the intent to leave by using the information on whether individuals are willing to open savings accounts and participate in self-help groups since these decisions cost both time and effort. Their returns, I argue, are higher if the individual is planning to stay. I find evidence that individuals who lie on more shortest paths between other agents in the network are significantly less likely to travel outside their village for work risking dilution of existing network relationships. I also find that they are more likely to open savings accounts.

I use a theoretically motivated instrumental variables approach to identify the effect of centrality since network position is endogenous. I allow agents in the model to form coalitions along network-paths with a fixed probability.[6] For example, i_1 and i_2 can

[6]This assumption also reduces the number of possible equilibria. Choi et al. (2017) also consider refinements such as coalition-proof or strong Nash equilibrium.

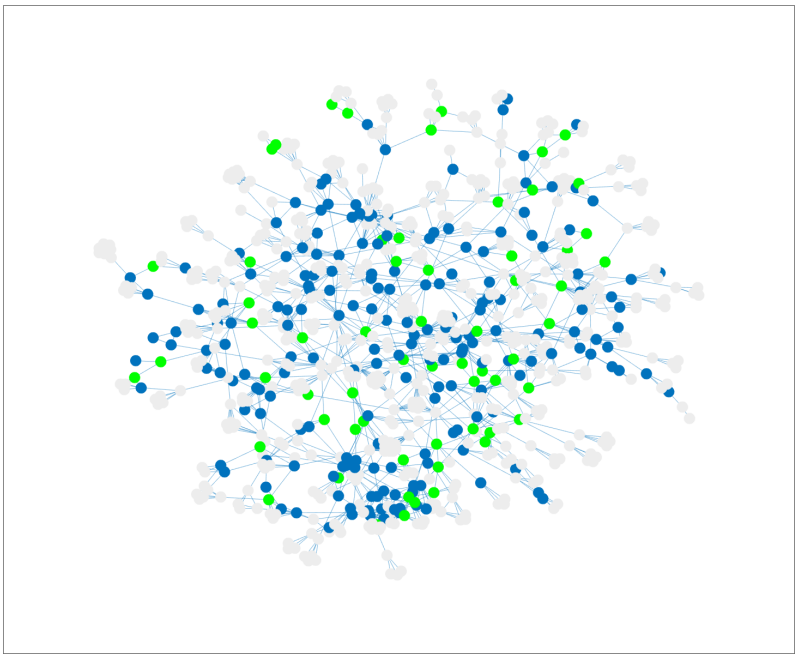
form a coalition, thereby resolving their coordination concerns while setting prices, and compete with the agents on the other path driving their prices to zero. In line with the network-formation model proposed by Goyal and Vega-Redondo (2007), this then implies that risk-neutral agents have an incentive to invest in lying on the shortest paths between two traders only if they are not surrounded by others who have done so already. This is because their expected benefits are falling in the probability of a coalition forming against them. I use this to motivate the instrument strategy used in the empirical analysis. I also discuss the validity of this instrument and perform robustness checks using both alternative specifications and alternative instruments. I also measure exogenous and endogenous peer effects to show that network position matters even when these interaction effects are incorporated. I instrument for endogenous peer effects as per the method specified in Bramoullé et al. (2009); De Giorgi et al. (2010). All specifications control for individual characteristics, endogenous and exogenous peer covariates, village and caste fixed effects.

Finally, I shed light on competing mechanisms by which the network position of peers can influence agent decisions. For example, peers who lie on many shortest paths can increase an agent's willingness to leave the network and work outside because (a) they provide competition in the market for access and reduce the agent's benefits from the network or (b) they provide information on jobs gathered from their contacts that the agent does not possess. I present network-level correlations to check if more unequal networks that contain agents with more market power are less likely to have rule violators. I compute characteristics of the centrality distributions and measure changes in the connectedness of the network when agents are removed from the network to proxy for their market power. I do this by computing the Fiedler value of the network (Fiedler, 1973) with and without each agent being present in the network.[7] I find correlational evidence supporting a potentially negative relationship between the proportion of agents who travel to work outside and the presence of between-central agents in their network. However, the results are not conclusive because the data within a network cannot be exploited due to endogeneity and there are a limited number of networks available for analysis.

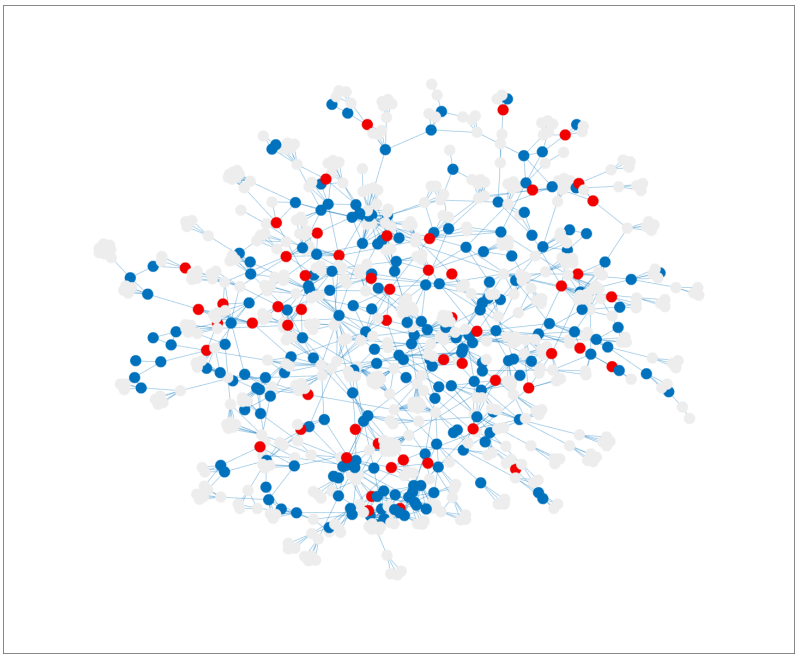
The network plots in Figure 1.0.1 use the data provided by Banerjee et al. (2013) and depict borrowing networks in a village in Karnataka, India. The colours indicate whether an individual travels outside the village for work (green), owns a saving account (red), or does not do so (blue). The nodes for which data is not available are in grey. According to the main hypotheses of this paper, nodes lying on fewer shortest paths are more likely to be green and less likely to be red. I proceed as follows.

In Section 2, I discuss the contributions of the paper to existing literature. In Section 3, I illustrate a theoretical model that posits the existence of an underlying 'market for access', motivates the choice of the centrality measure, and establishes the relationships between the variables of interest. I also provide a rationale for the instrumental variables approach

[7] This is discussed in detail in Section 4 and Section 5.6.



(a) Nodes highlighted in green (blue) work (do not work) outside the village.



(b) Nodes highlighted in red (blue) have (do not have) a savings account.

Figure 1.0.1: Example of a Borrowing Network (Village 4)

that is used for estimation and discuss why agents in specific network positions can find it in their interest to credibly punish those whose decisions impose a negative externality. I discuss the data source and various choices made for the empirical specification in Section 4. I discuss the concerns regarding endogeneity and how the empirical analysis deals with them. I proceed with the empirical analysis to test the hypotheses and discuss the results in Section 5. I also run different robustness checks and discuss alternative specifications which include identification of both exogenous and endogenous peer effects. I briefly discuss how individual decisions are impacted by the network position of their peers and the centrality distribution of their village in Section 6. I conclude in Section 7.

2 Contribution

This paper contributes to the existing literature in the following ways.

First, while I do not focus on risk-sharing, the results suggest that specific agents can benefit from facilitating intra-network transfers more than others depending on their network position. A large proportion of the existing literature that studies risk-sharing in social networks does not use the right group inside which transfers are exchanged (Mazzocco and Saini, 2007; Munshi, 2016). Exceptions to this include papers such as Munshi and Rosenzweig (2009, 2016) which study how risk-sharing among castes reduces migration. Munshi and Rosenzweig (2009) show that risk-sharing among subcastes (*jatis*) reduces permanent migration in India and that households in richer subcastes are less likely to migrate. Munshi and Rosenzweig (2016) find that poorer households benefit more from caste-based risk-sharing and consequently have a lower probability of migration. However, this literature does not incorporate the structure of the network inside which these exchanges are made. Individuals who are differently placed in the network can benefit differently from the economic exchange that takes place on the network. Growing evidence suggests that network attributes matter in affecting economic decisions such as migration. Blumenstock et al. (2019), for example, use communication networks in Rwanda to investigate this.

I contribute to this literature by identifying specific agents who can benefit more from the status quo and can find it in their favour to uphold rules that restrict mobility. I focus on borrowing networks but remain agnostic about the nature of transactions that these agents are facilitating. I show that two individuals in the same borrowing network, with identical individual and peer-level attributes, may have different probabilities of going for work outside the village dependent on where they are located within the group and how they can leverage their position. These empirical results are in line with experimental findings by Choi et al. (2017) who find that prices are lower (higher) when there is perfect (no) competition among traders. In my setting, I suggest that imperfect competition allows specific access providers to charge positive prices and be less likely to leave the network.

Second, I apply and test the implications of theoretical models that show that "essential" agents who lie on *all* shortest paths can charge positive prices to allow exchange (Choi

et al., 2017) and how this affects agents decisions to form links (Goyal and Vega-Redondo, 2007). The role of agents who connect different groups has also previously been studied in the literature in sociology such as Burt (1992, 2004) who show that the entrepreneurial agents who bridge "structural holes" in the network can benefit from access to new information and ideas. Fafchamps (2003) discuss how trust-based exchange in social networks depends on intermediaries who can appropriate the trade surplus. Fafchamps and Labonne (2020) use a model to show that politicians in power can find it in their favour to extend more services to between-central agents and present empirical evidence from the Philippines that supports this hypothesis. Condorelli and Galeotti (2016); Galeotti and Goyal (2015) show that agents with high betweenness centrality can charge higher prices and claim higher profits while facilitating trade in complete multi-partite networks.[8] I empirically test the predictions using data from rural India and comment on the implications of the result on rural-urban mobility.

Third, I provide a network-based explanation for punishment. I propose that agents lying on more shortest paths are incentivised to exclude others when others make choices that negatively affect the visibility or usability of the network-path containing them. On the other hand, an agent's decisions that lead to dilution of their network links can also impose a positive externality on very central competitors who can now access a larger market. These dynamics, I discuss both theoretically and empirically, can affect how an individual responds to the network position of their peers and how unequal network positions within the village can affect the proportion of individuals who travel to work outside, or more broadly, violate a rule. Munshi and Rosenzweig (2016) discuss that households with migrant members can be excluded by rural Indian networks. Hoff and Sen (2005) note that the "kin-system" can also reduce migration. Fafchamps (2003) discuss conditions under which agents can be prevented from violating contracts via threats of exclusion and when these threats are individually rational.[9] Jordan et al. (2016) show that third-parties that observe defection punish the offending party to signal that they can be trusted. Breza et al. (2015) experimentally find that central individuals are better at being such third-parties since they can affect the reputation of the agent and execute the punishment. Contributing to this literature, I discuss that between-central agents can credibly threaten exclusion when they are the affected party. This is because they earn a higher discounted stream of future payoffs from the status quo, face the negative externalities of other's actions, and have a higher incentive to signal their type for future interactions. I provide descriptive evidence to check if networks with agents who have substantial market power are more exclusionary.

Finally, existing research shows how market-based interventions can affect migration and rural network links. For example, Lagakos et al. (2018) calibrate a model to compare

[8] See Condorelli and Galeotti (2016) for an exhaustive review of the literature on network intermediaries.

[9] Fafchamps (2003) also provide a detailed overview of the literature on how cooperation is achieved in decentralised markets.

subsides that promote migration with unconditional cash transfers and rural employment programs. They find that subsidising migration has the highest positive welfare impacts on households that are least well off. Meghir et al. (2019) find that temporarily subsidising migration in Bangladesh led to improvements in intra-village risk-sharing but an analogous permanent subsidy can reduce it. Morten (2016) also deduce from a dataset in rural India that encouraging temporary migration can negatively affect informal insurance. Banerjee et al. (2021) find that the provision of microfinance can erode informal network links even among those who are not likely to participate in it. I argue that it is important to study the heterogeneous welfare impacts of migration subsidies and micro-finance interventions by taking the network-positions of the affected individuals into consideration. As per the underlying theoretical mechanisms and empirical evidence provided in this paper, individuals who lie on more shortest paths have a higher marginal loss due to the erosion of links. This is an important observation for two reasons. First, it helps us to identify the predicted non-users of microfinance (or any alternative substitute) who may need additional assistance. Second, after the deterioration of network links, these agents will not find it in their interest anymore to punish others who violate rules and this will potentially improve mobility. However, it could also be that these agents are potentially more likely to join the formal credit systems themselves to compensate for the disproportionate loss in both network benefits *and* the benefits from brokering in the market for access. This can be true especially if migration is too costly an option. Thus, the long term impacts of formal credit (and other equivalent interventions) can be analysed in more detail by measuring the differential impacts of network position on an agent's economic decisions and their decisions to impose social sanctions.

3 Theory

The section is divided into three distinct parts, each of which generates an empirically testable prediction. The theoretical setup introduced here will allow us to understand (a) why agents located in specific network positions can benefit more from the network and be less likely to violate rules, (b) why these agents would find it in their favour to credibly threaten others who violate rules, and (c) why investments in these network positions are substitutes. While (a) and (b) are concerned with the main hypotheses of interest, (c) underlies the instrument strategy used to address the endogeneity of network position in the empirical specification.

3.1 The Market For Access

I present the model and results in Choi et al. (2017) in this section. Any modifications made to their theoretical setup are mentioned as they are introduced. I will first discuss the setup of the game and then discuss the equilibrum strategies of the players. This will allow me to show that agents who lie on many shortest paths among other agents in the network will have higher equilibrium payoffs.

Setup

Consider an undirected network G of agents in the set $N=\{1,2,...,n\}$.[10] A path between two unconnected agents s and t in N is a sequence of distinct nodes starting from s and ending at t such that each node between s and t has an undirected edge connecting them to the previous and subsequent node. All pairs of agents s and t engage in trade. Trade can involve a transaction of goods and services or the exchange of information. Trade between any two agents can only take place if the agents lying on the network path between the traders facilitate it.[11] Agents play the following game.

Consider two unconnected agents s and t in the network who wish to engage in trade. All the nodes lying on a shortest path between s and t play the game where their strategy is to declare a positive price p to help in facilitating the trade between s and t. We can define nodes lying on a path between s and t to be 'brokers' who provide agent s and t 'access' to each other.[12] The trade between s and t has a fixed value v_{st} and takes place if the sum of prices announced by the agents lying on the path P^*_{st} chosen by s and t is less than or equal to v i.e. $\sum_{i\in P^*_{st}} p^i \leq v_{st}$. I do not model how the fees are split among the agents lying on the path chosen by the traders. Unlike Choi et al. (2017), I assume that s and t only consider paths of the shortest length while deciding which path to use to facilitate the transaction.[13] Let the number of such shortest paths be equal to η_{st}. Agents s and t choose the path with the lowest total price, henceforth called the 'cheapest path' out of the η_{st} shortest paths between them.[14] Let the total number of such cheapest paths be equal to κ^*_{st} and the total number of cheapest paths between s and t an agent i lies on be equal to κ^i_{st}. Broker i receives a payoff of 0 if they do not lie on the cheapest path and a payoff of $\frac{\kappa^i_{st}}{\kappa^*_{st}}\ p^i$ otherwise.

Equilibrium Strategies

I now discuss the prices that the brokers will set in equilibrium. Choi et al. (2017) prove the existence of Nash equilibrium price profile p^* in which "essential" agents lying on *all* cheapest paths between the traders charge positive prices that exhaust the value of the trade. For example, consider a circle network with six agents and choose agents s and

[10] The network is undirected so the corresponding adjacency matrix A has elements $a_{st} = 1$ if s has an undirected link to t and 0 otherwise.

[11] Existing literature relates social capital with transaction costs. For example, Fafchamps and Minten (2001) discuss the role played by social capital in reducing transaction costs and use data from Madagascar, Benin, and Malawi to show that more connected traders have high output. Individuals in the model considered here make use of their social capital i.e. the brokers lying on shortest paths between them and the other trading party.

[12] We can apply this terminology to rural risk-sharing networks. Agent s may be in a borrowing relationship with agent t whom agent s doesn't know directly. This could be because agent i's immediate peers face correlated shocks and cannot be borrowed from or lent to. So agent s must get in touch with other agents who can provide access to agent t.

[13] The total number of paths between two agents can be very large and it is not plausible to expect that s and t will observe the posted prices of agents lying on all paths between them.

[14] The set of cheapest paths is a subset of the set of shortest paths.

t such that there are two agents between them from either side. Let these agents be i_1 and i_2 on the first path and j_1 and j_2 on the second path. It is easy to check that any equilibrium where trade takes place must be one where either (a) all the intermediaries i_1, i_2, j_1, j_2 charge a zero price (i.e. no one is "essential"), or (b) where i_1 and i_2 charge a positive price summing to v_{st}, and j_1 and j_2 both charge a price larger than v such that no one has an incentive to deviate. Agents i_1 and i_2 are essential agents in (b) since they lie on the only cheapest path. In this case, $\eta_{st} = 2$ but $\kappa^*_{st} = 1$.

To refine the set of equilibria, I allow agents lying on a shortest path between two traders to form coalitions along the path with a non-zero probability $\rho \in (0, 1)$.[15] I assume that agents lying on two different paths cannot form a coalition. So, for any traders s and t and a shortest path $\{s, j_1, j_2, t\}$, the nodes $\{j_1, j_2\}$ function as a single node with probability ρ. I assume that ρ does not depend on the length of the path.[16] What does coalition-formation imply for the equilibrium type (b) described above? If j_1 and j_2 can form a coalition, it would mean that i_1 and i_2 can face competition from them and they would then end up receiving a payoff 0.[17] The probability of the existence of a competing coalition (and consequent Bertrand-style competition) is falling in the fraction of shortest paths an agent lies on.

Equilibrium Payoffs

The expected gains for a broker i from a trade between s and t can then be written as follows

$$\begin{aligned} \pi^i_{st} &= g^i_{st}(1-\rho)^{\eta^{-i}_{st}} p^{*i}_{st} \\ &= g^i_{st}(1-\rho)^{(1-\phi^i_{st})\eta_{st}} p^{*i}_{st}. \end{aligned} \tag{3.1}$$

where g^i_{st} is an indicator of whether a least-cost shortest path containing agent i between s and t exists. I will allow g^i_{st} to be affected by the perception of s and t whether such a path exists- this will be discussed in the next subsection. η^{-i}_{st} is the number of shortest paths between s and t that i does not lie on and ϕ^i_{st} is the fraction of shortest paths between s and t agent i lies on. p^{*i}_{st} is the price posted by i in the Nash equilibrium of the game discussed above.

The term $(1-\rho)^{(1-\phi^i_{st})\eta_{st}}$ is the probability that no coalition is formed on a path that does not contain agent i. This can be derived in the following manner. The probability that agents lying on a path don't form a coalition is equal to $(1-\rho)$. The number of shortest

[15] Choi et al. (2017) also study refinements such as strong Nash equilibria and coalition proof equilibria. They discuss, for example, that strong Nash equilibria do not exist in a circle network. The assumption that agents cannot form a coalition with *any* randomly chosen agent lying on other paths seems reasonable in the context of village networks with caste-dependent hierarchies.

[16] This is not a critical assumption here since given the network locations of the two traders, all the shortest paths between them, by virtue of being the shortest, must be of the same length.

[17] This does not depend on i_1 and i_2's ability to form a coalition. They have no incentive to deviate from p^*.

paths between s and t that do not contain i are equal to $\eta_{st}^{-i} = (1-\phi_{st}^{i})\eta_{st}$. The probability that none of these paths forms a coalition is derived accordingly. The probability that a competing coalition is not formed can also be written as $(1-\rho)^{\eta_{st}^{-i}}$. In equilibrium type (b) of the example discussed above, the payoff for agent i_1 will be equal to $(1-\rho)^{1}p_{st}^{*i_1}$ since the shortest path containing j_1 and j_2 can form a coalition with probability ρ in which case the price i_1 will be able to charge will be equal to zero.

For any network G where all pairs of nodes s and t engage in trade, the expected benefits obtained by node i can be written in the following manner.

$$\pi^{i} = \sum_{s,t \neq i} g_{st}^{i}(1-\rho)^{(1-\phi_{st}^{i})\eta_{st}} p_{st}^{*i}. \tag{3.2}$$

This generates the *first prediction* of the model- that individuals who lie on more shortest paths have higher expected benefits from the market for access and mirrors the existing findings in Galeotti and Goyal (2015) and Choi et al. (2017).[18]

3.2 Rules

Now, I allow all agents $i \in N$ to make an additional decision $r_i \in \{0,1\}$ after they decide their strategies p_{st}^{i*} in above game. Agents who choose $r_i = 0$ are said to adhere to the 'rule' and those who choose $r_i = 1$ are said to violate it. $r_i = 1$ could correspond to making decisions such as working outside the village, migrating, or marrying outside the caste.

I show how rule violation can affect payoffs. This will allow us to show that agents who lie on many shortest paths are less likely to violate rules. I assume that what matters for a broker i is not just lying on a shortest path but that the trading duo is aware that i lies on this path or that this path is functional. To this effect, I allow g_{st}^{i} to be scaled to reflect the assessment of s and t as to whether there exists a shortest path between them that agent i lies on (the visibility of the path) or whether shortest paths containing agent i are functional (the usability of the path). I assume that i's choice r_i affects the perceived visibility and usability of the paths on which i lies. The subjective assessment of s and t as to whether a shortest path containing i exists (previously equal to g_{st}^{i}) is now equal to $\delta(r)g_{st}^{i}$ where r is the profile of actions of all agents lying on the shortest paths containing i. It depends on agent i's choice in that $\delta(r_i = 0) = 1$ and $\delta(r_i = 1) \in [0,1)$. A decrease in the value of δ effectively captures an effect similar to that of a loss in network links of the broker who has violated the rule.

I assume that g_{st}^{i} can also be affected by the actions of other agents on the path. So s and t might not consider that i lies on a shortest path between them if i violates the rule or if agents lying on the same shortest paths as i violate the rule. This creates externalities between the action r_j of an agent j lying on the same shortest path as i and the visibility

[18] Galeotti and Goyal (2015) also find that agents who lie on many shortest paths can charge positive prices and make positive profits in complete multi-partite networks.

of i's shortest path to s and t. For example, if j marries outside her caste or has a family member who migrates, it is assumed that this makes the path containing i and j less visible/usable for s and t. This can be sustained by underlying beliefs that are not modelled here. Agent j may be perceived to be less likely to commit to their links since they break rules and other agents may not be linking with them anymore. Alternatively, in the case of temporary migration, the links to and from j may not be usable.

Rule Violations without Punishments

Consider the case where punishments or threats cannot be imposed. Let the net benefit for agent j of choosing $r_j = 1$ be equal to a fixed scalar $w \geq 0$ for all $j \in N$

Given a profile of equilibrium prices and $\delta(r_j = 1) = \delta$, agent j will only break the rule if-

$$\sum_{s,t \neq j} (1-\delta) g^j_{st} (1-\rho)^{(1-\phi^j_{st})\eta_{st}} p^{*j}_{st} \leq w. \tag{3.3}$$

Thus, j is less likely to violate the rule if they lie on a higher fraction of shortest paths among other agents in the network. They are more likely to violate the rule if the outside option w is high.

The above trade-off does not include the punishments that can be credibly imposed on agent j for violating the rule. I will now discuss why other agents may find it beneficial to punish j.

Rule Violations with Punishments

What happens to agent i's payoff if agent j breaks the rule and chooses $r_j = 0$? Recall that the probability of coalition forming against i depends on the number of paths that do not contain i i.e. η^{-i}_{st}. We can rewrite η^{-i}_{st} as $\sum_{j \neq i} \delta_j g^j_{st}$ where $\delta_j = \delta(r_j)$. If an agent who does not lie on the shortest paths containing i violates a rule, this lowers the probability of a coalition forming against i since η^{-i}_{st} falls. Thus, whether or not i benefits from rule violations depends on the network position of the agent violating the rule. Agents who do not lie on the same paths as i and are competing with i in the market for access will inevitably benefit i if they violate rules. Agents whom i is directly connected to are more likely to lie on the same shortest paths as i and more likely to reduce i's payoffs if they violate a rule. In this case, agent i will be worse off without getting the benefit w that j has access to. Agent i can threaten agent j that they will impose a penalty on j's payoff if j breaks the rule. Agent i can convince other agents to not interact with j and reduce j's network benefits. Agent i can also incur a positive cost in doing so.

j's decision to violate the rule can also affect i's future payoffs if this were a repeated game. I do not model this dependence between j's rule violation and the visibility/usability of i's paths in the next period. However, I conjecture that if i cares about the future and lies on many shortest paths such that his payoffs from the market for access are high,

then he may find it in his favour to punish j. For example, consider a discounted sum of the payoffs described in the static setup (in Equation 3.2) added across multiple time-periods in which the posted-prices game is played repeatedly and agents decide to follow or violate rules in every time period. If agent j in i's network neighbourhood breaks the rule in time period τ, then this affects $\delta^{i\tau} g^i_{st}$ due to the externalities described above. However, it can also negatively affect $\delta^{i\tau+1} g^i_{st}$. This is because other agents may perceive i to be weak if they do not observe a punishment and can then be more likely to break the rule themselves- thereby creating a link between r_j in time τ and $\delta^{i\tau+1}$.This generates the *second prediction*- agents who benefit more from brokering in the market for access (i.e. those who lie on more shortest paths and have higher discounted payoffs) will be more likely to credibly punish those who break rules.

I will illustrate this further using a simple example of a signalling game.

Example

Define an extensive form signalling game played on network G, shown in Figure 3.2.1. I model the interactions of three agents i, j, and k located on this network. First, agent j decides whether to break the network rule and choose $r_j \in \{0, 1\}$. Agent i in j's neighbourhood can be of two types- i_w and i_s who are weak and strong respectively. Agent j, as I will discuss, can have priors over this proportional to the fraction of shortest paths that agent i lies on. The weak type i_w does not receive benefits from punishing other agents while the strong type does. Once i's type is realised, i decides whether to punish agent j if they have violated the rule. The punishment also acts as a signal to agent k who observes i's choice to punish j and updates their belief about i's type. Then, k decides whether to break the rule or not and i decides whether to punish k. The strong type i_s also builds reputation by punishing k since this generates future payoffs from other interactions with the same or other agents who may not wish to break the rule if they observe punishments in the history of the game. The payoffs can be explained as follows.

Agent i has three types of payoffs $\pi^h_i, \pi^m_i, \pi^l_i$ which are realised when no one breaks the rule, either one of k or j break the rule, or both break the rule such that $\pi^h_i > \pi^m_i > \pi^l_i$. These correspond to the total discounted stream of payoffs that i receives from the market for access i.e. the discounted sum of the payoffs listed in Equation 3.2. They are negatively affected, as discussed above, by j and k's decision to violate the rule. Agent i also has a cost of punishing other agents equal to $c > 0$. This is also the cost incurred by the punished agents who upon breaking the rule receive $w > 0$ and face cost c if punished. Agents j and k receive π_j and π_k respectively if they do not break the rule. Type i_s benefits from signalling via punishment and gains an additional future stream of payoffs θ if they punish agent j and θ' if they punish both agents j and k.[19] I assume that $\theta' > \theta$ i.e. the benefit generated by two punishments is assumed to be a stronger deterrent that can prevent future agents from breaking the rules.

[19]This benefit of punishment, as discussed earlier, can be interpreted as the increase in the visibility of i's path in future i.e. an increase in $\delta^{i\tau+1}$ if $r_{j\tau} = 1$.

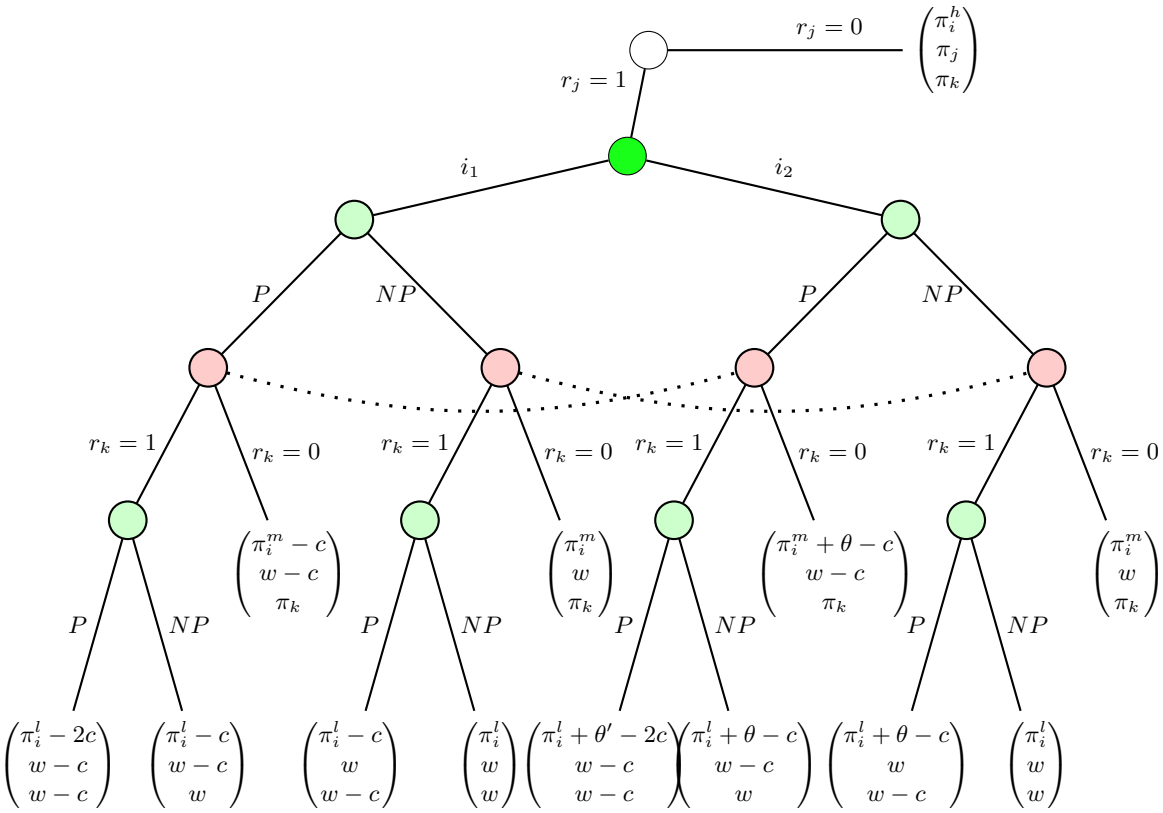


Figure 3.2.1: This figure shows the extensive form representation of the signalling game. Agent i's nodes are shown in green, Agent j in white, and Agent k in pink. The bright green node is nature that determines agent i's type. The dotted lines connect decision nodes in the same information set.

There exists a separating Perfect Bayesian Equilibrium (PBE) of this game in which j decides to not break the rule and chooses $r_j = 0$, i_w never decides to punish, i_s always decides to punish, and k decides to not break the rule upon observing punishment and breaks the rule otherwise. Under such separating equilibrium, k believes that i is of type i_w after observing no punishment and i is of type i_s after observing punishment with probability 1. Note that the strong type i_s who receives additional payoffs from punishment can be interpreted as an agent who lies on many shortest paths, benefits more from the status quo if agents do not break rules, and has more to lose in case they do.

I derive the conditions under which this strategy profile is a PBE below-

1. i_w has a dominant strategy to not punish k and i_s has a dominant strategy to punish k in the last stage of the game. It is easy to check that this is true when the costs of punishing are not too high and when the future payoffs of punishing are high enough. The conditions are as follows:

$$\theta' - \theta > c \text{ and } \theta > c > 0. \tag{3.4}$$

2. Given that type i_w will never punish and i_s will always punish, k will choose $r_k = 1$ when playing with type i_w and $r_k = 0$ with type i_s. The conditions for this are as follows:

$$w - c < \pi_k < w. \tag{3.5}$$

3. Now we impose conditions that ensure that i_w will always decide to not punish j and i_s will decide to do so. Under the proposed PBE, if i_w punishes j, k will think of them to be type i_s with probability 1, will not break the rule, and i_w will receive $\pi_i^m - c$. If they do not punish j, k will know that they are i_w and they will receive π_l. So, π_l must be greater than $\pi_i^m - c$. Similarly, if type i_s doesn't punish j, then k will break the rule assuming they're i_w, and they will receive $\pi_i^l + \theta - c$. If they do, they will receive $\pi_i^m + \theta - c$.

   So under the suggested PBE it must be true that:

$$\pi_i^m - c < \pi_i^l < \pi_i^m. \tag{3.6}$$

   i.e. the loss in network benefits if both k and j break the rule are not large enough to convince i_w to punish but are also not small enough to prevent i_s from wanting to do so.

4. Finally, agent j must decide whether to break the rule or not depending on their priors about i's type and the knowledge that under this PBE, type i_w will not punish them but type i_s will do so. j does not observe any signal from i since they are the first player but their priors can depend on i's centrality such that $Pr(i = i_w | \sum_{s,t} \phi_{st}^i)$

is decreasing in $\sum_{s,t} \phi^i_{st}$. This is because an agent i who lies on many shortest paths will, as we have previously discussed, be less likely to leave the network G since they receive higher benefits from the market for access. η^{-i}_{st} is low for such agents. This means that they are more likely to have a higher stream of future payoffs that they wish to protect from rule-violators. Thus, j will not break the rule when

$$Pr(i = i_w | \sum_{s,t} \phi^i_{st}) w + (1 - Pr(i = i_w | \sum_{s,t} \phi^i_{st}))(w - c) < \pi_j. \tag{3.7}$$

This tradeoff is easier to satisfy when i lies on many shortest paths.

3.3 Network Formation

Now, I allow agents to unilaterally choose their network links given the equilibrium price that they charge in the resulting market for access. I will use the agent's best responses to generate the third prediction that will motivate the instrument strategy in the empirical specification. Consider the utility that a risk-neutral agent i receives from network G:

$$U^i(G) = b(G) - c(G) + \sum_{s,t \neq i} g^i_{st}(G)(1 - \rho)^{(1-\phi^i_{st}(G))\eta_{st}(G)} p^{*i}_{st}(G). \tag{3.8}$$

$b(G)$ is the benefit from network G rising in the number of connections (i.e. degree) in the network. $c(G)$ is the cost i pays to build and maintain the network and is rising in the agent's network degree as well as the number of shortest paths they lie on. The marginal benefit of a link is proportional to both direct benefits $b(G)$ and indirect expected benefits via the market for access. The marginal cost of a link may additionally depend on the type of the link being formed- a link that bridges different parts of the network (thereby increasing ϕ^i_{st} for some s and t in different components) can be more costly since it may have to be built with an agent whose peers are not directly known or known via existing peers.

The network-formation process in which intermediaries can charge to facilitate transactions is previously modelled in Goyal and Vega-Redondo (2007). The primary difference between the setup here and in their model is that the intermediation benefits here are proportional to the payoffs in the Nash equilibria of the posted prices game discussed above where agents can form coalitions along paths in the network. This modification is made to emphasise that agents will prefer to build links that make them lie on shortest paths among other agents if many such shortest paths do not exist already.

Consider an agent i deciding to form one of two types of links. The first type of (bridging) link creates a shortest path between two agents s and t of the same length as the existing shortest paths between s and t and is i's first shortest path connecting the traders. The marginal benefit of this link is equal to the network benefits and the benefit from the market for access, the latter of which is equal to $(1 - \rho)^{\eta^{-i}_{st}}$. Clearly, the marginal benefit

is lower if η_{st}^{-i} is high. The second type of (standard) link does not generate any such indirect benefits. If the cost of building a bridging link is low enough, and there are not many existing shortest paths between nodes s and t then the agent will strictly prefer to build the bridging type of link as opposed to the standard one that only gives them direct benefits. If there are already many shortest paths, then agents will best respond by not building the costly bridging link. This motivates the *third prediction* of the model: that an individual i's best response in terms of whether they wish to lie on a shortest path between s and t is decreasing in the number of existing shortest paths between s and t.[20]

3.4 Predictions

The theoretical setup generates the following empirically testable predictions.

Prediction 1:

$$\frac{\partial Pr(r_i = 1|\sum_{s,t}\phi_{st}^i)}{\partial \sum_{s,t}\phi_{st}^i} < 0 \ \forall i, s, t \in N.$$

Agents i with a high $\sum_{s,t}\phi_{st}^i$ are more likely to adhere to the rule and choose $r_i = 0$. This is clear from the inequality in equation 3.3.

Prediction 2:

$$\frac{\partial Pr(r_i = 0|\sum_{s,t}\phi_{st}^j)}{\sum_{s,t}\phi_{st}^j} \leq 0 \ \forall i, j, s, t \in N \text{ and where } j \in N(i).$$

This prediction follows from the conjecture discussed in the example above. An agent j in i's network neighbourhood $N(i)$ who lies on more shortest paths is likely to be a strong type in the signalling game considered above. This allows them to credibly execute credible punishments to prevent violations of rules by agent i that negatively impact them. Prediction 2 can be checked empirically by computing the correlation between the network position of an individual's peers on the individual's decision or by verifying if the number of agents k who break the rule $r_k = 0$ are lower in networks where there exist agents lying on many shortest paths i.e. where these threats are likely to be implemented.

Prediction 3:

$$U(\eta_{st}^i = 1|\eta_{st}^j = \eta) - U(\eta_{st}^i = 0|\eta_{st}^j = \eta) > U(\eta_{st}^i = 1|\eta_{st}^j = \eta') - U(\eta_{st}^i = 0|\eta_{st}^j = \eta') \text{ for any } \eta < \eta'$$

$\forall i, j, s, t \in N$. This implies that the returns to investing in a shortest path for agent i fall if another agent j has already invested in many of these paths. This is because agents

[20] Note that the marginal benefit for agent i of creating a link that makes him lie on a shortest path between s and t depends only on the number of existing paths that the i does not lie on. Holding fixed the number of such paths, i does not receive additional market for access related benefits by creating links that make him lie on more than one shortest path between s and t. This simplification is made to highlight the relationship of interest. We can also allow g_{st}^i to be increasing in the number of shortest paths i lies on. This can be true, for instance, if s an t are more likely to realise that i lies on a shortest path if i lies on many shortest paths.

can only charge a strictly positive price in the market for access if the existing number of shortest paths between the traders in question is low. This can be inferred from Equation 3.2. This prediction implies that we can expect negative correlations between the number of shortest paths agent i lies on and the number of shortest paths agents around them lie on. This is because if an agent around i has already invested in shortest paths, i would have a lower incentive to form such links.[21] As I will discuss, an agent's preferences to link to those similar to them (that is currently not accounted for by the model) may also affect the observed correlations between the network position of i and j who are peers.

The empirical analysis in the next section aims to test these predictions. I will primarily focus on prediction 1 and provide a more complete test of the centrality effect by (a) trying to address the endogeneity of agent centrality (using prediction 3 and other alternative instruments), (b) controlling for exogenous and endogenous peer effects, and (c) running a variety of robustness checks. I will run descriptive checks to test prediction 2.

4 Identification

Banerjee et al. (2013) collect a unique dataset ranging across 75 villages in rural Karnataka, India. This paper uses the data provided by them - a cross-section of household characteristics, individual characteristics, and adjacency matrices for a variety of undirected networks at both household and individual levels.[22] Adjacency matrices are provided in the data for each of the 75 villages characterizing a variety of social interactions taking place in the villages such as advice-giving, borrowing or lending money, borrowing or lending kerosine/rice, going to each other's homes, visiting the temple together, etc, and a combination of all these relationships henceforth referred as the overall network. These matrices are symmetric square matrices whose ijth element is equal to 1 if a relation is present and is 0 otherwise. I will now explain the choices made for the empirical specification and discuss how I deal with the endogeneity of the network measures.

4.1 Specification

Choice of Network

I use the adjacency matrices of the borrowing networks to compute the measures of interest as a part of the main empirical strategy. A link g_{ij} in borrowing network G exists if i reports j as someone whom they would borrow Rs. 50 from for a day. The network is undirected as it proxies for financial relationships among individuals. Using

[21] An underlying assumption here is that agents know the investment decisions i.e. centralities of other agents while playing the game. This is supported by recent empirical evidence that shows that agents in rural social networks can identify ideal candidates to target to spread information without the need for a network map (Banerjee et al., 2014).

[22] The authors also provide useful READ ME documents that describe the data and the folder. No code provided by the authors was used.

borrowing networks to compute the measures has an intuitive appeal since these reported relationships may represent risk-sharing transfers or even sharing of information about work opportunities. An individual who lies on many shortest paths on this network is likely to be one who can be contacted by others to provide access to potential risk-sharers and facilitate exchange in the network.

I will consider centrality measures obtained from three other networks which vary in how conservative they are (compared to the the borrowing network) in assuming a link between two agents respectively. This is done to ensure robustness. First, I will construct and use a 'maximum' economic network in which a link exists if the individuals report *any* borrowing or lending relationship in terms of money, kerosine, or rice. Unlike the borrowing network, the economic network assumes a link if the agents engage in *any* of these economic interactions. Second, I will use the overall network available in the data which is even less conservative in assuming a link and includes non-economic interactions as well. The overall network contains a link among individual if they report having *any* relationship such as borrowing/lending money, advice taking/giving, visiting each other's houses, contacting during medical emergencies etc. This network is the union of all the networks contained in the data. Both networks provide rich variation in the number of an individual peers' peers that, I will discuss, is critical for the validity of the instrument. However, these networks can be susceptible to measurement error since a link reported erroneously in any of the networks will be treated as a link in the union. Ambrus et al. (2014) discuss the problem of measurement error and construct and "and" network to correct for this. In addition to these networks, I also discuss the results on this more conservative economic network (also computed by Ambrus et al. (2014)) that assumes a link exists between i and j if i reports that they will be happy to both borrow and lend both money *and* kerosine/rice to j. Note that this network, by construction, is sparser than the others and the variation in the number of peers' peers of an individual is considerably low. I will discuss the implications of these choices on the results.

Choice of Network Centrality

I measure the market power of each agent in the market for access by computing their betweenness centrality. The model shows that given a number of shortest paths between two traders, an agent who lies on more shortest paths will be less likely to have a coalition forming against them and more likely to charge a positive price. I compute the betweenness centrality of each agent by using the adjacency matrices of the borrowing networks. The betweenness centrality of an agent i can be written as follows (Freeman, 1977; Jackson, 2010)

$$\phi_i = \sum_{s,t \neq i} \frac{\eta^i_{s,t}}{\eta_{s,t}}$$

where $\eta_{s,t}$, as before, is the number of shortest paths between s and t and $\eta^i_{s,t}$ is the

number of shortest paths between s and t that agent i lies on. I argue that a high betweenness centrality corresponds to higher benefits from the market for access due to a lower probability that a coalition can form against the agent. This is because a between central agent lies on many shortest paths among others in the network and can potentially charge positive prices in the equilibrium of the posted-prices game. I first discuss the characteristics of the centrality measure as observed in the data.

Correlations with Demographic Characteristics: The correlations between betweenness centrality and demographic variables are presented in Table A.1. I find that betweenness centrality is positively correlated with the respondent's age, level of education, economic status (in terms of ownership of latrines, private electricity, number of rooms, beds), whether they're a native in the village, and negatively correlated with the respondent being female. Older agents who are natives have presumably spent a high amount of time to build and maintain links which is why they are likely to be more between-central. This is also in line with the network formation literature on preferential attachment (Simon, 1955; Price, 1965, 1976; Barabási and Albert, 1999) which suggests that new entrants in the network link to already well-connected agents. Abbasi et al. (2012) show that betweenness centrality explains preferential attachment better than degree centrality in academic networks. Additionally, norms around gender can prevent women from building social links as shown by Andrew et al. (2020) in Odisha, India. This can explain why women are less likely to be between-central in this dataset. These regressions control for village and caste fixed effects, and the values of these individual characteristics averaged at the peer level.

Relationship with the Fiedler Value: The Fiedler value of a graph is the second-lowest eigen value of the Laplacian and the magnitude of this eigen value indicates how connected the graph is (Fiedler, 1973). If an agent with a high betweenness centrality is removed from the borrowing network, then the Fiedler value of the network must reduce if their removal makes the network less connected. I find that the correlations between agent betweenness centrality and the difference in the Fiedler value (after and before their removal) are negative for all villages indicating that this reasoning is correct. Agents in Ambrus et al. (2014) receive the surplus from risk-sharing agreements in accordance with their Myerson value. Similarly, between-central agents can also bargain for better outcomes for themselves because their absence can reduce the connectedness of the network. This is a competing mechanism that can explain the sign of the regression coefficients observed in the data.

Distribution: Betweenness centrality has a very unequal distribution in that there exist a few agents who are very central and a majority who are not. The kernel density plots for betweenness centrality for the first five villages are shown in Figure A.1. The 95th percentile is plotted as a vertical line. This graph provides suggestive evidence that some agents are disproportionately between and is in line with the theoretical prediction that agents do not find it in their interest to invest in shortest paths if there exist other agents

who already lie on many such paths. This can generate the observed inequality in the centrality distribution.

Choice of Dependent Variable

The data includes a variable measuring whether the individual travels to work outside the village. Recurrently going outside the village to work could imply that the individual is willing to risk being removed from the network or diluting their existing links. The magnitude of the relationship can be expected to be smaller in this case as compared to what it would be if there were a variable capturing permanent migration. The variable for working outside the village is binary. Around 37% of those who travel outside the village for work, work in agriculture or animal husbandry. Other occupations for such individuals include working on construction sites, working as a driver, wood-cutter, and other kinds of daily labour.

Interpretation of the Dependent Variable: The model suggests that agents who lie on more shortest paths are less likely to break rules if these rules result in loss of network benefits. I interpret the decision to travel outside the village for work as the violation of a 'rule' that can potentially result in a loss of network benefits. This is in line with Morten (2016) who, for instance, find that temporary migration can reduce risk-sharing or Munshi and Rosenzweig (2016) who find that households with migrants are excluded from the network. I also compute the Fiedler value of the borrowing networks in the data and show that the higher the proportion of agents who travel outside the village for work, the lower the Fiedler value. This suggests that the networks are less connected and easy to partition if the proportion of agents working outside the village is high. This is shown in Figure A.2.

An individual's decision to commute to work outside the village can dilute network links and can translate into permanent migration. Migration can then lead to the social exclusion of the household as observed by Munshi and Rosenzweig (2009, 2016) and Hoff and Sen (2005). As per the model, if the decision to travel for work outside the village dilutes existing network links, then it would not be undertaken by an individual who lies on several shortest paths and benefits from the market for access. Further, the negative correlation between proportion of individuals travelling to work outside and the connectedness of the network also explains why agents lying on many shortest paths in the network can be willing to punish those who travel to work outside, to preserve the status quo.

In addition to an individual's decision to travel outside the village for work, I also test the impact of betweenness centrality on two other decisions- participation in a self-help group and opening a savings account. I argue that an agent who wishes to leave the network to migrate will not be likely to open a savings account in the village or participate in a self-help group. Individuals who are more between-central should not treat either of these two decisions as violations of network rules since they are likely indicators of a commitment to

stay. I also discuss and empirically evaluate the merit of competing interpretations under which the decision to open a savings account is not a commitment to stay in the village but instead to receive remittances or save for future migration. Estimating the impact of individual betweenness on these three decisions is a way to test the second prediction of the model- that individuals who hold higher market power in the market for access should be less likely to leave the network.

Choice of the Computational Unit

The data contains adjacency matrices at both the household and individual level. As a part of the main empirical strategy, I will compute variables at the level of the individual. I will consider the household-level approach in the robustness checks. Household centrality will be computed and the dependent variables will be whether the household has a member working outside the village, a member with a savings account, or a participant in a self-help group. As I will show, the main results are dependent on the computational unit and the centrality and rule-breaking relationships do not hold when computed at the level of the household.

Choice of Functional Form

I estimate the parameters of interest using a linear probability model. I am interested in computing marginal effects and the marginal effects computed from a probit/logit model and a linear probability model can be close (Angrist and Pischke, 2008). I will use instrumental variables with more than one endogenous variable in most cases and we know that non linear models can be complex when instrumental variables are used (Angrist and Pischke, 2008). Further, the specifications in this paper will include cluster-robust standard errors with each village being the cluster unit, to ensure that the intra-cluster correlation is taken into account. In a probit model with clustered errors, quasi-maximum likelihood estimation suffers from inconsistency (Greene, 2012). Clustered standard errors also manage heteroskedasticity (Cameron and Miller, 2015), which is one of the fundamental shortcomings of the linear probability model (Wooldridge, 2015).

Specification

Given these choices, I estimate the following relationship relating an individual i's decision d_i (to travel for work outside, open a savings account, or participate in a self-help group) on their betweenness centrality, demographic outcomes, and the characteristics of their peer neighbourhoods in terms of the average betweenness centrality of their peers, their average decisions, and their demographics. I also present results from competing specifications where some of these covariates are not included.

$$\mathbb{D} = \beta_{0v} + \beta_{0c} + \beta_1\phi + \beta_2\mathbb{G}\phi + \beta_3\mathbb{G}\mathbb{D} + \beta_4\mathbb{X} + \beta_5\mathbb{G}\mathbb{X} + u_{vc}$$

Here, D is the vector of decisions, G is the adjacency matrix of the network, ϕ is the vector of the centrality measure, $\mathbb{X}$ is the vector of demographic characteristics such as age, education, gender, mother-tongue, religion, whether the individual is a native or not, whether the individual is the head of their household, speaks english etc and economic characteristics such as number of rooms, beds, whether the house has a latrine or not, electricity etc. $G\phi$, GD, and GX include peer-centrality effects, endogenous peer effects, and exogenous peer effects. Village and Caste fixed effects for villages v in $\{1, 2, ..75\}$ and caste c in $\{1, 2, 3, 4\}$ are included as well.

Given that the decisions to work outside, save, and participate in a self-help group might impact one another, I additionally control for the two other decisions (and their peer-level averages) while studying the impact of betweenness on the third. Now, I discuss endogeneity concerns and ways in which I try to address them. The reason for controlling for the network position of one's peers is also justified in the next subsection.

4.2 Identification

Correlations

First, I will compute correlations of betweenness centrality measure with the decision to travel for work outside the village. This is to check if there is evidence for a trade-off between rule-breaking and betweenness centrality. Lying on many shortest paths should be negatively correlated with the decision to work outside the village as per the inequality in Equation 3.3. However, reverse causality can be a concern in interpreting the regression coefficient as an estimate of the causal relationship between centrality and working outside. This is because the data measures network centrality and the decision to travel to work outside of the village at the same time. Travelling for work outside can reduce interactions within the village and potentially affect the individual's betweenness centrality. Despite the reverse causality, the correlation between the two measures is informative since it suggests the existence of a trade-off between network position and the decision to leave. As discussed above, I control for demographic and economic variables in all specifications and additionally control for peer-level characteristics and other centrality measures in competing specifications to check if the correlation persists.

I also report the correlations between betweenness centrality and decisions to open a savings account and participate in a self help group. As I will discuss, these decisions can be interpreted as a commitment to stay in the village and in line with the predictions of the model, a between central agent can find it in their favour to take these decisions. Reverse causality is a concern here as well since participation in such groups can potentially affect agent centrality. However, as before, the correlations are informative of the trade-off highlighted by the model and should be positive in this case.

It may be of additional interest to comment on how changes in betweenness centrality can affect mobility. For example, we know from existing research that micro-finance

interventions can adversely affect networks (Banerjee et al., 2021). In such a case, the causal-link between network position and mobility may be useful to assess the long-run impacts of such interventions. Additionally, a hypothetical intervention that specifically targets the betweenness centrality of specific agents by incentivising network connections to reduce their market power, may gauge its success depending on how it will affect mobility.

Instruments

I attempt an instrument strategy to address this. The instrument strategy and the strong underlying assumptions are briefly described below.

Effect of Betweenness Centrality

The third prediction of the model suggests that in an equilibrium network, agents who lying on many shortest paths should be surrounded by those who do not lie on many such paths. To explore this, I regress an individual's betweenness on the average betweenness centrality of those who are at a distance of 1,2,3, and 4 links away from them. As shown in the first column of Table 4.2.1, I find that individual betweenness is positively correlated with the average betweenness of their immediate peers and the coefficient is negative when the network distance increases.[23] It is important to note that while this evidence is consistent with the model's prediction, the evidence can be consistent with other network formation models as well. This is a concern especially given the strong assumptions of the model that (a) coalition formation is only allowed along paths and (b) individuals can observe the network-position investments of others in their network.

However, in line with the observations in Table 4.2.1, I attempt to estimate the coefficient on betweenness using two stage least squares by instrumenting individual betweenness with the average betweenness centrality of those at a shortest distance of two. These averages are computed by using the centrality of agents to who the agent in question is not connected. [24] The instrument's validity relies on certain assumptions.

First, I assume that an individual's centrality (and any correlated unobservable characteristics) do not affect the average centrality of those at a distance of 2. In order to explore this further, I argue that any bias due to this should potentially be lower as the number of individuals, over whom the average is computed to construct the instrument, increases. I use the variation in the number of individuals at a shortest distance of 2 and run all specifications for sub-samples restricted only to those for whom the number of their peers' peers is above a certain threshold. *Second*, I assume that any unobserved characteristics of an individual's peers do not both affect the individual's

[23] I also run the regression after excluding those above the 99th, 95th, 75th, and 50th percentile in the centrality distributions to check if outliers might be affecting the results. This is done in Columns 2-5. The coefficients become smaller but they are still negative and significant in most cases.

[24] This is reminiscent of the method in Bramoullé et al. (2009); De Giorgi et al. (2010) in that the average is taken over an individual's peers' peers who are not directly connected to them.

Table 4.2.1: *Justification for the Choice of Instruments*

Click to go back.

VARIABLES	Betweenness Centrality (ϕ_i)				
	All	Exclude $\phi_i >$ 99th percentile	Exclude $\phi_i >$ 95th percentile	Exclude $\phi_i >$ 75th percentile	Exclude $\phi_i >$ 50th percentile
Avg Peer Between (Shortest distance=1)	0.381**	0.299**	0.187**	0.0579*	0.0222
	(0.170)	(0.120)	(0.0841)	(0.0342)	(0.0168)
Avg Peer Between (dist=2) (Shortest distance=2)	-0.573***	-0.396***	-0.272***	-0.123***	-0.0533***
	(0.0740)	(0.0664)	(0.0481)	(0.0236)	(0.0138)
Avg Peer Between (dist=3) (Shortest distance=3)	-0.198**	-0.0492	-0.0481	0.0300	0.0159
	(0.0933)	(0.0545)	(0.0408)	(0.0243)	(0.0147)
Avg Peer Between (dist=4) (Shortest distance=4)	-2.358***	-1.523***	-0.972***	-0.362***	-0.152***
	(0.229)	(0.150)	(0.113)	(0.0435)	(0.0289)
Observations	9,884	9,741	9,214	6,763	4,197
R-squared	0.328	0.340	0.270	0.148	0.125

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: All regressions control for individual demographic and economic covariates such as age, gender, education, religion, mother-tongue, native-status, number of rooms, number of beds, type of electricity, type of latrine, type of roof, head of household or not, and whether they speak English. Exogenous peer effects are also computed by taking the average of these covariates across each individual's surveyed peers and all specifications control for these. Caste and village fixed effects are also included. In addition, this table also includes as controls an indicator of whether the individual has a savings account, travels to work outside the village, participates in a self help group, and the fraction of their peers who do these.

betweenness and the instrument. I include several exogenous characteristics of the individual's direct peers including their betweenness centrality while running the IV specifications to attempt to justify the absence of correlated unobservable characteristics.

While attempting the IV is a useful demonstrative exercise, the results must be interpreted with appropriate caution given the assumptions discussed above. I will discuss any additional robustness checks as we proceed.

Effect of Peers' Decision to Travel for Work Outside

I now discuss the instrument I use for the proportion of peers who travel to work outside the village. This is to measure the effect of peer decisions on individual decisions to work outside. The data does not contain information on individual characteristics for all the individuals in the village. I compute the average characteristics of surveyed neighbours in the borrowing network. Banerjee et al. (2013) use stratified random sampling to decide whom to survey and used religion and location as strata. Peer averages are computed over a random subset of an individual's peers alleviating the concern of selection.

Manski (1993) classify the peer effect we are interested in as endogenous due to the "reflection problem" i.e. there is simultaneity between the decisions to work outside of an individual and their friends. I instrument for the proportion of an individual's peers who decide to travel for work outside (and similarly for decisions to save or participate in self help groups) by using the average characteristics of an individual's peers' peers as per the procedure discussed in Bramoullé et al. (2009); De Giorgi et al. (2010). These characteristics include the number of beds and rooms in their house (to act as a proxy for economic status) and their level of education (to act as a proxy for their ability to get jobs).[25] In line with Bramoullé et al. (2009), I include a network fixed effect in all specifications. I also conduct checks to test for correlated effects as suggested by Goldsmith-Pinkham and Imbens (2013) by noting how differences in regression residuals for agents i and j are affected by differences in observed characteristics when i and j are connected and are not connected by an edge. The results of these tests are discussed in the next section. I do not proceed further to address the issue of correlated effects due to the limitations of the data (i.e. the network is observed in only 1 time period) and because identification of peer effects is not pertinent to answer the main hypothesis of interest.

Table 5.1.1: *Effect of Betweenness in the Borrowing Network on Working Outside*

Click to go back.

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
Betweenness	-1.97e-06***	-1.01e-05**	-1.10e-05**	-1.82e-05***	-1.11e-05*
	(5.38e-07)	(5.06e-06)	(5.56e-06)	(6.28e-06)	(6.67e-06)
Avg Peer Between	6.43e-08	5.56e-06**	4.86e-06**	6.63e-06***	2.43e-06
	(9.92e-07)	(2.78e-06)	(1.99e-06)	(2.22e-06)	(2.29e-06)
Avg Peer Works Out	0.234***	0.668**	0.633**	0.673**	0.753**
	(0.0193)	(0.294)	(0.301)	(0.328)	(0.371)
Observations	9,904	9,853	7,834	5,462	3,035
R-squared	0.219	-0.021	-0.012	-0.113	-0.083
FS F Stat		28.83	10.05	6.857	5.525
Pred. Prob <0		12.86	11.47	14.10	14.10
Pred. Prob >1		2.029	1.659	2.105	2.043
Pred. Prob <0.5 (D=0)		76.83	77.37	78.71	79.39
Pred. Prob >0.5 (D=1)		59.24	60.39	59.36	60.13
Hansen-J Statistic		0.252	0.458	0.454	0.415
Kleibergen-Paap Statistic		0.0314	0.0317	0.0176	0.0289
Anderson-Rubin P Value		0.0361	0.0319	0.00633	0.0631

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: All regressions control for individual demographic and economic covariates such as age, gender, education, religion, mother-tongue, native-status, number of rooms, number of beds, type of electricity, type of latrine, type of roof, head of household or not, and whether they speak English. Exogenous peer effects are also computed by taking the average of these covariates across each individual's surveyed peers and all specifications control for these. Caste and village fixed effects are also included. In addition, this table also includes as controls an indicator of whether the individual has a savings account and participates in a self help group, and the fraction of their peers who do so. The FS F Statistic is the F statistic of the first stage regression of betweenness centrality.

Table 5.1.2: *Effect of Betweenness in the Borrowing Network on Owning a Savings Account*

Click to go back.

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
Betweenness	4.35e-06***	1.50e-05	1.54e-05**	1.00e-05*	4.32e-06
	(5.10e-07)	(1.02e-05)	(6.22e-06)	(6.07e-06)	(7.78e-06)
Avg Peer Between	-8.00e-07	-1.26e-05	-1.08e-05*	-5.12e-06**	-3.43e-06
	(1.46e-06)	(9.83e-06)	(5.54e-06)	(2.46e-06)	(2.49e-06)
Avg Peer Savings	0.189***	2.023	1.728	1.176*	0.805
	(0.0258)	(1.671)	(1.091)	(0.700)	(0.800)
Observations	9,904	9,853	7,834	5,462	3,035
R-squared	0.326	-0.584	-0.265	0.052	0.160
FS F Stat		28.05	9.987	6.670	4.932
Pred. Prob <0		24.29	19.19	9.758	2.801
Pred. Prob >1		14.75	12.58	8.861	7.743
Pred. Prob <0.5 (D=0)		71.83	71.58	71.31	70.55
Pred. Prob >0.5 (D=1)		61.04	64.01	69.15	74.70
Hansen-J Statistic		0.357	0.572	0.683	0.686
Kleibergen-Paap Statistic		0.631	0.386	0.304	0.393
Anderson-Rubin P Value		0.158	0.159	0.169	0.762

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: All regressions control for individual demographic and economic covariates such as age, gender, education, religion, mother-tongue, native-status, number of rooms, number of beds, type of electricity, type of latrine, type of roof, head of household or not, and whether they speak English. Exogenous peer effects are also computed by taking the average of these covariates across each individual's surveyed peers and all specifications control for these. Caste and village fixed effects are also included. In addition, this table also includes as controls an indicator of whether the individual travels to work outside the village and participates in a self help group, and the fraction of their peers who do so. The FS F Statistic is the F statistic of the first stage regression of betweenness centrality.

Table 5.1.3: *Effect of Betweenness in the Borrowing Network on SHG Participation*

Click to go back.

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
Betweenness	9.68e-07**	3.74e-06	4.35e-06	3.41e-06	5.58e-06
	(3.88e-07)	(7.03e-06)	(4.37e-06)	(6.32e-06)	(9.73e-06)
Avg Peer Between	-4.04e-07	-2.24e-06	-2.63e-06	-2.23e-06	-1.05e-06
	(5.16e-07)	(3.98e-06)	(1.97e-06)	(2.06e-06)	(1.38e-06)
Avg Peer SHG	0.212***	-1.101	-0.0108	-0.583	0.0936
	(0.0201)	(2.169)	(0.726)	(1.334)	(2.001)
Observations	9,904	9,853	7,834	5,462	3,035
R-squared	0.475	0.037	0.397	0.252	0.323
FS F Stat		29.29	10.22	6.645	5.592
Pred. Prob <0		30.79	33	31.76	32.26
Pred. Prob >1		0.596	0.0128	0.0366	0.0329
Pred. Prob <0.5 (D=0)		90.82	95.43	94.18	95.50
Pred. Prob >0.5 (D=1)		59.95	86.82	79.72	83.62
Hansen-J Statistic		0.850	0.283	0.727	0.839
Kleibergen-Paap Statistic		0.923	0.429	0.627	0.935
Anderson-Rubin P Value		0.319	0.379	0.488	0.778

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: All regressions control for individual demographic and economic covariates such as age, gender, education, religion, mother-tongue, native-status, number of rooms, number of beds, type of electricity, type of latrine, type of roof, head of household or not, and whether they speak English. Exogenous peer effects are also computed by taking the average of these covariates across each individual's surveyed peers and all specifications control for these. Caste and village fixed effects are also included. In addition, this table also includes as controls an indicator of whether the individual has a savings account and travels to work outside the village, and the fraction of their peers who do so. The FS F Statistic is the F statistic of the first stage regression of betweenness centrality.

5 Results

5.1 Effect on Working Outside the Village

Centrality Effect

The correlations reported in Table B.1 show that betweenness centrality is negatively correlated with the decision to travel to work outside and the negative correlation persists even after the average decisions of peers are taken into consideration. These correlations control for demographic and economic variables and controls at the level of the peer neighbourhood are also included in Columns 2 and 3. The negative relationship reported here points towards the trade-off highlighted in the model in that individuals who lie on fewer shortest paths can find it easier to satisfy the inequality in Equation 3.3. Critically, the correlation between betweenness centrality and travelling to work outside persists even when other measures of centrality including degree and eigen-vector centrality are controlled for in Column 3.

The IV results are presented in Table 5.1.1. Model 1 presents the results of an OLS regression while Models 2-5 show the results of the two stage least square regressions where centrality and the average proportion of surveyed peers who travel to work outside are instrumented. Model 2-5 use the average betweenness of an individual's peers' peers as an instrument. Model 2 includes all agents while models 3-5 do not consider agents whose number of peer's peers are less than the first quartile, the median, and the third quartile of the number of peers at a shortest distance of 2. The variation in the number of individuals at a distance of 2 can be seen in Figure B.1. The borrowing network is more sparse than the overall network which is why the number of individuals at a distance of 2 is low here. This is seen by comparing subplots (a) and (b) in Figure B.1. This is why it is difficult to exploit the variation in the number of individuals at distance 2 without losing a large portion of the data.

The results of the first stage regressions for betweenness and proportion of peers travelling to work outside the village are presented in Tables B.2 and B.3 respectively. As expected, betweenness centrality is negatively correlated with the average betweenness of peers' peers who are not directly connected to the individual. This correlation becomes stronger as we exclude those whose neighbours at distance 2 are below a threshold as in Models 2-5. I also find that the proportion of peers who travel for work outside the village is falling in the education level of peers' peers. This suggests that peers who are surrounded by educated individuals may be more likely to find jobs within the village. This is also substantiated by the observation that roughly 37 % of individuals who report travelling for work outside the village work in agriculture or animal husbandry both of which do not require education. Those with educated peers might be less likely to take up such jobs

[25] I use multiple instruments to have a stronger first stage and to be able to test the over identification restrictions. I also report robustness results from the set of regressions where betweenness and peer effects are exactly identified. I use the average education level of an individual's peers' peers as an instrument in these regressions.

outside. Note also that the first stage F statistics (for betweenness) are very low which is why I will also report the Anderson Rubin p value for the null hypothesis that there is no effect of betweenness centrality (Anderson and Rubin, 1949).

The second stage results are presented in Table 5.1.1. I find that a standard deviation increase in the betweenness centrality of an agent reduces the probability of working outside the village by ~ 1.5 percentage points as per the OLS coefficient. This changes to a ~ 7.8 percentage point reduction as per the IV coefficient in Model 2 where all individuals are retained compared to ~ 14.1 percentage point reduction in Model 4 where only those with the number of individuals at a shortest distance of 2 greater than the median are retained. Further, this coefficient is higher than the less conservative Model 3 where the individuals with the number of peers' peers greater than the first quartile are retained. The rise in the magnitude of the coefficient (across Models 2-4) goes against the claim that the coefficient on betweenness in Model 2 is larger in absolute magnitude because individual betweenness is likely to impact the average betweenness of their peers. If this were the case, the coefficient would be lower in models 3 and 4. The Anderson-Rubin p value suggests rejection of the null hypothesis for all the considered specifications. I also report various measures that check if the linear probability model predictions are sensible. I report the percentage of predicted probabilities below 0 and above 1. I find that these are a small proportion of the overall sample. I also report the percentage of cases where the predicted probabilities are above 0.5 and the individual travels to work outside the village (i.e. $D = 1$) and the percentage of cases where the predicted probabilities are below 0.5 and the individual does not travel outside the village for work. I find that these percentages are high and range between $\sim 60 - 80\%$. The relevant over-identification and under-identification tests also do not suggest any cause for concern. [26]

I also run models 2-5 using Limited Information Maximum Likelihood (LIML) which is median-unbiased when the number of instruments is greater than the number of endogenous regressors (Angrist and Pischke, 2008) which is true in this case. These results are reported in Table B.4. Angrist and Pischke (2008) also suggest that weak instruments are less of a concern when LIML coefficients are close to two stage least squares. I find this to be the case in Models 3-5.

Peer Effect

The results in Table 5.1.1 also show that individuals with a higher proportion of peers who travel outside the village for work are more likely to do so themselves. The sign and significance of the coefficient is robust to various specifications. As per Model 2, a 10 percentage point increase in the proportion of peers who work outside, raises the probability of the individual working outside by ~ 7 percent. As discussed earlier, while the reflection problem is tackled by the approach specified in Bramoullé et al. (2009);

[26] These include the Kleibergen Paap rk statistic for under identification (Kleibergen and Paap, 2006) and Hansen's J statistic for over-identification (Hansen, 1982).

De Giorgi et al. (2010), correlated effects are still a concern. I include village-level and caste-level fixed effects to capture any common shocks that may take place for individuals within a given village and caste. However, this strategy may not address the problem entirely since individuals joined by a link may face common shocks or the decision to form links in the borrowing networks, as we discussed earlier, may itself be endogenous.

Correlated Effects

I run two checks to assess if this may be a cause for concern. These are suggested in Goldsmith-Pinkham and Imbens (2013) and discussed by Bramoullé et al. (2020). I compute the error terms from Model 2 in Table 5.1.1 for each agent. Then, for each agent i and j, I compute the absolute value of the difference in the residuals and differences in observable characteristics when they are and are not connected by an edge in the network. If connected agents who have a higher difference in observable characteristics have a smaller gap in residuals, then it could suggest that there are unobservable characteristics that affect their decision to link. This could potentially affect the coefficient on the peer effect term in the regression. Similarly, correlated effects may be a concern if unconnected agents have a smaller gap in observable characteristics and a larger gap in residuals. The scatter plots for the residual gaps (computed for Model 2) and the total absolute difference in observed characteristics are plotted in figure B.2 in the appendix. The differences in observed characteristics, as expected, are higher for those unconnected by an edge as opposed to those who are connected. I also regress the residual gap on the difference in observed characteristics for the node-pairs connected and unconnected by an edge. I find that the relationship between the residual-gap and the difference in observed characteristics is positive and only significant for the sub-samples of edges that do not exist in the data. These results are shown in Table B.5. The coefficients is very small and positive. Also, as evident from the figures, there does not seem to be an obvious negative relationship which is what we would expect as per the test in Goldsmith-Pinkham and Imbens (2013). I do not proceed to address this concern any further. It may be easier to address this issue by modelling endogeneity in link formation using two realisations of each network. Addressing this concern is also not currently relevant to the main hypothesis of interest that concerns individual centrality.

Effect of Peer Betweenness

Note that these regressions also control for the average betweenness of an individual's peers for reasons discussed in the identification section. I also run the above specifications without controlling for this variable and find that the coefficient on the betweenness centrality is always negative but lower in absolute value than those obtained here. This is consistent with interpreting average peer betweenness as an omitted variable given that betweenness has a negative effect in and of itself and is positively correlated with average peer betweenness which has a positive effect on an individual's probability of working outside. Due to these correlations, the specifications that do not control for average peer betweenness underestimate the effect of betweenness centrality. I

discuss the interpretation of this coefficient in the next section on network externalities. Before that, I will first discuss the effect of betweenness centrality on whether the individual opens a savings account or participates in a self help group.

5.2 Effect on Opening a Savings Account and SHG Participation

I now discuss the impact of betweenness centrality on an individual's decision to open a savings account and their decision to participate in self-help/savings groups. Both the decisions to save and participate in SHGs are proxies for an individual's commitment to not travel outside the village for work for reasons discussed below. Betweenness centrality is endogenous in that opening a savings account or participating in a self-help group can impact network links. The instrument for betweenness centrality is the same as before and Models 2-5 only vary in the individuals they exclude depending on the number of peers' peers. Note that these regressions also additionally control for the individual's decisions to work outside the village.

The correlations between betweenness centrality and decisions to open a savings account or participate in a SHG are reported in Tables B.6 and B.10 respectively. I find that these decisions are positively correlated with centrality in both cases. This shows that individuals who are more central are also likely to be those who have a savings account and who participate in a self help group, although causality between the two cannot be established. This positive correlation, as I will argue, is in line with the model prediction that relates network position with rule breaking. Note that even though the sign of the coefficient is positive, the decision to participate in a self help group is no longer significantly correlated with betweenness centrality after degree and eigen-vector centrality are controlled for. I now discuss the IV results for both the variables and also justify their use as proxies to indicate a commitment to stay in the village.

Savings Accounts

The results in Table 5.1.2 show that agents who are more between are more likely to open savings accounts as per the specifications in Models 1, 3, and 4. The IV coefficient is not significant when all individuals are included but becomes significant once we exclude those whose peers at a shortest distance of 2 are below a certain threshold. Model 3, for instance, retains all individuals with any number of peers at distance 2 and suggests that an increase in 1 standard deviation in betweenness centrality increases the probability of having a savings account by $\sim$ 12 percentage points. Model 4 suggests an 8 percentage point effect. Model 5 where only those individuals whose number of peers at distance 2 are larger than the third quartile are retained, do not find any effect. The instruments are weak in this case (as per the low first stage F Statistic) and the Anderson Rubin statistic also does not reject the null. The LIML results are presented in B.7 and the coefficient in Model 3 is close to the 2SLS coefficient.

Existing literature finds that the provision of microfinance, for example, can dilute network

links (Banerjee et al., 2021). In the case of savings accounts, a similar finding should then imply that individuals who have access to formal credit should be less likely to be able to maintain their network links. The correlation between the betweenness centrality of an individual and the probability of them having a savings account should be negative if this is true. The results suggest that this is not the case. Being between-central and having a savings account are positively correlated suggesting that the proposed mechanism might be in place i.e. individuals who are between-central plan to stay in the village and hence open savings accounts. As before, I also report the results of LPM related checks and find that majority of the predicted probabilities lie in the unit interval and predict success (failure) fairly accurately when they lie above (below) the threshold of 0.5.

Testing for Alternative Interpretations

I interpret the decision to save as a commitment to stay in the village. It can be argued that individuals may open savings account only because they wish to migrate in future or because they wish to receive remittances from those in their family who have migrated. In both cases, opening savings accounts is not evidence of a commitment to stay in the village.

I control for an individual's own decision to travel outside the village for work in all specifications of the savings regressions. In the first alternative specification, I additionally control for the interaction term of an individual's betweenness centrality and their decision to travel to work outside the village. This is to capture the future migration effect in that an individual who wishes to migrate in future may be working outside already. In the second alternative specification, I control for whether an individual has a member in their family who travels for work outside the village and an interaction term between this variable and betweenness centrality. This is to capture, albeit imperfectly, the remittance effect highlighted above. The positive effect of betweenness centrality, if driven by the future migration or remittance effect, should be driven by those who travel to work outside or have a family member working outside. The interaction terms in these alternative specifications should be positive and significant.

I do not find this to be the case. These alternative specifications are presented in Tables B.8 and B.9. The coefficient on betweenness is significant and positive in Models 1 and 3 and positive and insignificant otherwise. The coefficient on the interaction term is always insignificant. The data does not contain a variable on the individual's intention to migrate or information on whether they have a migrant in their family. This is why I cannot conduct additional analysis to support the proposed interpretation.

Savings Groups and SHGs

Feigenberg et al. (2013) find that a higher frequency of microfinance meetings have a positive long term impact on network links. The return to participation in such groups and meetings, I argue, is higher for those who envision staying in the network i.e. those who are more between central. This implies that individuals who are more between-central

in the network should be more likely to participate in self-help groups. Table 5.1.3 shows that the impact of betweenness on individual participation in self-help groups is positive but it is only significant in the non-IV specifications. The LIML results presented in Table B.11 are not significant either. However, the correlation between betweenness centrality and SHG participation is always positive. I now run robustness exercises to check if the impact of network position on these decisions is affected by alternative specifications.

5.3 Robustness Checks

I complement the specification in the main results by running several robustness exercises. This is to check if the identified effects of (a) an individual's betweenness centrality and (b) the average decision of their peers, on their decision to travel for work outside, open a savings account, or participate in a self-help group are sensitive to other specifications that, for example, control for alternative centrality measures, use different networks, or use the household as the unit of computation rather than the individual. As before, I also report the results of the LPM checks in each case to check if the predicted probabilities lie in the unit interval and accurately predict if the individual travels to work outside or not.

Outliers: It can be argued that the first stage coefficient when betweenness centrality is regressed on average betweenness centrality of peers' peers is affected by specific individuals who are very central. For example, an individual with a very high betweenness centrality can reduce other agent's investments in shortest paths even if the number of such agents is very high. Exploiting the variation in the number of such agents will not help in understanding the magnitude of this effect. I run the same regression as in Model 2, excluding all the agents whose centrality is above the 95th percentile. This is to ensure that the effect is not entirely due to the presence of extremely central individuals. The results of this robustness check are shown in the first column in Table C.1. The effect of betweenness centrality on an agent's decision to travel for work outside the village is still negative although only significant at 10 %. I do not detect any effect on the decisions to save or participate in self-help groups.

Alternative Instruments: Model 2 in Table C.1 uses the average betweenness of an individual's neighbours at a shortest distance of 2-4 to instrument for betweenness centrality instead of computing this for neighbours at a shortest distance of 2.[27] I do not find an effect in this case potentially due to a weaker first stage compared to Model 2 in the main specification.

I also run alternative specifications where I instrument for the fraction of peers who travel for work outside using the average education of any individual's peers' peers not directly connected to them. The system is exactly identified in this case as opposed to the main

[27]The use of multiple centrality-based instruments has also been suggested previously by Liu and Lee (2010) and executed in Lee et al. (2012). However, they use the Bonacich centrality measure to estimate peer effects as opposed to the effect of network position.

model and I find that the effect of betweenness is robustly negative across all specifications and slightly larger in magnitude than the main specification. This is shown in Table C.2. Finally, I use the number of years their peers' peers have spent residing in the village and the average proportion of natives among their peers' peers to instrument for betweenness centrality respectively. An individual whose peers' peers have stayed in the village for a long time or are natives would benefit less from the market for access since there are potential competitors. I find that average residence time and average native status are both weak instruments but the coefficient in the first stage is negative as predicted in both cases. The coefficient on betweenness is negative and also significant in some specifications. These results are presented in Tables C.3 and C.4.

Other Centrality Measures: Next, I run a specification where centrality measures such as degree and eigen vector centrality are included as controls and instrumented using a similar strategy.[28] I undertake this exercise to show that lying on shortest paths affects agent decisions as opposed to other correlated variables such as being more connected or having very influential peers. Disentangling these effects is not possible using this dataset especially because the inclusion of various correlated centrality measures reduces the power to detect the effect of any. I find that betweenness centrality has a significant negative impact on the decision to travel outside the village for work even when degree and eigen-vector centrality is controlled for. These results are shown in table C.1. Models 3-4 include degree and eigen vector centrality as controls. Model 3 controls for these centrality measures while instrumenting only for betweenness centrality and is exactly identified. Model 4 additionally instruments for degree and eigen vector centrality using peer-level averages of these measures computed at a shortest distance of 2 and is exactly identified. Model 5 instruments for all three measures of centrality using peer averages computed at a distance of 2,3,4 links for each and is over-identified. Similar robustness exercises are also conducted for the models that predict whether an individual has a savings account and whether they participate in a self-help group. These are presented in Tables C.5 and C.6. I find that despite the correlation between these centrality measures, betweenness centrality has a significantly negative impact on the decision to travel for work outside (at 10%) and a significantly positive impact on the decision to save (at 1-10%) in most specifications.

Computational Unit: I run the same regressions at the level of the household where a binary variable indicating if the household has a member who travels to work outside is regressed on household betweenness centrality, household-level demographic and economic controls, and both endogenous and exogenous peer averages computed at the household level. The instrumentation strategy is the same as the main specification at the individual level. These results are presented in Table C.7. I find that the betweenness centrality of the household does not influence these decisions and peer effects, computed at the level of

[28] While degree centrality measures the number of direct connections, eigen-vector centrality is higher for those who have more central peers. See Jackson (2010) for a discussion of these measures.

the household, are also absent in most specifications. This suggests that while individual agents can make use of their betweenness centrality to benefit from the market for access, it may not be true for households because they do not function as a single agent.

Type of Network: I run the same regressions on three different types of networks to check if the result is robust to these different choices. Even though the theoretical setup is more applicable to networks on which transaction and information flows happen, it is agnostic about the type of network. I first use the overall network where a link exists between i and j if they interact in *any* capacity. These networks are less conservative in assuming the existence of a link. There is considerable variation in the number of peers at a distance of 2. These results are presented in Table C.8.

I also run the regressions for a more conservative network type i.e. the economic network where a link between i and j exists if i mentions that they borrow from *or* lend money/kerosine/rice to agent j. Table C.9 shows the results from this specification. In both these cases, I find that betweenness centrality negatively affects the individual's decision to travel for work outside the village and the effect is significant across most specifications. I also run the regressions on an even more conservative network which assumes the presence of a link only if the agent borrows and lends both money and kerosine/rice to the other agent. I do not find any effect of betweenness centrality in this case. The Anderson-Rubin statistic does reject the null in two cases where the sign of the coefficient switches to be positive. This network is very sparse and it is not clear why individuals would only engage in economic transactions with those whom they engage in *all* kinds of economic relationships as opposed to one or more.

5.4 Network Externalities

5.5 Effect of Peer Betweenness

I control for the betweenness centrality of an individual's peers in all specifications since the instruments are valid conditional on controlling for this endogenous variable. The coefficient on this variable is positive (and robustly so) when considering the impact on the decision to work outside. This can be seen in Tables 5.1.1 and C.1. However, cannot be interpreted causally. This is because individuals who travel outside the village for work may have peers who are not between-central. This could be because their decision adversely affects the network links and centrality of their peers. On the other hand, individuals who travel for work outside may have peers who are between-central because the individuals who work outside now provide less competition in the market for access. These explanations are the rationale for negative and positive externalities that were highlighted in the theoretical setup. An individual's peers' shortest paths going via them might get diluted or destroyed if they work outside- this creates a downward bias in the coefficient on average peer betweenness. Alternatively, their peers might lie on more shortest paths if they work outside because the market for access is less competitive- this creates an upward bias in the coefficient on average peer betweenness. While the argument

that individual centrality cannot affect the average centrality of a high number of peers can be reasonable, it is not reasonable to expect the average centrality of an individual's peers to not affect the average centrality of peers at a distance of 4 or more paths away. This is why an analogous instrument strategy cannot be used in this case. Thus, the existing specification suffers from reverse causality and this affects the interpretation of the effect of the average centrality of peers.

Consider an exercise where we rule out mechanisms that could not be true if we were to believe that the positive sign of the coefficient on average peer betweenness were indeed correct. Higher average peer betweenness could imply that the individual, conditional on their betweenness, can access the network for transactions making use of their peers who lie on many shortest paths or be less likely to violate rules given that their peers might punish them. These network benefits or punitive costs reduce the incentives to work outside. This could not be the case as per the sign of the observed coefficient, as in this case, more central peers should imply a lower probability of working outside. Alternatively, higher average peer betweenness implies that individual betweenness is high (because of the homophily effects discussed earlier) and consequently the probability of working outside is low. This effect is ruled out by controlling for individual betweenness. The positive coefficient on average peer betweenness also challenges this interpretation.

Two alternative mechanisms could potentially be at work. Higher average peer betweenness implies that individuals are less likely to charge rents themselves since they are surrounded by those who are better suited to be transaction facilitators. The positive coefficient on betweenness centrality of peers suggests that this could indeed be the case. Alternatively, individuals could receive access to information about jobs via their central peers. The role played by networks in providing information about jobs has been well documented in existing literature (Topa, 2011). High peer betweenness could lead to better access to information about jobs outside the village. The positive coefficient on average peer betweenness also supports this hypothesis.

Peer betweenness also affects an individual's decisions to save in that individuals who have a savings account have fewer between-central peers or individuals with fewer between-central peers are more likely to save. This can be seen in Tables 5.1.2 and C.5. Reverse causality is a concern in these regressions as well but the significance of the coefficients (and the consistently negative sign on them) imply that there is a strategic relationship between an individual's decision to travel for work outside, open a savings account, their network position, and the network position of their peers. In the next subsection, I run additional checks to assess if networks with more between-central individuals or more inequality in the betweenness centrality distribution have a lower proportion of agents who work outside. These village-level correlations provide more evidence to understand the role of both peer centrality and inequality in the centrality distribution on individual decisions.

5.6 Effect of Network-level Measures

I provide descriptive evidence to analyse the impact of the presence of between-central agents in the village on the proportion of individuals who travel for work outside the village. I argue that networks with agents who have high market power (in terms of high betweenness centrality) should have a lower proportion of agents who travel for work outside the village.

The data contains 75 different networks and I will make use of the variation in the structure of the borrowing network to check this. First, I compute the proportion of the village that travels to work outside. Consider Figure D.1 that shows the kernel density of betweenness centrality among villages for which this proportion is above or below the median. I find that while the p-value for the two-sided Kolmogorov Smirnov test does not reject the null that the distributions are identical, the one-sided test rejects the null that the two distributions contain values of similar magnitude against the alternative that the distribution for villages above the median has lower values of betweenness. This provides some evidence for a negative correlation between the proportion of individuals who travel for work outside and the betweenness centralities of agents in that village. This could be true because due to both the network benefits of high betweenness and the perceived threat of being excluded by peers who are very between central. It can also be argued that we observe this negative relationship because working outside reduces the shortest paths individuals lie on. However, this should then also increase the betweenness of those who have stayed behind. It is not clear ex-ante how a greater proportion of individuals working outside would affect the betweenness centrality distribution in a specific direction. Next, I compute some village-level characteristics indicating the market power held by its population. These include the standard deviation, skewness, and the average difference in Fiedler Values of agents if they are or aren't removed from the network. As per the mechanisms specified in the model, networks with a more unequal distribution of betweenness should have a lower proportion of rule-violators due to anticipated punitive effects. Agents in a complete network have no market power in terms of their betweenness centrality. However, agents in these village networks can hold substantial market power, earn high discounted future payoffs, and be willing to punish those who lead to loss of network benefits. Consider an agent who is very between central. If they are removed from the network, the connectedness of the network can reduce, and consequently, the Fiedler value of the network (previously discussed in Section 4) can also reduce. A network where this reduction is large, on average, should have a lower proportion of rule violators. Figure D.2 plots the average difference in Fiedler values for all villages. I use the variation in this to study the effect of network-based market power on average choices of agents in the network.

The correlations are presented in Table 5.6.1. In the first column, I find evidence of a positive correlation between the average Fiedler differences and the proportion of agents travelling to work outside (p-value=0.12). This means that villages where the difference

Table 5.6.1: *Effect of Village-Level Characteristics on Proportion Working Outside*

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VARIABLES	Proportion of individuals who travel to work outside			
Average Difference in Fiedler Value of $G - \{i\}$ and G	18.14			13.41
	(11.55)			(12.67)
Skewness		-0.0102		-0.0175*
		(0.00843)		(0.0101)
Standard Deviation			3.95e-06	7.62e-06
			(5.38e-06)	(6.95e-06)
Constant	0.400***	0.376***	0.319***	0.396***
	(0.0395)	(0.0317)	(0.0362)	(0.0635)
Observations	75	75	75	75
R-squared	0.033	0.020	0.007	0.072

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

between the new and old value (for $G-i$ and G respectively) is large, on average, have a higher proportion of agents travelling to work outside. This is in line with the proposed hypotheses- as agent market power increases, this difference becomes more and more negative and the proportion of those who travel to work outside also falls. Consider the negative correlation between skewness and the proportion of individuals working outside in Column 3. Having more agents on the right tail increases network benefits or punitive costs such that others do not want to travel for work outside. It could also be argued that the network has a skewed centrality distribution because agents who work outside (whom we know are those who are less between) do not invest in shortest paths while those who do not do so are very central.

Similar to the effects of peer centrality and the concerns with interpretation addressed earlier, the endogeneity of the centrality distributions cannot be ignored. The correlations provide some evidence in the direction of the proposed hypothesis but neither the magnitude of the effects or the mechanisms can be conclusively established due to endogeneity and the limited number of networks available in the data.

6 Conclusion

In this paper, I discuss that individuals who lie on more shortest paths in their rural networks can benefit from their network position and be less likely to violate network rules that result in a loss of links. I find that individuals in borrowing networks in rural Karnataka are less likely to travel outside the village for work and more likely to open savings accounts (indicating an intention to stay) when they are more 'between'. I show that this relationship is robust across most specifications. Reducing the market power of between central agents by increasing access to information and markets may address the low mobility concerns documented in the literature. I also discuss a broader implication of centrality-induced market power- individuals who lie on many shortest paths can find it in their favour to credibly punish those who violate sub-optimal rules or norms that preserve the status quo. This punishment is not likely to be enforced on an individual who is a competitor who also lies on many shortest paths. These results on punishments and exclusion rely on the existence of self-fulfilling beliefs that relate specific actions with the expected dilution of network links. These underlying beliefs make the paths containing the rule-violators less salient for other agents.

While I cannot address the endogeneity of the network measure entirely, the instrument strategy used in this paper also highlights a mechanism of interest in and of itself. Investments in network position are considered substitutes. This generates heterogeneity in the centrality distribution ensuring that an individual's actions can have externalities on others. Moreover, these externalities are not merely equal to the direct loss in network benefits but can be positive or negative depending on the location of the rule-breaking and the affected individual. This provides an alternative explanation for the incentives to exclude and their relationship of these incentives with network centrality.

The data from Banerjee et al. (2013) used in this paper contains one temporal realisation of the rural networks in 75 villages. The authors measured a second realisation of these networks and the data is likely to be released soon. The two network realisations can be used to further address the endogeneity concerns. An extended version of this paper can include this. This will also allow me to address another hypothesis of interest that was briefly considered in the paper. The effect of the network position of an individual's peers on their decisions can be used to identify mechanisms such as high social capital and exclusion.

Appendix

A Descriptive Results

Table A.1: *Betweenness Centrality and Demographic Outcomes*

Demographic Variables	Betweenness Centrality in the Borrowing Network	Demographic Variables	Betweenness Centrality in the Borrowing Network
Education	141.3***	Speaks English	-345.6
	(20.13)		(629.1)
Female	-2,107***	Number of Rooms	542.9***
	(257.8)		(170.3)
Age	27.38***	Number of Beds	186.5
	(8.615)		(114.5)
Household Head	646.3**	Private Electricity	1,365***
	(283.6)		(497.1)
Village Native	923.0***	Govt. Electricity	432.2
	(205.5)		(454.1)
Hindu	8,397***	Owned Latrine	1,046***
	(2,168)		(347.2)
Muslim	4,735*	Common Latrine	-2,509
	(2,418)		(1,609)
Hindi	-682.9	Thatch Roof	2,510
	(1,905)		(2,882)
Kannada	160.4	Tile Roof	2,085
	(1,726)		(2,923)
Marathi	-4,986**	Stone Roof	2,068
	(2,133)		(3,016)
Tamil	151.3	Sheet Roof	1,437
	(1,830)		(3,016)
Telugu	377.6	RCC Roof	2,132
	(1,862)		(3,099)
		Roof (Other)	1,519
			(2,650)
Observations	9904		
R-squared	0.185		

Notes:- The table shows results from the same regression where betweenness centrality is regressed on individual covariates. Additional controls include the peer-level averages of the individual-level covariates listed above and caste and village fixed effects. Individual decisions to travel to work outside, save, participate in SHGs and their corresponding peer averages are also controlled for. Standard errors are clustered at the village level.

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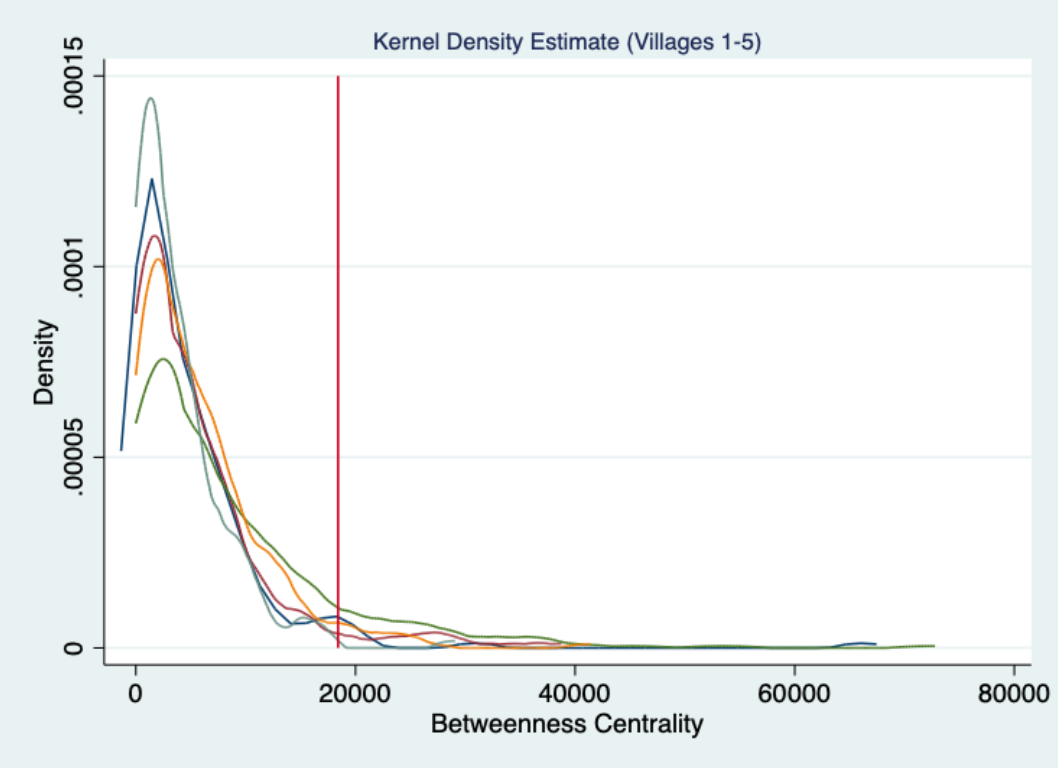


Figure A.1: Betweenness Centrality Distribution for the first 5 villages in the dataset collected by Banerjee et al. (2013). The vertical line is the 95th percentile.

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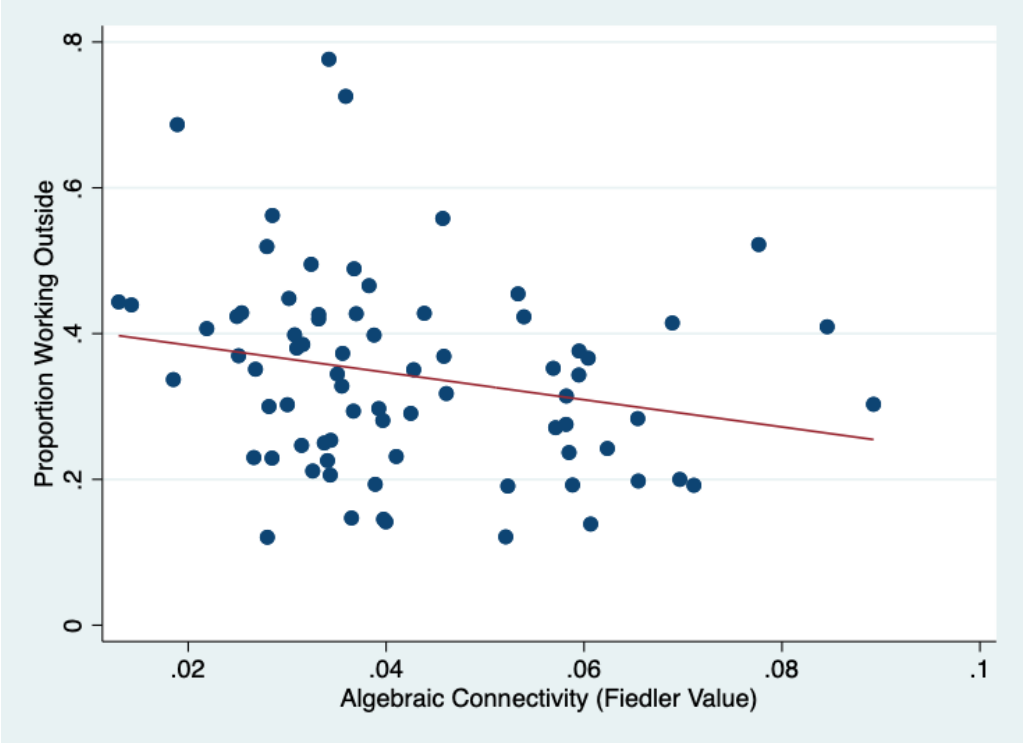


Figure A.2: Relationship between the Fiedler Value and Proportion of Individuals in the largest network component who travel outside the village for work

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B Main Results

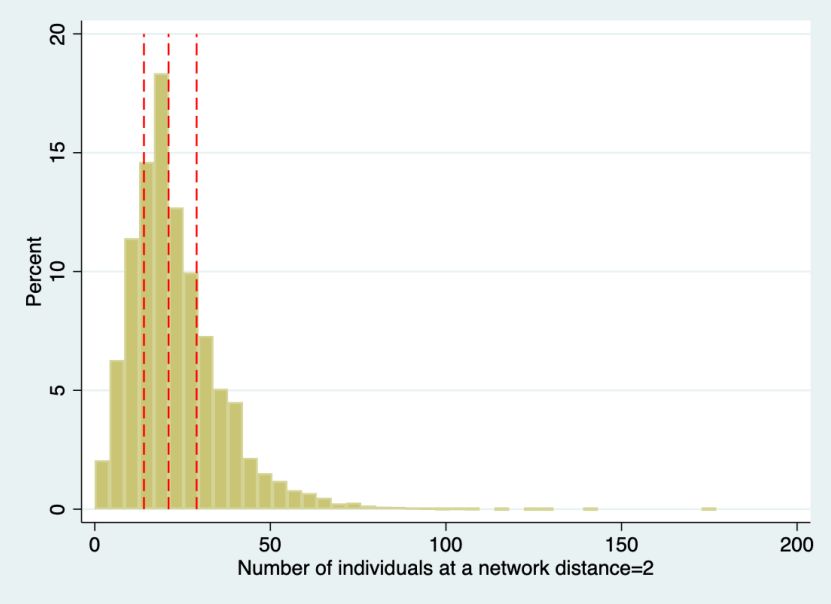
Table B.1: Correlations between Travelling for Work Outside and Betweenness Centrality

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3
Betweenness	-1.95e-06***	-1.96e-06***	-1.56e-06**
	(5.72e-07)	(5.41e-07)	(5.96e-07)
Avg Peer Works Out		0.234***	0.234***
		(0.0191)	(0.0191)
Observations	10,566	9,904	9,904
R-squared	0.190	0.219	0.220

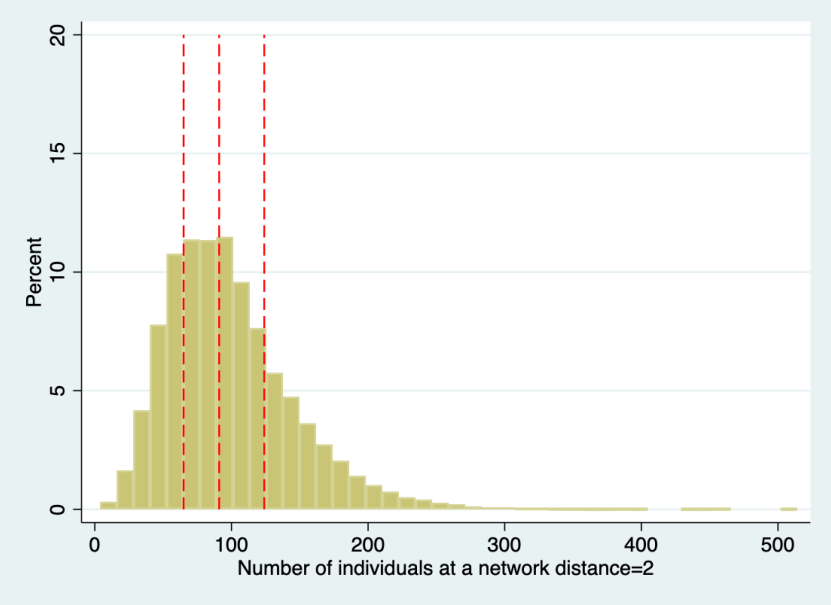
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: All regressions control for individual demographic and economic covariates such as age, gender, education, religion, mother-tongue, native-status, number of rooms, number of beds, type of electricity, type of latrine, type of roof, head of household or not, whether they speak English, and the decision to open a savings account and participate in a SHG. Column 2 additionally controls for exogenous peer effects (i.e. the individual variables averaged at the level of the peer neighbourhood) and the proportion of peers who make the decision. Column 3 additionally controls for Degree and Eigen-vector Centrality.

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(a) Borrowing Network



(b) Overall Network

Figure B.1: Histogram of the number of individuals at a shortest distance of 2. The first, second, and third quartile are plotted as dashed lines. Models 3-5 use the sub-sample to the right of the dashed lines in (a).

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Table B.2: *First Stage for Betwenness Centrality in the Borrowing Network*

VARIABLES	(1) Model 2	(2) Model 3	(3) Model 4	(4) Model 5
Avg Peer Between (dist=2)	-0.365***	-0.449***	-0.534***	-0.763***
	(0.0795)	(0.143)	(0.153)	(0.183)
Avg Educ (dist=2)	-74.57	-37.72	-93.41	-90.16
	(50.44)	(59.48)	(99.77)	(204.4)
Avg Rooms (dist=2)	511.5***	638.0**	912.8***	1,252**
	(188.8)	(249.8)	(346.9)	(589.6)
Avg Beds (dist=2)	239.8*	217.6	64.83	-473.2
	(136.2)	(186.1)	(244.5)	(446.8)
Observations	9,853	7,834	5,462	3,035

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table B.3: *First Stage for the Proportion of Peers Working Outside in the Borrowing Network*

VARIABLES	(1) Model 2	(2) Model 3	(3) Model 4	(4) Model 5
Avg Peer Between (dist=2)	-1.47e-06	-3.98e-08	-2.25e-06	-3.80e-06
	(2.00e-06)	(3.27e-06)	(4.02e-06)	(5.08e-06)
Avg Educ (dist=2)	-0.00745***	-0.00903***	-0.0131***	-0.0167***
	(0.00255)	(0.00322)	(0.00403)	(0.00525)
Avg Rooms (dist=2)	-0.00751	-0.00449	-0.00189	-0.00231
	(0.00848)	(0.00813)	(0.00832)	(0.0101)
Avg Beds (dist=2)	0.00225	0.000104	-0.000908	-0.00180
	(0.00671)	(0.00748)	(0.00624)	(0.00706)
Observations	9,853	7,834	5,462	3,035

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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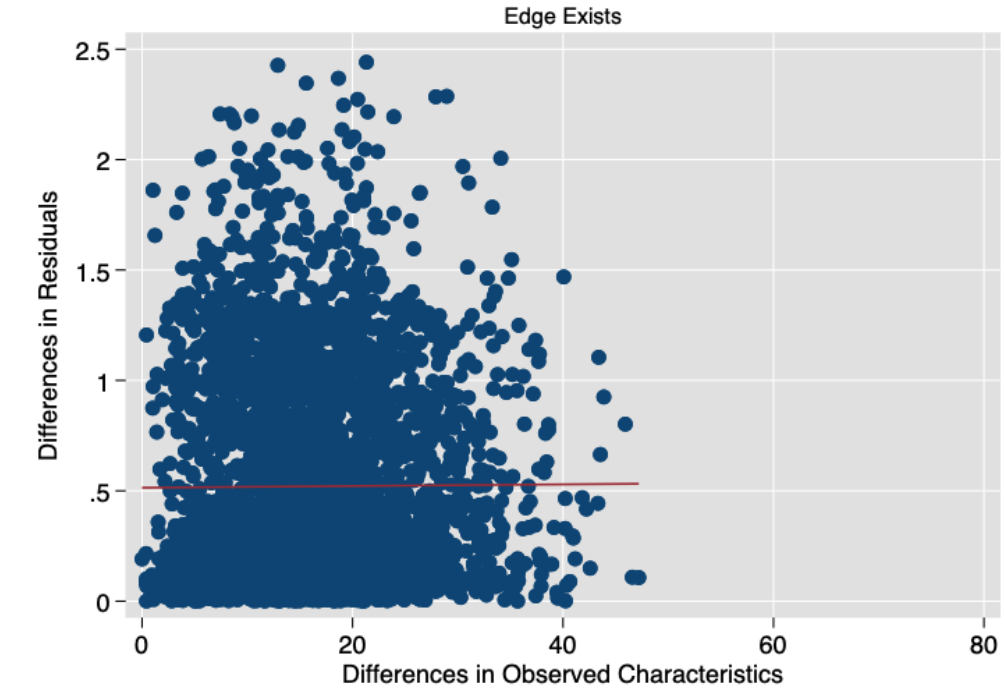
Table B.4: *Effect of Betweenness in the Borrowing Network on Working Outside (LIML)*

Travels to Work Outside	Model 1	Model 2	Model 3	Model 4	Model 5
Betweenness	-1.97e-06***	-1.06e-05**	-1.10e-05*	-1.86e-05***	-1.16e-05*
	(5.38e-07)	(5.30e-06)	(5.66e-06)	(6.50e-06)	(6.98e-06)
Avg Peer Between	6.43e-08	6.08e-06**	4.96e-06**	6.80e-06***	2.59e-06
	(9.92e-07)	(3.02e-06)	(2.04e-06)	(2.29e-06)	(2.37e-06)
Avg Peer Works Out	0.234***	0.763**	0.662**	0.698**	0.790**
	(0.0193)	(0.360)	(0.323)	(0.344)	(0.396)
Observations	9,904	9,853	7,834	5,462	3,035
R-squared	0.219	-0.070	-0.023	-0.127	-0.103
FS F Stat		28.83	10.05	6.857	5.525
Pred. Prob <0		14.98	12.01	14.52	14.76
Pred. Prob >1		3.322	1.889	2.398	2.208
Pred. Prob <0.5 (D=0)		76.86	77.42	78.78	79.31
Pred. Prob >0.5 (D=1)		58.30	60.18	59.17	59.50
Hansen-J Statistic		0.284	0.464	0.457	0.424
Kleibergen-Paap Statistic		0.0314	0.0317	0.0176	0.0289
Anderson-Rubin P Value		0.0361	0.0319	0.00633	0.0631

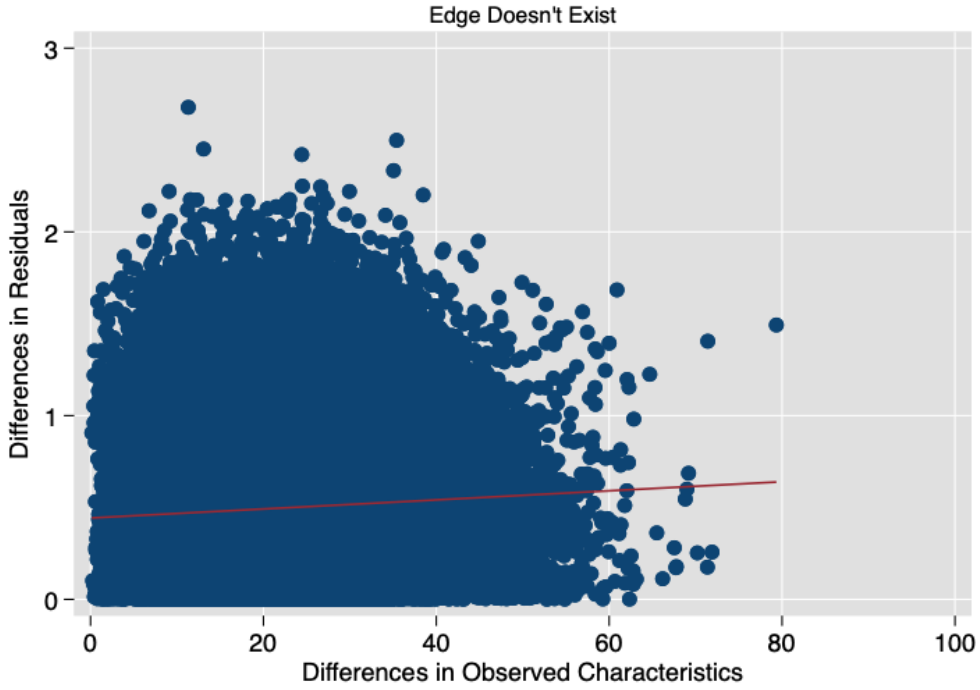
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: All regressions control for individual demographic and economic covariates such as age, gender, education, religion, mother-tongue, native-status, number of rooms, number of beds, type of electricity, type of latrine, type of roof, head of household or not, and whether they speak English. Exogenous peer effects are also computed by taking the average of these covariates across each individual's surveyed peers and all specifications control for these. Caste and village fixed effects are also included. In addition, this table also includes as controls an indicator of whether the individual has a savings account and participates in a self help group, and the fraction of their peers who do so. The FS F Statistic is the F statistic of the first stage regression of betweenness centrality.

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(a) The graph only includes edges that exist in the networks data.



(b) The graph only includes edges that do not exist in the networks data.

Figure B.2: Testing for Correlated Effects as per Goldsmith-Pinkham and Imbens (2013)

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Table B.5: *Testing for Correlated Effects as per Goldsmith-Pinkham and Imbens (2013)*

VARIABLES	(1) Difference in Residuals (Edge Exists)	(2) Difference in Residuals (Edge Doesn't Exist)
Difference in Observed Characteristics	0.000377	0.00247***
	(0.00137)	(0.000622)
Constant	0.514***	0.443***
	(0.0460)	(0.0222)
Observations	3,807	97,041
R-squared	0.000	0.003

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table B.6: Correlations between Owning a Savings Account and Betweenness Centrality

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3
Betweenness	4.27e-06***	4.22e-06***	3.90e-06***
	(5.00e-07)	(4.73e-07)	(5.15e-07)
Avg Peer Savings		0.188***	0.189***
		(0.0260)	(0.0260)
Observations	10,566	9,904	9,904
R-squared	0.307	0.326	0.326

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: All regressions control for individual demographic and economic covariates such as age, gender, education, religion, mother-tongue, native-status, number of rooms, number of beds, type of electricity, type of latrine, type of roof, head of household or not, whether they speak English, and the decision to travel outside for work and to participate in a SHG. Column 2 additionally controls for exogenous peer effects (i.e. the individual variables averaged at the level of the peer neighbourhood) and the proportion of peers who make the decision. Column 3 additionally controls for Degree and Eigen-vector Centrality.

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Table B.7: *Effect of Betweenness in the Borrowing Network on Owning a Savings Account (LIML)*

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
Betweenness	4.35e-06***	1.86e-05	1.61e-05**	1.02e-05	4.39e-06
	(5.10e-07)	(1.72e-05)	(6.76e-06)	(6.26e-06)	(7.98e-06)
Avg Peer Between	-8.00e-07	-1.76e-05	-1.17e-05*	-5.36e-06**	-3.60e-06
	(1.46e-06)	(1.92e-05)	(6.47e-06)	(2.66e-06)	(2.72e-06)
Avg Peer Savings	0.189***	2.946	1.907	1.245	0.863
	(0.0258)	(3.423)	(1.304)	(0.768)	(0.873)
Observations	9,904	9,853	7,834	5,462	3,035
R-squared	0.326	-1.633	-0.390	0.025	0.148
FS F Stat		28.05	9.987	6.670	4.932
Pred. Prob <0		30.68	21.11	10.55	3.229
Pred. Prob >1		20.98	13.95	9.172	8.138
Pred. Prob <0.5 (D=0)		69.52	71.08	71.03	70.26
Pred. Prob >0.5 (D=1)		57.47	63.07	68.49	74.07
Hansen-J Statistic		0.563	0.620	0.692	0.688
Kleibergen-Paap Statistic		0.631	0.386	0.304	0.393
Anderson-Rubin P Value		0.158	0.159	0.169	0.762

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: All regressions control for individual demographic and economic covariates such as age, gender, education, religion, mother-tongue, native-status, number of rooms, number of beds, type of electricity, type of latrine, type of roof, head of household or not, and whether they speak English. Exogenous peer effects are also computed by taking the average of these covariates across each individual's surveyed peers and all specifications control for these. Caste and village fixed effects are also included. In addition, this table also includes as controls an indicator of whether the individual has a savings account and travels to work outside the village, and the fraction of their peers who do so. The FS F Statistic is the F statistic of the first stage regression of betweenness centrality.

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Table B.8: *Effect of Betweenness in the Borrowing Network on Owning a Savings Account (Alternative Explanation-1)*

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
Betweenness	4.45e-06***	1.89e-05	1.82e-05**	1.12e-05	4.76e-06
	(5.21e-07)	(1.54e-05)	(8.20e-06)	(7.38e-06)	(8.86e-06)
Interaction: Betweenness x Travels outside for work.		-1.14e-05	-1.01e-05	-4.88e-06	-1.89e-07
		(1.21e-05)	(6.44e-06)	(5.84e-06)	(6.26e-06)
Travels outside for work		0.107	0.104*	0.0720	0.00916
		(0.0919)	(0.0592)	(0.0647)	(0.0883)
Avg Peer Savings	0.189***	2.303	1.868	1.248*	0.804
	(0.0258)	(2.034)	(1.177)	(0.721)	(0.817)
Avg Peer Between	-7.75e-07	-1.37e-05	-1.11e-05*	-5.19e-06**	-3.49e-06
	(1.47e-06)	(1.18e-05)	(5.91e-06)	(2.51e-06)	(2.56e-06)
Constant	0.0893				
	(0.255)				
Observations	9,904	9,853	7,834	5,462	3,035
R-squared	0.326	-0.867	-0.371	0.022	0.159
FS F Stat		24.94	8.221	6.412	5.653
Pred. Prob <0		26.59	20.66	10.69	2.768
Pred. Prob >1		16.64	13.64	9.099	7.776
Pred. Prob <0.5 (D=0)		70.98	71.01	71.18	70.46
Pred. Prob >0.5 (D=1)		59.71	63.07	68.86	74.66
Hansen-J Statistic		0.412	0.640	0.709	0.698
Kleibergen-Paap Statistic		0.690	0.390	0.290	0.376
Anderson-Rubin P Value		0.195	0.183	0.201	0.764

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: All regressions control for individual demographic and economic covariates such as age, gender, education, religion, mother-tongue, native-status, number of rooms, number of beds, type of electricity, type of latrine, type of roof, head of household or not, and whether they speak English. Exogenous peer effects are also computed by taking the average of these covariates across each individual's surveyed peers and all specifications control for these. Caste and village fixed effects are also included. In addition, this table also includes as controls an indicator of whether the individual travels to work outside the village and participates in a self help group, and the fraction of their peers who do so. The FS F Statistic is the F statistic of the first stage regression of betweenness centrality.

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Table B.9: *Effect of Betweenness in the Borrowing Network on Owning a Savings Account (Alternative Explanation-2)*

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
Betweenness	4.30e-06***	2.09e-05	2.00e-05**	1.24e-05	5.12e-06
	(6.00e-07)	(1.75e-05)	(9.45e-06)	(8.47e-06)	(9.55e-06)
HH has member who travels out for work.		0.0657	0.0863	0.0555	-0.0232
		(0.0922)	(0.0710)	(0.0748)	(0.0981)
Interaction: Betweenness x HH has member who travels out for work.		-1.37e-05	-1.24e-05	-6.28e-06	-4.25e-07
		(1.47e-05)	(7.93e-06)	(7.06e-06)	(7.37e-06)
Avg Peer Savings	0.188***	2.220	1.830	1.271*	0.791
	(0.0258)	(1.938)	(1.177)	(0.730)	(0.862)
Avg Peer Between	-8.17e-07	-1.32e-05	-1.07e-05*	-5.27e-06**	-3.46e-06
	(1.47e-06)	(1.10e-05)	(5.74e-06)	(2.53e-06)	(2.67e-06)
Constant	0.0915				
	(0.256)				
Observations	9,904	9,853	7,834	5,462	3,035
R-squared	0.326	-0.789	-0.349	0.010	0.161
FS F Stat		26.55	8.122	6.287	5.289
Pred. Prob <0		25.96	20.35	10.93	2.603
Pred. Prob >1		16.06	13.22	9.154	7.710
Pred. Prob <0.5 (D=0)		71.09	71.15	71.04	70.66
Pred. Prob >0.5 (D=1)		59.98	63.41	68.55	74.93
Hansen-J Statistic		0.385	0.636	0.750	0.693
Kleibergen-Paap Statistic		0.676	0.396	0.289	0.371
Anderson-Rubin P Value		0.213	0.193	0.212	0.778

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: All regressions control for individual demographic and economic covariates such as age, gender, education, religion, mother-tongue, native-status, number of rooms, number of beds, type of electricity, type of latrine, type of roof, head of household or not, and whether they speak English. Exogenous peer effects are also computed by taking the average of these covariates across each individual's surveyed peers and all specifications control for these. Caste and village fixed effects are also included. In addition, this table also includes as controls an indicator of whether the individual travels to work outside the village and participates in a self help group, and the fraction of their peers who do so. The FS F Statistic is the F statistic of the first stage regression of betweenness centrality.

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Table B.10: Correlations between Participation in SHG and Betweenness Centrality

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3
Betweenness	8.72e-07**	9.01e-07**	4.75e-07
	(4.17e-07)	(3.78e-07)	(4.69e-07)
Avg Peer SHG		0.212***	0.211***
		(0.0201)	(0.0200)
Observations	10,566	9,904	9,904
R-squared	0.457	0.475	0.476

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: All regressions control for individual demographic and economic covariates such as age, gender, education, religion, mother-tongue, native-status, number of rooms, number of beds, type of electricity, type of latrine, type of roof, head of household or not, whether they speak English, and the decision to travel outside for work and open a savings account. Column 2 additionally controls for exogenous peer effects (i.e. the individual variables averaged at the level of the peer neighbourhood) and the proportion of peers who make the decision. Column 3 additionally controls for Degree and Eigen-vector Centrality.

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Table B.11: *Effect of Betweenness in the Borrowing Network on SHG Participation* (LIML)

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
Betweenness	9.68e-07**	2.64e-06	3.67e-06	2.63e-06	5.52e-06
	(3.88e-07)	(1.12e-05)	(6.23e-06)	(8.47e-06)	(1.31e-05)
Avg Peer Between	-4.04e-07	-1.76e-06	-2.55e-06	-2.14e-06	-1.05e-06
	(5.16e-07)	(5.96e-06)	(2.44e-06)	(2.51e-06)	(1.41e-06)
Avg Peer SHG	0.212***	-1.681	-0.339	-0.895	0.0750
	(0.0201)	(4.178)	(2.027)	(2.087)	(2.894)
Constant	-0.231				
	(0.142)				
Observations	9,904	9,853	7,834	5,462	3,035
R-squared	0.475	-0.375	0.343	0.139	0.322
FS F Stat		29.29	10.22	6.645	5.592
Pred. Prob <0		32.37	31.92	31.67	32.06
Pred. Prob >1		1.929	0.0128	0.220	0.0329
Pred. Prob <0.5 (D=0)		88.96	94.78	92.77	95.49
Pred. Prob >0.5 (D=1)		45.58	84.44	71.02	83.08
Hansen-J Statistic		0.902	0.358	0.785	0.840
Kleibergen-Paap Statistic		0.923	0.429	0.627	0.935
Anderson-Rubin P Value		0.319	0.379	0.488	0.778

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: All regressions control for individual demographic and economic covariates such as age, gender, education, religion, mother-tongue, native-status, number of rooms, number of beds, type of electricity, type of latrine, type of roof, head of household or not, and whether they speak English. Exogenous peer effects are also computed by taking the average of these covariates across each individual's surveyed peers and all specifications control for these. Caste and village fixed effects are also included. In addition, this table also includes as controls an indicator of whether the individual has a savings account and travels to work outside the village, and the fraction of their peers who do so. The FS F Statistic is the F statistic of the first stage regression of betweenness centrality.

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C Robustness Checks

Table C.1: *Effect of Betweenness in the Borrowing Network on Working Outside (Robustness)*

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
Betweenness	-2.52e-05*	3.20e-07	-1.05e-05*	-9.78e-06**	-3.40e-06
	(1.42e-05)	(1.91e-06)	(5.43e-06)	(4.84e-06)	(2.78e-06)
Avg Peer Works Out	0.741**	0.687**	0.615**	0.638**	0.403**
	(0.310)	(0.296)	(0.281)	(0.281)	(0.203)
Avg Peer Between	6.91e-06**	-6.70e-08	9.20e-06*	4.98e-06	2.19e-06
	(3.25e-06)	(1.58e-06)	(5.41e-06)	(3.07e-06)	(2.71e-06)
Degree			0.0187	-0.000488	0.00465
			(0.0139)	(0.00786)	(0.00630)
Eigen			-4.842	0.394	-1.247
			(4.199)	(4.981)	(4.985)
Observations	9,183	9,845	9,853	9,853	9,845
R-squared	-0.084	-0.011	0.008	-0.006	0.081
FS F Stat	7.268	25.69	21.85	21.86	61.43
Pred. Prob ¡0	15.16	9.976	11.55	12.13	7.068
Pred. Prob ¿1	3.877	1.060	1.373	1.706	0.505
Pred. Prob ¡0.5 (D=0)	76.45	76.78	76.89	76.90	76.72
Pred. Prob ¿0.5 (D=1)	57.74	60.79	59.60	59.52	64.71
Kleibergen-Paap Statistic	0.0301	0.0485	0.0189	0.0256	0.0802
Hasen-J Statistic	0.345	0.722			0.413
Anderson-Rubin P Value	0.0388	0.400	0.0333	0.109	0.156
Robust standard errors in parentheses					
*** p<0.01, ** p<0.05, * p<0.1					

Notes: All regressions control for individual demographic and economic covariates such as age, gender, education, religion, mother-tongue, native-status, number of rooms, number of beds, type of electricity, type of latrine, type of roof, head of household or not, and whether they speak English. Exogenous peer effects are also computed by taking the average of these covariates across each individual's surveyed peers and all specifications control for these. Caste and village fixed effects are also included. In addition, this table also includes as controls an indicator of whether the individual has a savings account and participates in a self help group, and the fraction of their peers who do so. The FS F Statistic is the F statistic of the first stage regression of betweenness centrality.

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Table C.2: *Effect of Betweenness in the Borrowing Network on Working Outside when Peer Effects are Exactly Identified*

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
Betweenness	-1.97e-06***	-1.56e-05**	-1.35e-05*	-1.95e-05**	-1.29e-05*
	(5.38e-07)	(7.84e-06)	(7.81e-06)	(9.01e-06)	(6.61e-06)
Avg Peer Between	6.43e-08	9.24e-06**	6.11e-06**	7.09e-06***	2.74e-06
	(9.92e-07)	(4.36e-06)	(2.76e-06)	(2.47e-06)	(2.13e-06)
Avg Peer Works Out	0.234***	0.949**	0.700**	0.690**	0.758**
	(0.0193)	(0.402)	(0.311)	(0.337)	(0.380)
Constant	1.112***				
	(0.208)				
Observations	9,904	9,853	7,834	5,462	3,035
R-squared	0.219	-0.222	-0.056	-0.139	-0.110
FS F Stat		14.49	4.854	6.380	10.33
Pred. Prob <0		19.80	13.22	14.65	14.50
Pred. Prob >1		6.906	2.463	2.453	2.109
Pred. Prob <0.5 (D=0)		76.98	77.34	78.76	79.25
Pred. Prob >0.5 (D=1)		56.59	59.44	59.01	59.39
Kleibergen-Paap Statistic		0.00542	0.00482	0.00295	0.00656
Anderson-Rubin P Value		0.00663	0.0195	0.0117	0.0551

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: All regressions control for individual demographic and economic covariates such as age, gender, education, religion, mother-tongue, native-status, number of rooms, number of beds, type of electricity, type of latrine, type of roof, head of household or not, and whether they speak English. Exogenous peer effects are also computed by taking the average of these covariates across each individual's surveyed peers and all specifications control for these. Caste and village fixed effects are also included. In addition, this table also includes as controls an indicator of whether the individual has a savings account and participates in a self help group, and the fraction of their peers who do so. The FS F Statistic is the F statistic of the first stage regression of betweenness centrality.

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Table C.3: *Effect of Betweenness in the Borrowing Network on Working Outside using Average Residence Time (dist=2) as an instrument for Betweenness*

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
Betweenness	-1.97e-06***	-5.79e-07	-4.94e-06	-1.60e-05	-5.71e-06
	(5.38e-07)	(8.38e-06)	(8.62e-06)	(1.10e-05)	(1.20e-05)
Avg Peer Between	6.43e-08	6.16e-07	2.44e-06	5.94e-06	1.59e-06
	(9.92e-07)	(4.41e-06)	(3.83e-06)	(4.42e-06)	(2.99e-06)
Avg Peer Works Out	0.234***	0.730**	0.700**	0.693**	0.786**
	(0.0193)	(0.352)	(0.314)	(0.312)	(0.361)
Observations	9,904	9,464	7,752	5,446	3,031
R-squared	0.219	-0.031	-0.012	-0.088	-0.044
FS F Stat		7.227	5.954	4.052	1.835
Pred. Prob <0		13.13	12.30	14.01	14.10
Pred. Prob >1		2.161	1.889	2.142	2.010
Pred. Prob <0.5 (D=0)		76.75	77.40	78.58	79.39
Pred. Prob >0.5 (D=1)		58.43	59.88	59.48	60.13
Hansen-J Statistic		0.280	0.558	0.382	0.452
Kleibergen-Paap Statistic		0.0636	0.0423	0.0437	0.0545
Anderson-Rubin P Value		0.161	0.208	0.0604	0.204

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: All regressions control for individual demographic and economic covariates such as age, gender, education, religion, mother-tongue, native-status, number of rooms, number of beds, type of electricity, type of latrine, type of roof, head of household or not, and whether they speak English. Exogenous peer effects are also computed by taking the average of these covariates across each individual's surveyed peers and all specifications control for these. Caste and village fixed effects are also included. In addition, this table also includes as controls an indicator of whether the individual has a savings account and participates in a self help group, and the fraction of their peers who do so. The FS F Statistic is the F statistic of the first stage regression of betweenness centrality.

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Table C.4: *Effect of Betweenness in the Borrowing Network on Working Outside using Average Natives (dist=2) as an instrument for Betweenness*

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
Betweenness	-1.97e-06***	7.61e-07	-1.05e-05	-2.18e-05**	-1.36e-05
	(5.38e-07)	(9.30e-06)	(8.13e-06)	(9.30e-06)	(8.42e-06)
Avg Peer Between	6.43e-08	3.73e-08	4.92e-06	7.91e-06*	2.84e-06
	(9.92e-07)	(4.85e-06)	(3.87e-06)	(4.06e-06)	(2.63e-06)
Avg Peer Works Out	0.234***	0.795**	0.757**	0.729**	0.751**
	(0.0193)	(0.312)	(0.314)	(0.326)	(0.380)
Observations	9,904	9,853	7,834	5,462	3,035
R-squared	0.219	-0.068	-0.060	-0.193	-0.119
FS F Stat		10.38	7.383	6.052	3.325
Pred. Prob <0		14.88	14.01	15.65	14.73
Pred. Prob >1		3.251	2.948	3.057	2.109
Pred. Prob <0.5 (D=0)		76.92	77.44	78.73	79.21
Pred. Prob >0.5 (D=1)		58.05	59.16	58.34	59.08
Hansen-J Statistic		0.233	0.290	0.366	0.380
Kleibergen-Paap Statistic		0.0276	0.0306	0.0166	0.0313
Anderson-Rubin P Value		0.0500	0.0188	0.00706	0.0941

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: All regressions control for individual demographic and economic covariates such as age, gender, education, religion, mother-tongue, native-status, number of rooms, number of beds, type of electricity, type of latrine, type of roof, head of household or not, and whether they speak English. Exogenous peer effects are also computed by taking the average of these covariates across each individual's surveyed peers and all specifications control for these. Caste and village fixed effects are also included. In addition, this table also includes as controls an indicator of whether the individual has a savings account and participates in a self help group, and the fraction of their peers who do so. The FS F Statistic is the F statistic of the first stage regression of betweenness centrality.

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Table C.5: *Effect of Betweenness in the Borrowing Network on Owning a Savings Account (Robustness)*

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
Betweenness	2.76e-05	5.44e-06***	1.52e-05	1.64e-05	1.11e-05***
	(2.17e-05)	(1.94e-06)	(1.08e-05)	(1.07e-05)	(2.60e-06)
Avg Peer Savings	1.894	0.994	1.922	1.915	1.076***
	(1.555)	(0.759)	(1.725)	(1.724)	(0.401)
Avg Peer Between	-1.16e-05	-3.98e-06*	-1.66e-05	-1.92e-05	-1.11e-05**
	(9.57e-06)	(2.39e-06)	(1.67e-05)	(1.62e-05)	(4.34e-06)
Degree			-0.0178	-0.0287	-0.0212**
			(0.0253)	(0.0225)	(0.00904)
Eigen			3.729	11.64	9.288*
			(7.177)	(9.051)	(5.100)
Observations	9,183	9,845	9,853	9,853	9,845
R-squared	-0.489	0.103	-0.491	-0.491	0.057
FS F Stat	7.339	25.15	21.45	21.24	60.23
Pred. Prob ¡0	23.80	7.239	23.07	22.93	12.18
Pred. Prob ¿1	13.79	6.028	14.01	13.99	7.805
Pred. Prob ¡0.5 (D=0)	73.01	75.44	71.92	71.69	74.61
Pred. Prob ¿0.5 (D=1)	61.11	73.04	61.37	61.20	68.45
Kleibergen-Paap Statistic	0.657	0.618	0.683	0.687	0.0895
Hasen-J Statistic	0.454	0.187			0.320
Anderson-Rubin P Value	0.261	0.000480	0.203	0.140	5.12e-06
Robust standard errors in parentheses					
*** p<0.01, ** p<0.05, * p<0.1					

Notes: All regressions control for individual demographic and economic covariates such as age, gender, education, religion, mother-tongue, native-status, number of rooms, number of beds, type of electricity, type of latrine, type of roof, head of household or not, and whether they speak English. Exogenous peer effects are also computed by taking the average of these covariates across each individual's surveyed peers and all specifications control for these. Caste and village fixed effects are also included. In addition, this table also includes as controls an indicator of whether the individual has a savings account and travels to work outside the village, and the fraction of their peers who do so. The FS F Statistic is the F statistic of the first stage regression of betweenness centrality.

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Table C.6: *Effect of Betweenness in the Borrowing Network on SHG Participation (Robustness)*

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
Betweenness	7.50e-06	1.94e-06	2.97e-06	3.47e-06	2.31e-06
	(1.39e-05)	(2.88e-06)	(7.78e-06)	(6.78e-06)	(1.90e-06)
Avg Peer SHG	-1.105	-0.477	-1.052	-0.899	-0.435
	(1.721)	(1.645)	(1.956)	(2.014)	(0.748)
Avg Peer Between	-2.75e-06	-1.15e-06	-2.67e-06	-2.24e-06	-1.85e-06
	(3.47e-06)	(1.86e-06)	(8.24e-06)	(3.39e-06)	(2.21e-06)
Degree			-8.16e-05	0.00250	-4.10e-05
			(0.0222)	(0.00958)	(0.00625)
Eigen			-3.100	-1.864	-0.510
			(7.444)	(6.236)	(4.289)
Observations	9,183	9,845	9,853	9,853	9,845
R-squared	0.045	0.317	0.067	0.146	0.329
FS F Stat	7.350	26.12	21.81	22.44	60.40
Pred. Prob ¡0	30.82	31.10	30.60	30.35	30.56
Pred. Prob ¿1	0.650	1.020	0.535	0.313	0.0101
Pred. Prob ¡0.5 (D=0)	90.91	90.04	90.99	91.49	93.94
Pred. Prob ¿0.5 (D=1)	60.59	53.23	61.59	66.37	81.11
Kleibergen-Paap Statistic	0.843	0.959	0.914	0.926	0.819
Hasen-J Statistic	0.968	0.989			0.837
Anderson-Rubin P Value	0.468	0.962	0.385	0.595	0.121
Robust standard errors in parentheses					
*** p<0.01, ** p<0.05, * p<0.1					

Notes: All regressions control for individual demographic and economic covariates such as age, gender, education, religion, mother-tongue, native-status, number of rooms, number of beds, type of electricity, type of latrine, type of roof, head of household or not, and whether they speak English. Exogenous peer effects are also computed by taking the average of these covariates across each individual's surveyed peers and all specifications control for these. Caste and village fixed effects are also included. In addition, this table also includes as controls an indicator of whether the individual has a savings account and travels to work outside the village, and the fraction of their peers who do so. The FS F Statistic is the F statistic of the first stage of betweenness centrality.

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Household Level Regressions

Table C.7: *Effect of HH Betweenness in the Borrowing Network on Working Outside*

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
HH Betweenness	1.74e-05	-8.50e-06	-0.000164*	-0.000110	8.38e-05
	(1.27e-05)	(6.26e-05)	(8.86e-05)	(8.96e-05)	(8.05e-05)
HH Avg Peer Between	-7.54e-06	-2.53e-06	-1.30e-05	-4.96e-05	-3.01e-05
	(1.65e-05)	(2.01e-05)	(2.75e-05)	(3.03e-05)	(3.50e-05)
HH Avg Peer HH Works Out	0.0869***	0.537	1.159	0.971	-0.0157
	(0.0291)	(0.504)	(0.766)	(0.688)	(0.742)
Constant	1.445***				
	(0.336)				
Observations	6,246	6,238	4,669	3,094	1,541
R-squared	0.179	-0.021	-0.290	-0.105	0.036
FS F Stat		71	39.74	28.18	34.76
Pred. Prob <0		3.188	12.32	8.500	3.699
Pred. Prob >1		1.057	7.261	3.394	0.584
Pred. Prob <0.5 (D=0)		70.45	69.39	70.88	74.62
Pred. Prob >0.5 (D=1)		61.82	57.96	61.15	66.80
Hansen-J Statistic		0.484	0.538	0.971	0.101
Kleibergen-Paap Statistic		0.113	0.432	0.298	0.129
Anderson-Rubin P Value		0.653	0.155	0.609	0.152

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: All regressions control for household-level averages of covariates such as age, gender, education, religion, mother-tongue, native-status, number of rooms, number of beds, type of electricity, type of latrine, type of roof, and the proportion of individuals who speak English. Exogenous peer effects are also computed by taking the average of these covariates across each household's surveyed peers and all specifications control for these. Caste and village fixed effects are also included. This table also includes as controls an indicator of whether the household has a savings account and participates in a self help group, and the fraction of their peers who do so. The FS F Statistic is the F statistic of the first stage regression of betweenness centrality.

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Other Networks

Table C.8: *Effect of Betweenness in the Overall Network on Working Outside*

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
Betweenness	-2.53e-06***	-1.40e-06	-7.08e-06**	-5.00e-06**	-3.37e-07
	(7.74e-07)	(2.93e-06)	(2.75e-06)	(1.97e-06)	(2.09e-06)
Avg Peer Between	3.81e-07	-5.18e-07	3.48e-06	3.94e-06	7.92e-06***
	(2.26e-06)	(3.39e-06)	(2.97e-06)	(2.81e-06)	(2.47e-06)
Avg Peer Works Out	0.360***	0.317	0.470	0.556	-0.113
	(0.0267)	(0.273)	(0.349)	(0.396)	(0.650)
Observations	10,509	10,509	8,320	5,854	3,055
R-squared	0.224	0.085	0.072	0.054	0.031
FS F Stat		44.48	32.91	15	14.45
Pred. Prob <0		4.843	6.262	6.560	7.267
Pred. Prob >1		0.162	0.300	0.393	0.164
Pred. Prob <0.5 (D=0)		76.52	77.19	78.01	78.07
Pred. Prob >0.5 (D=1)		68.02	68.23	66.95	66.12
Hansen-J Statistic		0.152	0.364	0.864	0.348
Kleibergen-Paap Statistic		0.0254	0.0143	0.0296	0.0889
Anderson-Rubin P Value		0.386	0.0822	0.272	0.596

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: All regressions control for individual demographic and economic covariates such as age, gender, education, religion, mother-tongue, native-status, number of rooms, number of beds, type of electricity, type of latrine, type of roof, head of household or not, and whether they speak English. Exogenous peer effects are also computed by taking the average of these covariates across each individual's surveyed peers and all specifications control for these. Caste and village fixed effects are also included. In addition, this table also includes as controls an indicator of whether the individual has a savings account and participates in a self help group, and the fraction of their peers who do so. The FS F Statistic is the F statistic of the first stage regression of betweenness centrality.

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Table C.9: *Effect of Betweenness in the Economic Network (Max) on Working Outside*

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
Betweenness	-2.47e-06***	-6.89e-06*	-1.03e-05***	-9.48e-06**	-7.18e-06**
	(7.07e-07)	(3.82e-06)	(3.86e-06)	(4.33e-06)	(3.36e-06)
Avg Peer Between	-4.28e-07	4.20e-06	4.53e-06	3.99e-06	3.18e-06
	(1.97e-06)	(3.27e-06)	(2.99e-06)	(2.57e-06)	(2.74e-06)
Avg Peer Works Out	0.275***	0.695***	0.733***	1.194***	1.114***
	(0.0223)	(0.222)	(0.265)	(0.348)	(0.414)
Constant	1.208***				
	(0.249)				
Observations	10,311	10,307	8,234	5,787	3,048
R-squared	0.221	0.024	0.009	-0.145	-0.092
FS F Stat		28.26	24.73	25.97	25.83
Pred. Prob <0		10.31	10.18	18.46	16.80
Pred. Prob >1		1.523	1.555	4.579	2.854
Pred. Prob <0.5 (D=0)		76.88	77.09	78.38	79.42
Pred. Prob >0.5 (D=1)		61.34	62.01	59.66	60.39
Hansen-J Statistic		0.302	0.799	0.884	0.914
Kleibergen-Paap Statistic		0.00593	0.0183	0.00615	0.0154
Anderson-Rubin P Value		0.0359	0.0321	3.27e-06	0.0659

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: All regressions control for individual demographic and economic covariates such as age, gender, education, religion, mother-tongue, native-status, number of rooms, number of beds, type of electricity, type of latrine, type of roof, head of household or not, and whether they speak English. Exogenous peer effects are also computed by taking the average of these covariates across each individual's surveyed peers and all specifications control for these. Caste and village fixed effects are also included. In addition, this table also includes as controls an indicator of whether the individual has a savings account and participates in a self help group, and the fraction of their peers who do so. The FS F Statistic is the F statistic of the first stage regression of betweenness centrality.

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Table C.10: *Effect of Betweenness in the Economic Network (Min) on Working Outside*

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
Betweenness	-1.16e-06	1.26e-06	-7.09e-07	3.55e-06	7.19e-07
	(7.52e-07)	(3.18e-06)	(3.06e-06)	(3.72e-06)	(1.17e-05)
Avg Peer Between	1.47e-06	-2.11e-06	4.57e-07	-5.63e-06	-3.35e-07
	(1.90e-06)	(4.15e-06)	(3.93e-06)	(4.84e-06)	(1.71e-05)
Avg Peer Works Out	0.232***	0.784***	0.879***	1.041***	0.445
	(0.0203)	(0.263)	(0.257)	(0.241)	(0.337)
Constant	1.153***				
	(0.179)				
Observations	8,617	6,658	6,010	4,301	2,144
R-squared	0.230	-0.087	-0.155	-0.291	0.062
FS F Stat		20.58	21.73	3.763	1.506
Pred. Prob <0		17.54	21.06	27.46	13.17
Pred. Prob >1		3.791	5.541	8.165	0.552
Pred. Prob <0.5 (D=0)		78.17	78.72	79.81	82.44
Pred. Prob >0.5 (D=1)		58.10	56.67	54.07	65.92
Hansen-J Statistic		0.0109	0.0620	0.198	0.393
Kleibergen-Paap Statistic		0.0343	0.0285	0.0305	0.117
Anderson-Rubin P Value		0.0410	0.0386	0.00414	0.618

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: All regressions control for individual demographic and economic covariates such as age, gender, education, religion, mother-tongue, native-status, number of rooms, number of beds, type of electricity, type of latrine, type of roof, head of household or not, and whether they speak English. Exogenous peer effects are also computed by taking the average of these covariates across each individual's surveyed peers and all specifications control for these. Caste and village fixed effects are also included. In addition, this table also includes as controls an indicator of whether the individual has a savings account and participates in a self help group, and the fraction of their peers who do so. The FS F Statistic is the F statistic of the first stage regression of betweenness centrality.

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D Village Level Regressions

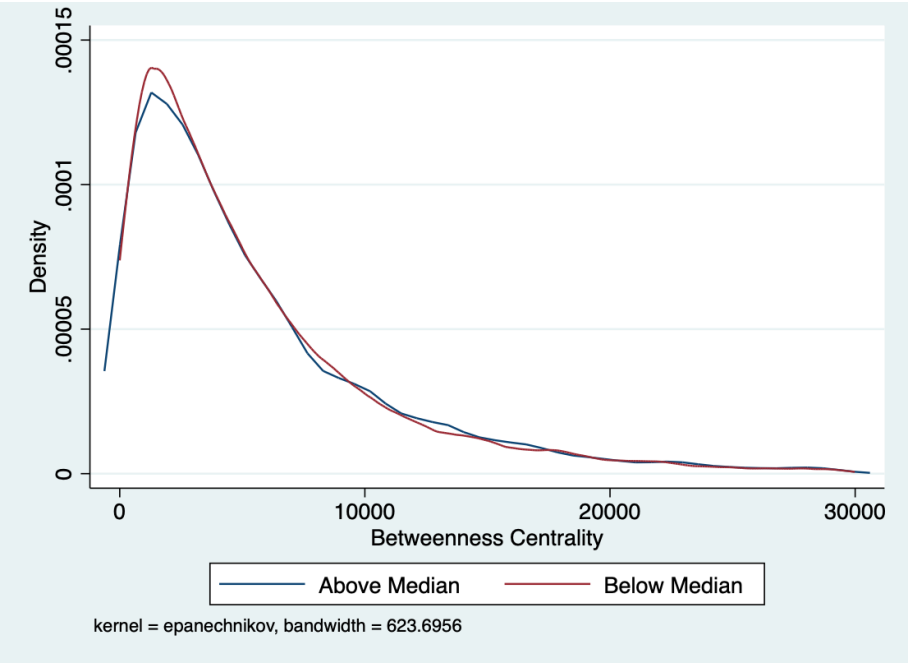


Figure D.1: Betweenness centrality distributions for villages below and above the median proportion of individuals working outside (truncated at betweenness centrality=30,000 for display). The K-S test rejects the null that the distributions are identical against the one-sided alternative that the betweenness centrality for villages above the median are lower.

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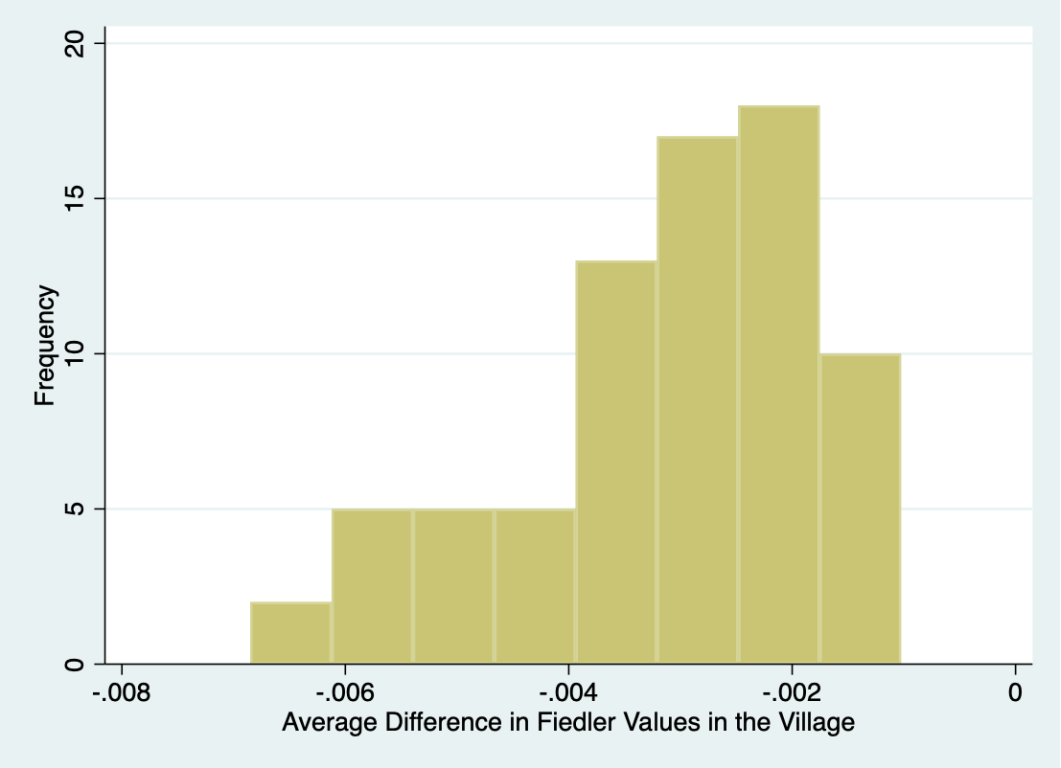


Figure D.2: The figure plots the average difference in the Fiedler value for the network G with and without agent i i.e. Fiedler($G - i$) - Fiedler(G), averaged across all $i \in G$.

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Conclusion

This thesis explores how social networks can affect individual outcomes in the context of (a) behavioural idiosyncrasies and social learning, (b) misperception formation and inter-personal dialogue, and (c) benefits from brokering and consequent reduction in mobility. In Chapter 1, I show that individual frustration and over-reaction can prevent the convergence of beliefs in networks if it is above a certain threshold. Crucially, this threshold depends on both the behavioural and network characteristics of the individuals. I also show that these idiosyncrasies can affect the accuracy of the long-run beliefs when they grow with network size. Finally, I express a conventionally used measure of network bottlenecks in terms of individual under-reaction. I show that under-reaction slows the speed of convergence as if the network were partitioned into two groups that do not pay attention to each other. I simulate these results on real-world and artificial networks and also discuss their relevance in understanding social norms and designing interventions to improve social learning.

In Chapter 2, my coauthor Ronak Jain and I present the results of a randomised controlled trial run with low-income individuals in Delhi, India aimed at increasing inter-personal dialogue and engagement with the community. We document positive effects of the belief-correction intervention in terms of an increased self-reported willingness to participate in community savings groups and listening service. We also find that individuals contribute more towards a community-oriented public good and find evidence of increased altruism among treated participants via a dictator game in the follow-up survey. We structurally estimate a theoretical model that helps us understand how misperceptions can arise and why belief correction interventions are warranted in the first place. Structurally estimating this model on secondary data allows us to show that belief-correction interventions can have heterogeneous long run impacts depending on the structure of the network. We develop network-based proxies for lack of inter-personal dialogue and find reduced form evidence for strategic complementarities.

In Chapter 3, I study the effect of an agent's network position on their decisions to risk the loss of existing network links and travel to work outside the village. I discuss existing theoretical models that show how agents lying on many paths among other agents in the network can benefit by being facilitators of transactions. I show that these agents are less likely to violate network-rules and more likely to punish those who violate them. I empirically test the predictions of the theoretical discussion on a secondary dataset. I use a theoretically motivated instrument strategy to identify the effect of network centrality since it is likely to be endogenous. The instrument strategy relies on the prediction that an agent is less likely to invest in shortest paths if other agents are already doing so. Having done this, I find evidence that between-central agents are less likely to travel to

work outside and more likely to open a savings account, suggesting an intention to stay. I discuss how these decisions additionally depend on the network position of an agent's peers, on the inequality in the distribution of network centrality, and the decisions of peers. I distinguish between endogenous and exogenous peer effects and identify the former using intransitive triads. Finally, I discuss the implications of these results on policies that aim to tackle rural-urban mobility.

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