RESEARCH AND TEACHING STATEMENT August 30, 2019
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Networks play a ubiquitous role in developing economies. Without well-functioning formal institutions, networks facilitate transactions that otherwise would not take place (Greif 1993; Munshi, 2014). My research improves our understanding of the impact of networks on economic interactions. I focus on two fundamental areas:

1) Social Learning: *How does information spread? How do opinions evolve? Why are misinformation traps persistent?* The degree of success or failure in social learning has major consequences in developing economies. Policymakers rely on extension services to encourage take-up of better practices (Beaman et al., 2019), technologies (Conley and Udry, 2010), health products (Kremer and Miguel, 2007), and financial services. Policies often use social knowledge to target the poor, assuming that society understands who is needy (Alatas et al., 2012). Job opportunities are passed along networks (Granovetter, 1973; Beaman and Magruder, 2012).

2) Informal Institutions: *How do the network positions of members of a group affect its capacity to maintain cooperation?* In developing economies, agents rely on networks for smooth exchange in the absence of formal financial access and effective institutions and legal systems. How are networks shaped to promote cooperation?[1] How does the entry of formal markets (e.g., credit) change the network?[2] Are there externalities to non-participants?

The language of networks is helpful in studying both social learning and cooperation through informal institutions. Analyzing communication networks aids policymakers in choosing whom best to seed information with to have it spread (e.g., Beaman et al., 2018), and informs researchers of misinformation traps. Examining networks elucidates which individuals can sustain cooperation in the presence of frictions like lack of commitment. Local and global externalities of introducing formal markets are also better understood through an attention to networks. My research methodology is eclectic. I collect observational data, conduct field and lab experiments, estimate structural and reduced-form models, and work on methodological problems. Theory guides my agenda.

I. SOCIAL LEARNING. My work examines when social learning succeeds or fails, as well as the resulting policy implications. Social learning has two aspects: *diffusion* and *information aggregation*. Diffusion is how information spreads from a set of agents to the wider population. It sets aside issues of uncertainty: there is a unit to be transmitted. Aggregation concerns how rational or boundedly rational agents combine signals of the truth. Every agent is informed and the analysis focuses on whether and how agents converge to a limit opinion (if any).

A. DIFFUSION. In "The diffusion of microfinance" (*Science,* 2013) with Abhijit Banerjee, Esther Duflo, and Matthew Jackson, I studied the take-up of microfinance in 43 villages in India, where we had collected detailed network data. We created a diffusion model rich enough to distinguish between theories of peer influence but simple enough to augment other economic models where diffusion matters (e.g., reputation). Our model provides a measure of influence we termed diffusion centrality, which nests many other measures. We knew which individuals the microfinance institution was likely to inform, so we used variation in their network location to estimate the model. Diffusion centrality of seeds predicted take-up. Cross-sectional estimation predicted the time series as well.

Targeting diffusion central individuals to spread information is useful for policymakers, but collecting detailed network data is costly. In "Using gossips to spread information…" (*The Review of Economic Studies,* 2019) with Abhijit Banerjee, Esther Duflo, and Matthew Jackson, I tested to see if agents could rank others by centrality as theory indicates (co-PI, NSF SES-1156182). First, we surveyed respondents in 33 villages and asked them to nominate others who, if seeded, could spread information widely. Nominated

[1] See, among others, Bramoulle & Kranton (2007), Bloch et al. (2008), Karlan et al. (2009), Jackson et al. (2012), Ambrus et al. (2014), Munshi (2014), Munshi & Rosenzweig (2016) for works that address these questions.
[2] See Feigenberg et al., (2013) who looks at changes in social capital among those who join microcredit.

individuals (gossips) were more central. Centrality was the only covariate selected by LASSO in predicting nomination among many variables (e.g., other network measures, geography, leadership). Second, we seeded information with 3-5 individuals in 213 villages in one of three ways: gossips, village leaders, or random. Gossip seeding maximized diffusion. Third, in 521 villages seeding information about upcoming vaccination camps with gossips outperformed incentives and blanketing the village with SMS reminders. Therefore, insights from theory provided a policy blueprint for identifying central individuals.

Another important application of diffusion is reputation. Besley and Coate (1995) argue social punishments through reporting poor behavior are crucial for informal financial systems. Joint liability microfinance, RoSCAs, and peer-driven financial institutions rely on reputation. In "Social networks, reputation, and commitment…" (*Econometrica,* 2019), with Emily Breza, I measured the impact of reputation. We constructed a financial institution at the pair level: a saver and a monitor. Savers saved over a 6-month period towards a self-set goal; monitors were notified bi-weekly of the progress. Motivated by a signaling model on a network, we studied whether being randomly assigned a more central monitor led to higher savings. We followed up 15 months after the end of the experiment. Reputational information about savers' responsibility level spread more widely if savers were randomized to more central monitors. Further, the savings gains had persisted, allowing subjects to better cope with shocks.

My largest scale, policy-relevant experiment is studied in "Selecting the most effective…," (Banerjee et al., 2019). We conducted an experiment in over 2000 villages evaluating numerous policies to promote vaccination: (1) incentives (none, convex, linear at varying amounts); (2) SMS reminders (none, 1/3, or 2/3 of the population); (3) seeding information with 5 agents (those trusted on health, gossips, trusted gossips, random, or none). We are looking at 75 policies and use machine learning to select the policies most associated with vaccination as well as a technique to select the best policy, overcoming the winner's curse (Andrews et al., 2018). We are finding the most cost-effective policy to be informing 5 gossips rather than using typical instruments (e.g., reminders, incentives, combinations thereof) which shows the value of using insights from network economics in policymaking.

In another policy experiment with Vivi Alatas, Markus Mobius, Cindy Paladines, and Ben Olken, "When celebrities speak: a nationwide Twitter experiment…" (2019), I quantified how much the identity of the information passer matters for diffusion. We recruited 43 celebrities with 11 million followers with help from the Indonesian government. We tweeted randomized text from their accounts to promote vaccination. We are studying if central nodes increase diffusion due to reach (numerous links) or endorsement (identity). Most studies ignore this distinction and it is difficult to causally estimate in the real world, which we do here.

B. INFORMATION AGGREGATION. In "Testing models of social learning…" (forthcoming at *Econometrica*, 2019) with Horacio Larreguy and Juan Pablo Xandri, I theoretically and empirically studied an incomplete information model of learning with coarse communication. Agents are drawn from a mixture of types—Bayesian, who face incomplete information about others' types, and DeGroot, who average their neighbors' previous period opinions. The theory studies (1) learning features of both types; (2) what network structures lead to failures of asymptotic learning; (3) whether realistic networks exhibit such structures. Studying data from experiments in India and Mexico, we structurally estimated the mixing parameter. The majority of learners were naïve, but this varies by setting.

I applied a similar model in a policy setting in "Network structure and the aggregation of information…" (*American Economic Review,* 2016) with Vivi Alatas, Abhijit Banerjee, Rema Hanna, and Ben Olken. Theory predicts which villages have network structures that better aggregate knowledge of the wealth distribution, indicating where community targeting is an effective redistributive tactic. Empirical results are consistent with theory.

The above assumes that agents are aware there is something to be learned. However, when new information is introduced to a community, typically few are seeded. How does this affect aggregation? In "Naive learning with uninformed agents" (R&R, *American Economic Review*, 2018) with Abhijit Banerjee, Emily Breza, and Markus Mobius, (co-PI, NSF SES-1326661), I am studying an extension of the DeGroot model where few agents are seeded. Society can effectively lose signals in the limit as efficiency relies on certain symmetries in the network.

I am also interested in incentives to participate in learning. This affects the quality of aggregation even with Bayesian agents. Consider a farmer struggling to use a new technology. The farmer wants to seek advice, but worries that doing so signals low ability and refrains. In "Signaling, shame, and silence…" (2019) with Ben Golub and He Yang, I am studying the stigma of seeking information as a friction to social learning, both theoretically and experimentally (co-PI, NSF SES-1658940). I moved these insights to a policy setting during India's demonetization with Abhijit Banerjee, Emily Breza, and Ben Golub, in "When less is more…" (R&R, *The Review of Economic Studies*, 2019). The rules surrounding cash exchange changed 54 times in 7 weeks in late 2016. We randomized how we delivered information to 225 villages. If stigma of seeking was a concern, knowing others received signals would discourage seeking. Consistent with this, we found seeding 5 households was better than broadcasting information to the entire village. Endogenous communication and knowledge of the rules were lower under broadcasting.

Emily Breza and I are continuing our line of inquiry in a policy setting. Caste-based affirmative action for local governance may naturally change village network structure and beliefs about other castes. We will look at how learning and technology adoption respond to such policies through network change (co-PI, NSF SES-1559469).

II. INFORMAL INSTITUTIONS.

A. NETWORK POSITION AND COOPERATION. I study how network position affects cooperation in two lab experiments in the field. In "Social networks as contract enforcement…" (*AEJ: Applied Economics*, 2018) with Cynthia Kinnan and Horacio Larreguy, I paired subjects and varied access to commitment contracts in a dynamic risk-sharing game (e.g., Ligon et al., 2002). Lack of commitment did not matter for socially close pairs but mattered for distant pairs. Most pairs in a network are distant, so lack of contracts impedes efficient transactions, making third parties valuable. In "Network centrality and informal institutions…" (2019) with Emily Breza and Horacio Larreguy, I focused on distant pairs. We asked which network members are efficiency-enhancing third parties. We found that agents worry about their image with central parties. This motivated "Social networks, reputation…" (*Econometrica*, 2019). I have received two NSF grants with Melanie Morten (co-PI, SES-1530791) and with Attila Ambrus and Matthew Elliott (co-PI, SES-1429959) to study cooperation and risk sharing in networks.

B. NETWORK FORMATION AND EVOLUTION. In "Changes in social network…" (R&R, *The Review of Economic Studies*, 2019) with Abhijit Banerjee, Emily Breza, Esther Duflo, Matthew Jackson, and Cynthia Kinnan, I examine how introducing microcredit affects network evolution. We model network formation and change using my work with Matthew Jackson in "A network formation model…" (2nd R&R, *The Review of Economic Studies*). Introducing formal credit can have a paradoxical general equilibrium effect: those uninvolved can suffer the greatest losses of social capital. The data comes from two studies: 75 villages and 104 slums. Microfinance was introduced to some networks in each setting. Using demographic, network, and eligibility data in a random forest classifier, we sort households by likelihood of joining. Introducing microcredit causes agents who were ex-ante unlikely to join to suffer the greatest loss of links and transfers among each other. This is contrary to most models of network formation, suggesting new directions for modeling networks.

In ongoing work, Ben Golub, Matthew Jackson and I study multiplexing in graph formation (co-PI, NSF SES-1629328). For instance, how are communication links distorted due to complementarities with financial links?

IV. ESTIMATION. Empirical networks are sparse and clustered but modeling them usefully for empirical work is difficult. In "A network formation model…" (2nd R&R, *The Review of Economic Studies*) we created a class of estimable models that allow for substantial link correlation, using a novel idea of building a graph as a projection of a series of subgraphs in which agents choose to participate. It is useful for many applications (e.g., risk-sharing). In "Econometrics of sampled…" (2016) with Randall Lewis, I studied problems with using partial network data. This led me to work on 3 subsequent papers on sampled network data (aggregated relational data) described below.

As collecting network data is costly, I have worked on two practical solutions. The first is discussed above in "Using gossips…" (*The Review of Economic Studies*, 2019). Second, I developed techniques to estimate network structure from less costly data in "Using Aggregated Relational Data…" with Emily Breza, Tyler McCormick, and Mengjie Pan (forthcoming, *American Economic Review*, 2019). We ask a sample, "How many of your links have trait *X*?" for some traits. This ARD lets us recover parameters of a network formation model, which permits sampling from a distribution over node- or graph-level statistics. We replicate the results of two experiments that used network data and draw similar conclusions with ARD alone. But ARD is useful only if the model's parameters can be consistently estimated. In our sequel "Consistently estimating…" (2019), we prove this and more general results.

ARD uses latent spaces (LS) to model networks, which are widely used in statistics, econometrics, and sociology. The logic is simple: agents reside in the LS; closer agents are more likely to link. The geometry of the LS (e.g., Euclidean, spherical, hyperbolic) affects what graphs can be modeled. Practical applications include risk-sharing village networks (clustered and cloistered), urban financial networks (clustered and vast), and supply chain networks (trees), which are each shown to typically fit in different geometries (spherical, Euclidean, and hyperbolic respectively). In "Identifying the latent space geometry …" (2019) with Shane Lubold and Tyler McCormick, I show how to estimate the geometry and make these choices in a data-driven way using the analysis of curvature.

III. TEACHING & OTHER ACADEMIC ACTIVITIES. I design syllabi and teach Econ 125 (upper-division undergrad) and Econ 216 (PhD level), development economics courses focusing on financial lives of the poor, information, public finance, and firm organization all with a networks perspective. I taught a network economics PhD class (Econ 291) and co-organize the development seminar (Econ 315). I also provided a lecture "Measuring Networks" as a part of the online content of MIT's MicroMasters Program in Data, Economics, and Development Policy (JPAL 102x).

I am invested in my RAs and students. Seven RAs have continued to PhDs, 4 to masters, and 3 to pre-doctoral programs. I frequently co-author with PhD students: 1 at Stanford and 2 at Harvard (both Economics) and 2 at University of Washington (Statistics).

To ensure that themes from network economics are disseminated, I have written two handbook chapters: "Econometrics of network formation," in the *Oxford Handbook on the Economics of Networks* and "Networks in economic development," with Emily Breza, Ben Golub, and Aneesha Parvathaneni in the *Oxford Review of Economic Policy*, each describing the extant literature. To this end, I organize an NSF funded conference series "Workshops on Network Economics" with Ben Golub, Matthew Jackson, and Sudipta Sarangi (co-PI SES-1757223).

IV. REFERENCES BY THE AUTHOR

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1. "The diffusion of microfinance," (with Abhijit Banerjee, Esther Duflo, and Matthew Jackson). *Science* (2013): Vol. 341 No. 6144 1236498
2. "Using gossips to spread information: Theory and evidence from two randomized controlled," (with Abhijit Banerjee, Esther Duflo, and Matthew Jackson). *The Review of Economic Studies*. (2019) doi:10.1093/restud/rdz008
3. "Social networks, reputation, and commitment: Evidence from a savings monitors experiment." (with Emily Breza). *Econometrica* 87.1 (2019): 175-216.
4. "Testing models of social learning on networks: Evidence from two experiments," (with Horacio Larreguy and Juan Pablo Xandri). [forthcoming at *Econometrica*]
5. "Network structure and the aggregation of information: Theory and evidence from Indonesia," (with Vivi Alatas, Abhijit Banerjee, Rema Hanna, and Ben Olken). *The American Economic Review* (2016): Vol. 106 No. 7
6. "Social networks as contract enforcement: Evidence from a lab experiment in the field." (with Cynthia Kinnan and Horacio Larreguy). *American Economic Journal: Applied Economics* 10.4 (2018): 43-78.
7. "Using aggregated relational data to feasibly identify network structure without network data," (with Emily Breza, Tyler McCormick, and Mengjie Pan). [forthcoming at *The American Economic Review*]

BOOK CHAPTERS.

1. "Econometrics of network formation," ed. Bramoulle, Yann, Andrea Galeotti, and Brian Rogers. *The Oxford Handbook of the Economics of Networks*. Oxford University Press, 2016.
2. "Networks in economic development," (with Emily Breza, Benjamin Golub, and Aneesha Parvathaneni) ed. Matt Elliott, Sanjeev Goyal, and Alex Teytelboym. *Oxford Review of Economic Policy*. [forthcoming]

WORKING PAPERS.

Revising

1. "Naïve learning with uninformed agents," (with Abhijit Banerjee, Emily Breza, and Markus Mobius). [R&R at *American Economic Review*]
2. "When less is more: Experimental evidence on information delivery during India's demonetization," (with Abhijit Banerjee, Emily Breza, and Benjamin Golub) [R&R at *The Review of Economic Studies*]
3. "A network formation model based on subgraphs," (with Matthew Jackson). [2nd round R&R at *The Review of Economic Studies*]
4. "Changes in social network structure in response to exposure to formal credit markets," (with Abhijit Banerjee, Esther Duflo, and Matthew Jackson) [R&R at *The Review of Economic Studies*]

In Progress

1. "Selecting the most effective nudge: Evidence from a large scale experiment on immunization" (with Abhijit Banerjee, Esther Duflo, Matthew Jackson, John Floretta, Harini Kannan, Francine Loza, and Anna Schrimpf)
2. "Signaling, shame, and silence in social learning," (with Benjamin Golub and He Yang). [submitted]
3. "Consistently estimating graph statistics using Aggregated Relational Data," (with Emily Breza, Tyler McCormick, and Mengjie Pan) [submitted]

4. "Network centrality and informal institutions: Evidence form a lab experiment in the field," (with Emily Breza and Horacio Larreguy). [submitted]
5. "Identifying latent space geometry in network models through analysis of curvature" (with Shane Lubold and Tyler McCormick)
6. "Econometrics of sampled networks," (with Randall Lewis)

V. External References

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