Dear Workshop Organizers,

I am writing to apply for the NBER Workshop on Development Economics and Networks for Early-Stage Researchers, to be held in Cambridge, Massachusetts, on December 5, 2026. I am a Ph.D. student in Agricultural and Applied Economics at the University of Illinois Urbana–Champaign.

I would be pleased to present my job market paper, *"Uncovering the Influence of Hidden Social Networks on Gendered Labor Norms: Evidence from Rural India."* The paper studies how social norms and peer behavior shape the division of productive and domestic labor within rural households when the relevant social ties are unobserved. More broadly, my research examines how social, political, and spatial networks shape household decisions and development outcomes, including migration responses to climate stress and the formation and evolution of networks over time.

The workshop is an exceptional fit for my research interests. I would particularly value feedback on my paper's approach to recovering latent influence networks and estimating peer effects without directly observed tie data. I am also eager to learn from work on incomplete network observation, endogenous network formation, and dynamic social structure, which will inform my future research agenda.

My faculty contact for a recommendation, should I be shortlisted, is:

Professor Angela Lyons
Department of Agricultural and Consumer Economics
University of Illinois Urbana–Champaign
anglyons@illinois.edu

Thank you for considering my application. I have enclosed my cover letter, CV, statement of motivation and research interests, and job market paper.

Sincerely,

Deepika Pingali

Deepika Pingali

Ph.D. Student, Agricultural and Applied Economics
University of Illinois Urbana–Champaign

Contact

414 Mumford Hall, University of Illinois Urbana–Champaign, Urbana, IL 61801
(415) 568-6987 • dsp7@illinois.edu
deepikapingali.github.io

Education

Ph.D. in Agricultural and Applied Economics 2022 – Present
Department of Agricultural and Consumer Economics (ACE),
University of Illinois Urbana–Champaign
GPA: 4.0/4.0
Graduate Minor: Gender Relations in International Development (GRID)

Master of Business Administration 2014 – 2016
Indian Institute of Management (IIM) Ahmedabad, India

B.E. (Honors), Electronics & Communication Engineering 2010 – 2014
Birla Institute of Technology and Science (BITS) Pilani, India

Research Fields

Development Economics • Data Science • Political Economy • Economics of Networks

Ph.D. Coursework

University of Illinois Urbana–Champaign GPA: 4.0/4.0

Microeconomic Theory: Applied Economic Theory; Risk and Information: Theory and Applications; Demand, Supply, Firms and Households; Equilibrium and Welfare Economics; Microeconomics.

Econometrics, Causal Inference & Machine Learning: Econometric Analysis I; Econometric Analysis II; Causal Inference; Machine Learning; Impact Evaluation; Data Science for Applied Economists; Geospatial Artificial Intelligence & Machine Learning; Introduction to Programming with Python for Data Science.

Development, Trade & Environment: Food, Poverty and Development; Food, Trade and Development; Environmental Economics; Supply Chain Management; Gender Relations and International Development; Gender and Environment in the Amazon; Special Problems (Individual Study).

Research & Professional Development: Advanced Research and Scholarly Communication; Thesis Research (ongoing, 2023–present).

Training and Workshops (Competitive)

- Winter School on Econometrics of Networks, VU Amsterdam, Online 2025
- Oxford Summer School on Economic Networks, Oxford, UK 2025
- I-GUIDE Summer School, Spatial AI for Extreme Events and Disaster Resilience, UCAR, Boulder, CO (NSF-supported) 2025
- CSWEP South PhD Student Mentoring Workshop, Houston, TX (scheduled) 2026

Technical Skills

Quantitative Skills: Data Science, Machine Learning, Causal Inference, Geospatial Analysis, Social Network Analysis, Network Econometrics
Software: Stata, R, Python, MATLAB

Publications

- Lyons, A., Kass-Hanna, J., **Pingali, D.**, Soliman, A., Zhu, D., Zhang, Y., & Montoya Castano, A. (2025). A geospatial analysis of food insecurity among refugee households in Lebanon using machine learning techniques. *Food Security.* (Earlier version circulated as ERF Working Paper No. 1729, Economic Research Forum.)
- Verma, P., Dengler, N., Lyons, A., & **Pingali, D.**(forthcoming). Beyond gravity models: Predicting human migration with spatial gates and graph neural networks. In *Proceedings of the 2026 ACM/IEEE Joint Conference on Digital Libraries (JCDL '26).*

Working Papers

- **Pingali, D.**(2026). *Uncovering the influence of hidden social networks on gendered labor norms: Evidence from rural India* [Job Market Paper].

  Abstract: Economics has traditionally characterized spousal labor sharing as the outcome of an intrahousehold bargaining process; however, these decisions are also shaped by norms embedded within and transmitted through social networks. This paper investigates the influence of peer behavior on labor sharing between spouses. A key empirical challenge is that social network ties are unobserved in most existing datasets. I overcome this by jointly estimating the latent social structure, peer effects, and contextual effects within a linear social interactions model via Adaptive Elastic Net Generalized Method of Moments, recovering network architecture without requiring directly observed network data. Using the *Village Dynamics in South Asia* (VDSA) dataset across 16 villages and approximately 629 households, I find that within-sample peer networks governing production and domestic labor-sharing differ in topology. Domestic norms exhibit a moderate social multiplier: a 10-percentage-point increase in peers' male-to-female domestic work ratio is associated with a 5.8-percentage-point increase in a couple's own ratio. The corresponding production peer effect is 5.4 percentage points. Exploratory analysis of the recovered networks shows that couples maintain influence ties with roughly three peers on average, and that this degree is stable across village sizes; as a result, estimated network density declines as villages grow larger, a mechanical consequence of a roughly fixed per-couple

relationship budget spread over a larger pool of potential partners. I also examine assortativity, the tendency to connect with similar peers. Production-norm networks are positively caste- and land-assortative, meaning same-caste and similarly-landed couples are tied more often than chance would predict; domestic-norm networks show no such assortativity on either dimension. Influence is likewise domain-specific: non-Hindu households have lower influence over production norms, while forward-caste households have somewhat higher influence over domestic norms, with a marginally significant effect. My findings provide novel insights and evidence on how network-mediated spillover effects are integral in shaping intrahousehold labor distributions.

- **Pingali, D.**(2025). *The effect of political capital on migration decisions in the context of climate change in India* [Working paper]. Available at SSRN: https://ssrn.com/abstract=5500739

  Abstract: Climate change is increasingly reshaping livelihoods through droughts, crop failures, rising sea levels, and extreme weather events, particularly in South Asia, Sub-Saharan Africa, and Latin America. Migration has become a crucial household strategy for managing these climate-induced risks. This paper examines how village-level political capital — households' close connections to local government officials — shapes migration decisions under environmental stress, and how this influence varies with the intensity of long-term climate stress. We develop a stylized expected-utility framework in which households weigh expected gains from migration against the costs and risks of remaining in place. The framework predicts a nonlinear, inverted U-shaped relationship: political capital has the largest effect at moderate levels of climate stress. Using data from the India Human Development Survey and ERA5 climate records, we implement a difference-in-differences approach. Empirical results confirm the model: at medium heat stress, political capital increases migration probability by 3.2 percentage points ($p < 0.05$), while its effect is smaller and statistically insignificant under low or extreme stress. These findings demonstrate that political access mediates climate adaptation, with implications for equitable migration policies and resilience strategies.

- Lyons, A., Polato e Fava, A., Kass-Hanna, J., **Pingali, D.**, & Liu, F. (2025). *Gender disparities in financial and digital financial inclusion: Insights from PISA data* [Working paper, under review]. Available at SSRN: https://ssrn.com/abstract=5384658

  Abstract: The global digital transformation of financial services has heightened concerns about gender disparities in financial inclusion and empowerment, particularly as gender gaps in financial literacy often emerge early in life. This study leverages data from the 2018 PISA assessment to examine gender differences in the relationship between financial literacy and both traditional and digital financial inclusion among youth. Using the Lewbel method to address endogeneity, the analysis reveals that financial literacy significantly enhances financial and digital financial inclusion. However, persistent gender disparities remain, especially in traditional financial inclusion, where girls are less likely than boys to own bank accounts or payment cards. Gaps in confidence are also notable, with girls up to 50 percentage points less likely to feel confident performing financial and digital financial tasks compared to boys. Encouragingly, participation in a financial literacy course significantly improves girls' confidence, highlighting its potential to reduce these disparities. Yet greater confidence does not necessarily translate to increased financial service participation, suggesting the continued presence of external barriers to financial inclusion. These findings underscore the need for targeted policy interventions to promote early financial education, digital skill development, and confidence-building among girls, laying a foundation for their economic empowerment in the digital age.

Works in Progress

- Lyons, A., **Pingali, D.**, & Soliman, A. *Using Machine Learning Techniques to Predict Internal Migration in the Brazilian Amazon.*
- Tripathy, P., Upadhyay, S., Alegbeleye, O. M., Senkardesler, E., **Pingali, D.**, Goddard, E., Thaker, J., Leiserowitz, A., & Marlon, J. *Mismatch Between Perceived and Assessed Flood Risk in India.*
- Lyons, A., **Pingali, D.**, Telles, T. S., Plassa, W., Soliman, A., & Storoe, B. *From Forest to Farm? Deforestation, Farm Lifecycles, and Long-Run Agricultural Sustainability in Brazil.*
- Lyons, A., **Pingali, D.**, Kass-Hanna, J., & Soliman, A. *Where Refugees Settle: Spatial Dependence and the Determinants of Syrian Refugee Distribution in Lebanon.*

Conference & Poster Presentations

- "Uncovering the Influence of Hidden Social Networks on Gendered Labor Norms: Evidence from Rural India" (sole author) [Job Market Paper].
  - ASSA/AEA Annual Meeting, Washington, DC, January 2027 (scheduled)
- "The Effect of Political Capital on Migration Decisions in the Context of Climate Change in India" (sole author).
  - Political Economy of Climate and Environment (PECE), Harvard University, Cambridge, MA, September 2026
  - Environmental and Climate Mobilities Network (ECMN), Wageningen University & Research, Wageningen, Netherlands, June 2026
  - European Political Science Society (EPSS), Belfast, United Kingdom, June 2026
  - Illinois Economics Association Conference, Chicago, IL, October 2025
- "Gender Disparities in Financial and Digital Inclusion: Insights from PISA Data."
  - Congreso Internacional en Alfabetización Financiera, Online, November 2025
  - International Conference on Empirical Economics, Penn State Altoona (Online), August 2025
  - Illinois Economics Association Conference, Chicago, IL, October 2024
- "A Geospatial Analysis of Food Insecurity Among Refugee Households in Lebanon Using Machine Learning Techniques."
  - ERF 30th Annual Conference, Rabat, Morocco, April 2024 (presented by A. Lyons)
  - Illinois Economics Association Conference, Chicago, IL, October 2024

Research and Teaching Experience

Senior Research Associate 2022 – Present
Department of Agricultural and Consumer Economics (ACE) & National Center for Supercomputing Applications (NCSA), University of Illinois Urbana–Champaign

- Leads research on forced displacement, climate change, and the socioeconomic vulnerability of disadvantaged populations, producing peer-reviewed publications, working papers, and presentations at international venues.

- Mentors and manages undergraduate researchers through NCSA's REU (Research Experiences for Undergraduates) and SPIN (Students Pushing INnovation) programs, as well as graduate students; mentees have gone on to co-author peer-reviewed publications and working papers arising from this research.

Teaching Assistant, ACE 474: Economics of Consumption Fall 2022
Department of Agricultural and Consumer Economics (ACE),
University of Illinois Urbana–Champaign

- Guided student teams through a Consumer Price Index (CPI) project modeled on U.S. Bureau of Labor Statistics methodology, advising them on constructing a custom price index to capture how college students' consumption baskets have shifted amid recent tariffs and rising inflation.
- Graded assignments and exams and held regular office hours to support student learning.

Teaching Assistant, ACE 270: Consumer Economics Spring 2024
Department of Agricultural and Consumer Economics (ACE),
University of Illinois Urbana–Champaign

- Managed grading responsibilities for assignments and exams.

Teaching Assistant, ACE 476: Behavioral Economics Fall 2026
Department of Agricultural and Consumer Economics (ACE),
University of Illinois Urbana–Champaign

- Support a semester-long student project by facilitating in-class activities held periodically to build student progress.
- Grade quizzes, homework, exams and activities and provide feedback to guide students' work on the project.

Fellowships & Awards

- Graduate Conference Travel Award, ACE — Summer 2026
- Wilken Farm Management Fellowship, ACE — Spring 2025
- University Block Grant Fellowship, ACE — Spring 2025
- Linse Scholarship, ACE — Spring 2024

Training and Workshops (Competitive)

- Winter School on Econometrics of Networks, VU Amsterdam, Online — 2025
- Oxford Summer School on Economic Networks, Oxford, UK — 2025
- I-GUIDE Summer School, Spatial AI for Extreme Events and Disaster Resilience, UCAR, Boulder, CO (NSF-supported) — 2025
- CSWEP South PhD Student Mentoring Workshop, Houston, TX (scheduled) — 2026

Service & Leadership

- Vice President, ACE Graduate Student Organization (GSO) — 2025 – 2026
- Secretary, ACE Graduate Student Organization (GSO) — 2023 – 2025

Other Professional Experience

Over five years in the international development sector across South Asia: managing grassroots programs and a social business, and advising INGOs and multilateral agencies. Areas of work include monitoring, evaluation and learning (MEL), program design and implementation, advisory services, fundraising, and branding & marketing.

Social Entrepreneurship

Founder, Vidhignya Enterprises Pvt. Ltd. 2017 – 2022

- Founded a venture promoting collective entrepreneurship among women from the informal economy, empowering them through skill-building and livelihoods interventions and connecting them to sustainable market linkages.

Development Consulting 2017 – 2022

- World Bank: land contracts and migration trends in India.
- World Bank & Access Development Services: supply-side financing barriers for women entrepreneurs.
- International Labour Organization: worker networks and labor conditions, New Delhi.
- UNDP: vision document for May Doe Kabar, a network of 20,000 rural women in Myanmar.
- DFID Global Innovation Fund: case studies of Indian firms.
- EU GENIE Program: review of the role of women's civil society organizations in India.
- Bangladesh-based INGO: design and review of a community empowerment program.
- Evaluation of international labor migration projects across Lebanon, Jordan, and South Asia.

Program Design & Implementation 2017 – 2022

- Directed grassroots anti-trafficking projects in Nepal (UN Trust Fund-funded NGO partnership), rescuing and rehabilitating trafficking survivors and supporting informal-sector workers through community networks.
- Directed a women's empowerment project in Varanasi and Koppal, India, benefiting 7,000 rural women through self-sustaining collectives.

Private Sector Experience

True North Private Equity, Mumbai 2016 – 2017

- Drove business development initiatives, launching and expanding new business verticals and shaping corporate strategy.

References

Available upon request.

Statement of Motivation and Research Interests

My research examines how socioeconomic decisions are shaped by social and spatial networks, as well as how those networks themselves emerge and change. I combine structural economic models with machine-learning tools and network econometrics to study social structure when the connections that matter for economic behavior are not directly observed in conventional data. Substantively, my work addresses how social norms shape household decisions, and how connections to political institutions affect adaptation and mobility,

My job market paper examines how social norms and conformity shape the intrahousehold division of labor in rural India. The paper jointly recovers a latent influence network and peer effects within it, despite the absence of directly observed social ties. I show that the influence structures associated with productive activities and domestic norms differ systematically in their topology and assortative matching. The project contributes to understanding how local social influence can constrain household choices, particularly in settings where gendered norms affect the allocation of work and time. A second strand of my work asks how networks can expand access to opportunity. In ongoing work on migration under climate stress, I study how village-level political capital shapes mobility decisions. I find that ties to institutional power at migrants' origin increase outmigration at moderate levels of environmental stress, suggesting that political and institutional connections can shape households' capacity to respond before environmental conditions become most severe. A third strand of my research asks how networks form. For future projects, I am interested in developing longitudinal network data from archival and administrative sources to study how relationships emerge, persist, and dissolve. This agenda will bring strategic models of network formation to empirical settings where ties can be observed repeatedly over time and linked to changing economic circumstances. Understanding this joint evolution is essential for studying whether observed network effects reflect influence, selection into relationships, or both.

I am especially interested in learning from and engaging with frontier empirical methods for settings in which nodes are absent from the data, ties are unobserved or incompletely observed, and networks are dynamic. My job market paper addresses one part of this broader agenda by treating the latent network as fixed and focusing on how to recover social influence when direct tie data are unavailable. The stronger challenge, i.e. allowing network structure, individual behavior, and economic outcomes to evolve jointly, will be central to my future research. I would benefit greatly from engaging with researchers developing empirical approaches to latent network structure, partial network observation, endogenous tie formation, and dynamic networks.This workshop is therefore an especially valuable opportunity to refine my job market paper and to develop the methodological foundations for my subsequent projects. I would be grateful for the opportunity to present the paper and receive feedback on its identification strategy, especially the assumptions needed to distinguish social influence from correlated behavior when the relevant network is unobserved. I would also welcome the chance to learn from other participants working on the measurement, estimation, and interpretation of networks in development settings, and to contribute perspectives from my work on gender norms, climate-related migration, political connections, and longitudinal social and spatial data.

Uncovering the Influence of Hidden Social Networks on Gendered Labor Norms: Evidence from Rural India

Deepika Pingali, University of Illinois Urbana-Champaign[1]

September 12, 2026

Abstract

Economics has traditionally characterized spousal labor sharing as the outcome of an intrahousehold bargaining process; however, these decisions are also shaped by norms embedded within and transmitted through social networks. This paper studies the influence of peer behavior on spouses' relative contributions to domestic and production labor in rural India. A key empirical challenge is that social network ties are unobserved in most existing datasets. I overcome this challenge by jointly estimating the latent social structure, peer effects, and contextual effects within a linear social interactions model. I use an Adaptive Elastic Net Generalized Method of Moments, recovering network architecture without requiring directly observed network data. Using the Village Dynamics in South Asia (VDSA) dataset across 16 villages and a balanced panel of 629 households, I find that within-sample peer networks governing production and domestic labor-sharing differ in topology. Domestic norms exhibit a statistically significant social multiplier. A 10-percentage-point increase in peers' relative male-to-female domestic work leads to a 5.8 percentage-point increase in a couple's own relative male-to-female domestic work. Similarly, a 10-percentage-point increase in peers' relative female-to-male production work leads to a 5.4 percentage-point increase in a couple's own relative female-to-male production work. Exploratory analysis of the recovered networks shows that couples maintain influence ties with roughly three peers on average, and that this degree is stable across village sizes. I also examine assortativity, the tendency to connect with similar peers. Production-norm networks are positively caste- and land-assortative, meaning same-caste and similarly landed couples are tied more often than chance would predict; domestic-norm networks show no such assortativity on either dimension. Non-Hindu couples are less central in production-norm networks, while forward-caste couples are more central in domestic-norm networks. My findings provide novel insights and evidence on how network-mediated spillover effects are integral in shaping intrahousehold labor distributions.

JEL Classification*: J16, D13, Z13, D85*

Keywords*: peer effects, social networks, gender norms, division of labor, structural identification*

[1] Deepika Pingali, PhD Student, University of Illinois Urbana-Champaign, Department of Agricultural and Consumer Economics, 326 Mumford Hall, 1301 W. Gregory Drive, Urbana, IL 61801 USA. Email: dsp7@illinois.edu

Uncovering the Influence of Hidden Social Networks on Gendered Labor Norms: Evidence from Rural India

1. Introduction

Consider two sets of spouses in the same village. In one, the wife shoulders most of the domestic work while her husband handles production; in the other, the spouses share both more evenly. Standard economic models typically explain such allocations through the lens of individual preferences, outside options, and economic constraints. But even within the same village, where households share a broad institutional and local economic environment, why do otherwise similar couples divide domestic and productive work so differently? Preferences are not formed in a vacuum and are often influenced by conformism effects transmitted through social networks. Decisions about who does which work are shaped not only by how spouses bargain between themselves, but by what they observe and absorb from their peers. And because couples are typically exposed to different sets of peers to varying degrees, this mechanism can generate the variation in labor-sharing norms that otherwise similar households display. Considering this, this paper explores the role of peer effects in determining intrahousehold division of labor. I specifically investigate whether couples' labor-sharing arrangements, in terms of both domestic tasks and economic production, respond to those of socially connected peers in the village.

To answer this question, I first conceptually model the spousal division of labor as the Nash equilibrium of a simultaneous-move game played within a social network. Each couple's labor-sharing decision responds to its own characteristics, the decisions of peer couples, and those peers' characteristics. A couple's utility increases when they are in conformity with peer behavior. This reflects the normative pressure that a social network transmits regarding the 'appropriate level' of spousal labor-sharing. Solving the model yields a linear social-interactions equation, formally analogous to a spatial autoregressive model, in which the weighting matrix captures social proximity rather than geographic distance, and the objects of interest are the endogenous peer and contextual effects.

Estimating the structure of village social networks is a prerequisite for exploring these relationships empirically. The central obstacle is that the relevant network data is entirely unobserved since most household surveys, VDSA included, do not record information on who respondents' peers are or who influences whom. Researchers typically address this deficiency in one of two ways, either by imposing a proximity structure based on geographic distance, caste, or kinship, or collecting costly dyadic network data through dedicated instruments. In lieu of either approach, I apply recent advances in the structural identification of social networks (De Paula et al., 2025). This allows me to jointly recover the latent social proximity matrix, and in turn the endogenous peer effect and contextual effects implied by my theoretical framework, using an Adaptive Elastic Net GMM estimator. Under the model's identification and time-invariance assumptions, the estimator jointly identifies the social-interactions matrix and peer-effect parameters rather than requiring us to impose ties using geography, caste, or kinship. Having

estimated the structure of peer networks and the spillover effects mediated by these networks, I then conduct several descriptive analyses to better understand the network's features: in particular, what village-level factors correlate with its density, and what features characterize central agents within the network. I explore features such as caste, religion, landholding status, education, women's self-help-group participation, or the age gap between spouses.

The main finding that I document is a statistically significant passthrough between households via peer networks. The networks governing domestic and production work-sharing differ in topology and effect size, though both exhibit a strong social multiplier. A 10-percentage-point increase in peers' relative male-to-female domestic work is associated with a 5.8-percentage-point increase in a couple's own; the corresponding production effect is 5.4 percentage points.

Analysis of the estimated networks yields further insights. Caste and landholding organize who exchanges production-labor norms with whom, net of village composition, but play no such role in domestic-norm ties. Centrality works differently: non-Hindu couples are less influential in the production network, while forward-caste couples are somewhat more influential in the domestic network. These patterns are descriptive, but indicate that identity markers may enter the two domains through different channels. My results also have relevance extending beyond the Indian setting, given that the determinants of intrahousehold labor allocations remain important in both developed and advanced economy contexts.

The paper contributes to three strands of literature. The first examines the intrahousehold division of labor. Early models treat this process as an economic choice, with spouses specializing by comparative advantage in market versus home production (Becker, 1981; Gronau, 1977). Later researchers extend this into bargaining models, wherein allocations are determined by each spouse's relative bargaining power, operationalized through threat points, individual consumption utility, and outside options such as wages, divorce settlements, and fallback positions (Manser & Brown, 1980; McElroy & Horney, 1981; Lundberg & Pollak, 1993; Browning & Chiappori, 1998). These frameworks are insightful, but they model labor allocation mainly as a negotiation between spouses. Even when they incorporate institutional factors such as divorce law or welfare access, they tend to abstract from the broader normative environment in which households are embedded and from which expectations about appropriate spousal behavior derive. This omission is likely to be important, particularly as studies on social norms and household time-allocation show that relative earnings do not fully explain housework patterns, and that women often continue to do a disproportionate share of housework even when they have stronger labor-market positions (Bittman et al., 2003; Hook, 2010; Stier & Lewin-Epstein, 2007). Related work argues that household specialization is shaped by gender norms rather than standard economic incentives (Lassen, 2021; Sevilla-Sanz et al., 2010). I extend this area of research by modelling the network structure through which norms operate, treating the latent social network as the channel through which they are transmitted and enforced, *complementing rather than replacing* intra-spousal bargaining models. In doing so, I identify a novel and important factor that influences intrahousehold decision-making.

The second strand of literature concerns peer effects on women's behavior in general. Numerous studies have shown that women's decisions respond to the actions and characteristics of those around them. Peer effects influence political participation, fertility decisions, and economic participation and enterprise (Beaman et al., 2009, 2012; Munshi & Myaux, 2006; Field et al., 2016). More recent work also shows that women's labor supply responds to the gender-role beliefs of their peers, with gender-egalitarian peer norms increasing mothers' employment and their share of paid work within the household (Cavapozzi et al., 2021). This literature establishes that women's choices tend to be socially embedded; however, existing work within this area largely studies the individual woman rather than the couple. I extend the analysis to the couple, asking how couples are influenced by peer couples in the way they share domestic and productive labor. This matters because in many rural settings the relevant unit of social comparison is not the individual but the couple as a gendered social unit.

The third is the structural identification of social interactions. Manski's (1993) reflection problem makes it difficult to separate endogenous peer effects from contextual effects and correlated effects. A growing econometrics literature confronts this challenge structurally. Bramoullé et al. (2009) establish the conditions on network structure under which endogenous peer effects and contextual effects can be separately identified. Essentially, the network should not be fully connected (a structure in which every node is linked to every other node). When nodes vary in terms of which other nodes they directly connect to, this variation makes it possible to distinguish endogenous peer effects from contextual effects. Lewbel et al. (2023) extend this literature to point-identify peer and contextual effects without observing any network links, exploiting heterogeneity across many small cross-sectional networks in which individuals are each observed once, though they do not recover the structure of the network itself. De Paula et al. (2025) instead reconstruct the latent network structure directly from panel data, estimating it jointly with the peer and contextual effects. I apply this latter approach to panel data from rural India, showing that questions about the social organization of gender norms can be answered even in settings in which data with which to directly observe the structure of networks is not available.

The remainder of the paper proceeds as follows. Section 2 develops the linear social interactions model, treating each couple's labor-sharing decision as a Nash equilibrium outcome and describing the conditions under which the latent network and the social interaction parameters are jointly identified. Section 3 introduces the VDSA data and the construction of the domestic and production labor-sharing measures. Section 4 describes the estimation procedure, which recovers the social proximity matrix, the endogenous peer effect, and the contextual effect via Adaptive Elastic Net GMM. Section 5 presents the results across both domains, including effect sizes, network topology, and the characteristics of the central agents. Section 6 concludes and discusses the implications for policies aimed at shifting entrenched labor division behaviors.

2. Conceptual Framework

Social networks shape norms by providing reference points for "appropriate" behavior. Figure 1 illustrates a stylized directed, weighted social network among couples in a village. Each node represents a couple, and an arrow from couple *i* to couple *j* indicates that *i*'s behavior serves as a

social reference point for *j*. The direction of the tie matters, couple *j* may be influenced by couple *i* without *i* being similarly influenced by *j*. Edge weights capture the strength or salience of this influence, such that couples connected by stronger ties place greater weight on one another's behavior when forming beliefs about what is socially appropriate. Thus, the network weights for each couple determines a subset of peers from which couples infer prevailing norms, while allowing these reference groups, to differ across couples.

[Insert Figure 1]

Following Blume et al. (2015), I use a linear social interactions framework to establish a conceptual understanding of social networks and the transmission of effects through these networks. I model the outcome of interest, intra-spousal labor allocation, as a strategic decision made by couples under the influence of peer couples' behavior. Each couple's labor allocation reflects not only its own preferences and constraints but also prevailing social norms. This approach is in line with canonical microeconomic utility models commonly employed in network economics literature, where an individual's marginal benefit depends on their own characteristics, peer characteristics (contextual effects), as well as peer choices.

Let u_i be the utility of a couple *i,* with $i = 1, \dots, N$. Couple *i* possesses characteristics denoted by x_i and engages in labor-sharing y_i, and is connected to other couples in the village by the exogenous row-normalized asymmetric weight matrix $\boldsymbol{W}$, the *ij*th element of which is denoted by w_{ij}. Couple *i*'s utility is assumed to be given by

$$u_i(y) = \theta_i y_i - \frac{1}{2} y_i^2 + \rho \sum_{j=1, j\neq i}^{N} w_{ij}\, y_i y_j, \tag{1}$$

with

$$\theta_i = \beta x_i + \gamma \sum_{j=1, j\neq i}^{N} w_{ij}\, x_j. \tag{2}$$

The parameter ρ captures peer effects, which are modelled as a strategic complementarity that rewards co-movement with peers' actions y_j. γ is the contextual effect, which is defined as the effects peers have on the agent not because of what they do, but because of their exogenous characteristics x_j. Finally, the coefficient vector β captures the effect of couple *i*'s own observed characteristics on its labor-sharing arrangement.

Taking the first order condition of u_i with respect to couple *i*'s labor-sharing yields

$$y_i = \rho \sum_{j=i}^{N} w_{ij}\, y_j + \beta x_i + \gamma \sum_{j=i}^{N} w_{ij}\, x_j. \tag{3}$$

Stacking the first-order conditions of the utility equation for all N couples allows for the Nash equilibrium to be characterized, and results in the standard spatial equation

$$\boldsymbol{y} = \rho \boldsymbol{W}\boldsymbol{y} + \beta \boldsymbol{x} + \gamma \boldsymbol{W}\boldsymbol{x}. \tag{4}$$

It is important to note that the weight matrix $\boldsymbol{W}$ does not reflect geographic distance, but rather the strength of social influence between individual couples. Adding a mean-zero error term to equation (4) yields the estimating equation given by

$$\boldsymbol{y} = \rho \boldsymbol{W}\boldsymbol{y} + \beta \boldsymbol{x} + \gamma \boldsymbol{W}\boldsymbol{x} + \boldsymbol{\epsilon}. \tag{5}$$

I follow De Paula et al. (2025) for the identification result and estimation technique. They demonstrate that certain reasonable assumptions allow for the identification of the unknown $\boldsymbol{W}$ as well as the parameters ρ, β, γ. The assumptions are as follows:

- The first assumption is that no individuals affect themselves, i.e. $w_{ii} = 0$. This is a standard condition in linear social interaction models.
- The second assumption controls the propagation of shocks and requires that the conformity effect ρ satisfy the conditions $|\rho| < 1$ and $\sum_j |\rho w_{ij}| < 1$ for all i; and that the L0-norm of the weight matrix is less than a finite constant C, or $||\boldsymbol{W}_0|| < C$. This is to ensure that the system is adequately stable, i.e., shocks dissipate rather than intensify as they transmit through the network.
- The third assumption is that network effects do not cancel out, i.e., $\beta\rho + \gamma \neq 0$, which is another standard assumption in the network literature. This assumption rules out the case in which the endogenous and exogenous effects exactly offset one another.
- The fourth assumption, given the panel structure of the data, is that $\boldsymbol{W}$ is row-normalized, i.e. each agent is influenced by its peers to the same total extent, with the sum of individual influence weights normalized to one for each agent. Row-normalization is what allows time fixed effects (correlated effects) to be included in the model, absorbing common shocks and separating them from the peer and contextual effects.
- The fifth assumption is that agents have differing numbers of links and strengths of these links – at least one pair is different, so that at least two diagonal elements of $\boldsymbol{W}^2$ are different from each other.
- The sixth assumption is that $\boldsymbol{W}$ is fixed over time.

De Paula et al. (2025) show that under these assumptions, the variation observed in the sample of exogenous covariates and outcomes can be generated only by a specific weight matrix $\boldsymbol{W}$ and specific values of the parameters ρ, β, γ, i.e., they are all mathematically identified.

3. Data and Descriptive Statistics

The analysis uses the Village Dynamics in South Asia (VDSA) dataset. The full survey covers 18 villages across six semi-arid Indian states. These include Andhra Pradesh, Telangana, Karnataka, Maharashtra, Madhya Pradesh, and Gujarat. These states represent typical agroecological and socio-economic conditions of semi-arid rural India. Within each village, households are drawn by stratified random sampling, so the sample is designed to be representative within each village, and the same households are surveyed monthly from 2010 to 2014, for 60

monthly periods. VDSA contains detailed information on household demographics, agricultural activity, labor allocation, income, transfers, and prices. Because the estimation technique requires a perfectly balanced panel (the latent network W is assumed fixed over time), each household must be observed in all 60 periods. Accordingly, we restrict the sample to households present throughout, which retains 16 of the 18 villages and 629 households. Thus, differences in estimates across specifications cannot be attributed to changes in sample composition.

Both key outcomes are measured in inverse hyperbolic sine (IHS) units, which approximate a log scale but, unlike the log, are defined at zero and so can retain the couples in which one spouse performs none of a given task.

The first outcome is the relative production burden, which measures the gap between spouses in income-generating labor. For each spouse, production days are the sum of days spent in market wage work, own-farm work, and livestock work. The variable is the inverse hyperbolic sine of the wife's production days minus the inverse hyperbolic sine of the husband's production days

$$Y_{it}^{P} = \text{asinh}(P_{it}^{W}) - \text{asinh}(P_{it}^{H}) \tag{6}$$

A positive value therefore means the wife performs relatively more production work than her husband, and a positive coefficient indicates that the variable in question shifts the production burden toward the wife, widening her share relative to his. A negative value, or a negative coefficient, indicates the opposite, i.e. production work is concentrated on, or shifts toward, the husband.

The second outcome is the relative domestic burden, which measures the gap between spouses in household work. Domestic days are each spouse's reported household-work days. The variable is the inverse hyperbolic sine of the husband's household-work days minus the inverse hyperbolic sine of the wife's household-work days:

$$Y_{it}^{D} = \text{asinh}(D_{it}^{H}) - \text{asinh}(D_{it}^{W}) \tag{7}$$

The order is deliberately reversed relative to the production measure, so that in both outcomes a positive value reflects the spouse who conventionally does less of that work doing more of it. A positive value therefore means the husband performs relatively more domestic work, and a positive coefficient indicates that the variable shifts the domestic burden toward the husband, raising his share relative to the wife's. A negative value, or a negative coefficient, indicates that domestic work is concentrated on, or shifts toward, the wife.

The regressors capture village-level economic and agricultural conditions that shape the allocation of labor within each couple, as summarized in Table 1. They do not determine whether many agricultural and livestock tasks must be completed, since crops still need to be sown, weeded, and harvested, and livestock must still be fed and tended according to the agricultural calendar. Instead, these conditions affect how couples allocate responsibility for those tasks and how they divide domestic work alongside production activities.

The first regressor is the relative opportunity wage, defined as the log ratio of the wife's village-level opportunity wage to the husband's village-level opportunity wage. It is measured in log rupees per day, so that a higher value indicates a higher female wage relative to the male wage. Each spouse is assigned the village-level, gender-specific daily wage corresponding to their main occupation. Farm workers are assigned the wage for the specific task on which they report spending the most time in a given month, while non-farm workers are assigned the corresponding non-farm wage. Where these wages are unavailable, the value is filled with the village-month average of farm and non-farm wages for that gender. This measure captures the relative market value of the wife's and husband's time and therefore the relative cost to the couple of assigning either spouse to production activities.

Two variables capture income received from outside the couple's own labor, both measured in IHS rupees per month. The first is government welfare transfers, received at the couple level; the second is private transfers, comprising gifts and remittances. Both are winsorized at the 99th percentile to limit the influence of extreme values, then IHS-transformed, and both equal zero in months when no transfer was received. These resources may affect labor sharing by relaxing household resource constraints and reducing the need for either spouse to supply income-generating labor, or by allowing the household to hire labor for production tasks.

The final two variables relate to crop cultivation and local crop-market conditions. The first is a cultivation indicator, equal to one when a recently harvested main crop is recorded for the couple-month and zero otherwise, following the timing of the agricultural calendar. The second is the crop price, in IHS rupees. This is the village-level price of the main crop most recently harvested by the couple, matched on crop and harvest season, and zero-filled for non-cultivating couple-months before the IHS transformation. Because the price is zero-coded for non-cultivators, the cultivation indicator and the price term are used together. The indicator captures the distinction between cultivating and non-cultivating couple-months, while the price term captures variation in crop returns among cultivating couples.

Together, these measures describe the local economic environment and the resources available to each couple. They capture conditions that may change the relative value of spouses' time, the resources available to the household, and the economic returns associated with agricultural production. In turn, these conditions may affect how couples divide production and domestic work, even when the underlying agricultural and livestock tasks themselves must still be completed. Descriptive statistics are presented in Table 2.

[Insert Table 1]

[Insert Table 2]

Figure 2 presents a binned scatter of each couple's production sharing outcome against the leave-one-out mean of the other couples in its village-period, before and after demeaning by two-way (household and period) fixed effects. In the raw data (left panel), own values and the village-

period peer mean are positively correlated ($r = 0.374$). After two-way fixed effects are demeaned (right panel), the residual correlation attenuates but remains positive ($r = 0.199$), indicating within-village dependence that survives the removal of fixed household differences and common period shocks. Figure 3 repeats the exercise for the domestic sharing outcome. The positive association is stronger in the raw data (left panel, $r = 0.728$) and again attenuates under two-way fixed effects while remaining clearly positive (right panel, $r = 0.362$). As with Figure 2, the persistence of positive correlation after demeaning points to within-village dependence in the outcome beyond fixed household and period effects. The persistence of this correlation motivates estimating a Spatial Autoregressive (SAR)-type model, which the empirical section uses to distinguish between endogenous peer effects and contextual effects.

[Insert Figure 2]

[Insert Figure 3]

Figure 4 plots average relative production and domestic burdens by agricultural season. It shows two related patterns. First, as agricultural pressure rises in the Kharif season (July–October), the relative production burden shifts toward women while the relative domestic burden shifts further toward women, as men make a smaller relative domestic contribution. The two shifts compound into an intensified double burden on women rather than offsetting one another. The lean season (March–May) is the reverse, with women's relative production burden lowest and men's relative domestic contribution highest. That the two demands compound rather than trade off is notable. This justifies studying the two outcomes separately.

[Insert Figure 4]

4. Identification and Estimation

The identification strategy relies on regressors that capture the economic conditions facing each couple. Farm and livestock tasks must generally be carried out on a schedule set by the crop and livestock cycle, rather than by day-to-day household decisions, so the relevant question is often which spouse's time is used to perform them, and at what opportunity cost. The opportunity cost of that time is the village-level, gender- and task-specific daily wage, i.e. what the local labor market pays, not what either spouse actually earns. Government welfare transfers are allocated through administrative rules,; the cultivation indicator follows the agricultural calendar; and the crop price is a market-level price taken as given by individual smallholder households. Private transfers capture changes in resources arriving from outside the couple's own labor, although they may respond to household-specific circumstances and are therefore interpreted more cautiously.

Couple fixed effects absorb permanent household-level differences, including persistent differences in landholdings, occupations, household composition, preferences, and bargaining position. Period fixed effects absorb shocks common to all semi-arid villages in a given month.

Conditional on these fixed effects, identification comes from changes over time in local wage and crop-price conditions and household transfer resources.

The identifying assumption is that, conditional on couple and period fixed effects and the observed controls, village-level disruptions affect couples' labor-sharing arrangements primarily through the local market conditions already measured in the data. For example, weather variation, agricultural conditions, or changes in local labor demand may affect the relative return to women's and men's labor or the value of agricultural production. These channels are captured by the village-level wage and crop-price measures.

The main threat to identification is an unobserved village-by-month shock that affects couples' labor-sharing through channels not captured by the observed wage, price, transfer, and cultivation measures. Such a shock could make nearby couples' outcomes move together for reasons unrelated to peer influence, which the estimator might misread as network dependence. The estimates should therefore be read as conditional on the absence of such confounding shocks. I assess this concern with placebo-network and permutation exercises, which test whether comparable dependence appears when the true within-village network structure is scrambled.

The estimation procedure closely follows De Paula et al. (2025). Before estimation, we residualize the outcome and all covariates with respect to couple fixed effects and month-by-year fixed effects. We then rescale each residualized variable to have unit standard deviation. Let $\dot{y}_i$ denote the resulting demeaned and standardized $\boldsymbol{N\ X\ 1}$ outcome vector, and $\dot{\boldsymbol{X}}_i$ denote the corresponding demeaned and standardized $\boldsymbol{N\,X\,K}$ matrix of covariates, where $\boldsymbol{N}$ is the number of couples and $\boldsymbol{K}$ is the number of covariates. The transformed estimation equation is

$$\dot{y}_i = \rho \sum_{j=i}^{N} w_{ij}\, \dot{y}_j + \beta \dot{x}_i + \gamma \sum_{j=i}^{N} w_{ij}\, \dot{x}_j + \epsilon_i \tag{8}$$

where $\boldsymbol{W}$ is the unknown directed and weighted network, ρ captures endogenous peer effects, β captures the effects of couples' own characteristics, and γ captures contextual effects arising from the characteristics of connected couples. The objective is to estimate the latent network $\boldsymbol{W}$ jointly with the structural parameters (ρ, β, γ).

Stage 1: Network trimming. The procedure first reduces the number of possible links that must be considered. Starting values are set to ($\rho = 0.5$, β from a simple OLS regression, $\gamma = 0$). For each possible directed link between two couples, we evaluate how much the relevant GMM moment conditions change when that link is included. Links whose contribution falls below the trimming threshold (η) are dropped and set to zero. This step eliminates links that appear uninformative at the initial values and leaves a smaller set of candidate network ties for estimation.

Stage 2: Elastic Net estimation. The second stage jointly estimates the candidate network and model parameters using an Elastic Net penalty. The procedure consists of an outer loop over the structural parameters and an inner loop over the network weights. In the outer loop, the optimizer updates the parameter vector (ρ, β, γ) using L-BFGS-B, a limited-memory quasi-Newton algorithm

that permits parameter bounds. Conditional on a candidate parameter vector, the inner loop constructs the matrix.

$$\epsilon_i = \dot{y}_i - \beta\dot{x}_i - \left(\rho \sum_{j=i}^{N} w_{ij}\, \dot{y}_j + \gamma \sum_{j=i}^{N} w_{ij}\, \dot{x}_j\right) \quad (9)$$

$$\dot{Y}_i = \dot{y}_i - \beta\dot{x}_i \quad (10)$$

$$\dot{X}_j = \rho\dot{y}_j + \gamma\, \dot{x}_j \quad (11)$$

$\dot{\boldsymbol{Z}}$ is the set of covariates of all the couples, with dimension $K\,X\,N$.

The inner-loop problem uses the GMM moment condition

$$E(Z\epsilon) = 0 \quad (12)$$

and minimizes the corresponding penalized objective function,

$$\underset{0<w_{ij}<1}{\operatorname{argmin}} ||\dot{\boldsymbol{Z}}(\dot{Y}_i - \sum \dot{X}_j w_{ij})||^2 + \lambda_1 \sum |w_{ij}| + \frac{\lambda_2}{2}\sum (w_{ij})^2 \quad (13)$$

Once estimated, the network weights are row-normalized so that the outgoing weights for each couple sum to one. The resulting normalized network is then substituted into the outer objective function, which evaluates how well the implied network and structural parameters satisfy the GMM conditions. The outer loop continues until convergence, defined by a sufficiently small gradient of the outer objective function. The output of this stage, denoted ***W1***, is an initial regularized estimate of the network. It is subsequently used to construct link-specific penalty weights for the adaptive estimation stage.

Stage 3: **Adaptive Elastic Net estimation**. The third stage repeats the joint estimation procedure using an Adaptive Elastic Net. Rather than applying the L1 penalty to every potential link, the adaptive procedure scales each link's penalty by a weight derived from its estimate in W1, with inverse exponent $\kappa=2.5$. Links estimated to be stronger in the first-stage Elastic Net receive relatively smaller penalties, whereas weak links receive larger penalties. This reduces shrinkage of likely meaningful links while more aggressively removing links with little support in the data. In this stage, the network weights are estimated row by row. For each couple, the vector of outgoing weights is obtained by solving a constrained quadratic program in CVXPY using the CLARABEL solver, subject to $\sum w_{ij} = 1$.

$$\underset{0<w_{ij}<1}{\operatorname{argmin}} ||\dot{Z}(\dot{Y}_i - \dot{X}_j \widetilde{w}_{ij})||^2 + \lambda_1 \sum \sigma|\widetilde{w}_{ij}| + \frac{\lambda_2}{2}\sum (\widetilde{w}_{ij})^2 \quad (14)$$

The resulting network estimate is denoted $\widetilde{W}_2$.

Stage 4 : **Unpenalized GMM estimation**. In the fourth stage, the estimated network is held fixed at $\widetilde{W}_2$, and the structural parameter vector (ρ,β,γ) is re-estimated by GMM without regularization. Removing the network penalty at this stage prevents the regularization bias in the

final structural parameter estimates= of endogenous peer effects, own-covariate effects, and contextual effects.

Stage 5: **Standard errors and tuning.** Finally, we calculate standard errors and select the two penalty parameters (λ_1, λ_2). Standard errors are computed using a rank-one Schur-complement sandwich estimator, which accounts for uncertainty from both network estimation and parameter estimation. The penalty parameters are selected using a Bayesian Information Criterion (BIC). The BIC is defined as the log of the unpenalized Adaptive Elastic Net residual sum of squares plus a complexity penalty that increases with the number of retained network links. We evaluate the criterion over a 20×20 grid, with λ_1 and λ_2 each running from 0.05 to 1.95, to find the best set of hyperparameters.

5. Results

This section presents the empirical estimates. We begin with a baseline two-way fixed-effects specification and show that, after accounting for persistent differences across couples and shocks common to all villages in a given month, the observed economic covariates explain very little of the remaining variation in relative labor sharing. We then turn to the network specification, in which these same covariates become economically and statistically important. Next, we characterize the estimated networks by examining their density across villages, their relationship to village composition, their internal structure, and the determinants of a couple's centrality within them.

Table 3 reports the baseline specification. Each couple's relative production- and domestic-sharing outcomes are regressed on the local economic variables, with couple and month-by-year fixed effects and standard errors clustered at the village level. The estimates use the same balanced panel of 629 couples used throughout the remainder of the paper.

For the production-sharing outcome (column 2), the only coefficient statistically significant at conventional levels is the IHS-transformed measure of private transfers (−0.0102, $p < 0.05$). The female-to-male wage ratio (0.0347), government welfare transfers (−0.0022), crop price (−0.0119), and cultivation indicator (0.1303) are statistically indistinguishable from zero. For the domestic-sharing outcome (column 1), none of the covariates is statistically significant at conventional levels. .

Figures 2 and 3 from the previous section show that the residual variation remaining after double demeaning is still correlated across couples within villages. In other words, after accounting for persistent couple-level differences and shocks common to all villages in a given month, the unexplained within-couple variation exhibits structured dependence across couples. This motivates the network specification.

Table 4 reports estimates from the network specification for the two outcomes of interest. I discuss domestic sharing first, followed by production sharing. For each outcome, I consider in turn the own-covariate coefficients, the endogenous peer-effects parameter, and the contextual

effects associated with the observed characteristics of couples to whom each couple is connected in the estimated network.

[Insert Table 4]

5.1 Domestic labor-sharing norms

A higher domestic-sharing ratio corresponds to a larger relative share of domestic work performed by the husband. The own-covariate coefficient on the female-to-male wage ratio is positive and statistically significant ($\beta = 0.158$, $p < 0.01$). Conditional on the estimated network structure and other covariates, a higher relative wage for the wife is associated with a shift in domestic work toward the husband. This pattern is consistent with a reallocation of household labor as the wife's relative market opportunity improves.

Government welfare transfers have a small positive own-covariate coefficient ($\beta = 0.019$, $p < 0.01$), while private transfers have a small negative coefficient ($\beta = -0.012$, $p < 0.01$). Higher welfare transfers are therefore associated with a modest increase in the husband's relative domestic-work share, while higher private transfers are associated with a modest shift in domestic work toward the wife. Crop price is negative and statistically significant ($\beta = -0.043$, $p < 0.01$), indicating that higher crop prices are associated with a shift in domestic work away from the husband. The recently harvested crop indicator is positive and statistically significant ($\beta = 0.262$, $p < 0.05$), indicating that domestic work shifts toward husbands in couple-months associated with a recently harvested crop.

The estimated endogenous peer-effects parameter is positive and precisely estimated ($\rho = 0.582$, $p < 0.01$). This indicates substantial dependence between a couple's relative domestic-work allocation and the relative domestic-work allocations of couples to whom it is connected in the estimated network. In particular, husbands tend to perform relatively more domestic work when connected couples exhibit the same pattern, conditional on own and contextual covariates.

The contextual coefficient on the female-to-male wage ratio is negative and opposite in sign to the own-covariate coefficient ($\gamma = -0.198$, $p < 0.01$). Thus, while a higher relative wage within a focal couple is associated with a shift in domestic work toward the husband, a higher relative wage among connected couples is associated with a shift away from the husband in the focal couple. Contextual welfare and private-transfer coefficients also reverse sign relative to the corresponding own-covariate coefficients: connected couples' welfare is negative ($\gamma = -0.039$, $p < 0.01$), whereas connected couples' private transfers are positive ($\gamma = 0.028$, $p < 0.01$). Both estimates are precisely estimated.

The contextual coefficient on the recently harvested crop indicator is positive and statistically significant ($\gamma = 0.654$, $p < 0.01$), reinforcing the positive association between the focal couple's own harvested-crop status and the husband's relative domestic-work contribution. By contrast, the contextual crop-price coefficient is small and statistically indistinguishable from zero ($\gamma = 0.005$). The opposite signs on the own and contextual wage-ratio coefficients may be consistent with

competition for labor in a shared local market, but the present specification cannot distinguish that explanation from other mechanisms.

5.2 Production labor-sharing norms

. A higher production-sharing ratio corresponds to a larger relative share of production work performed by the wife. The own-covariate coefficient on the female-to-male wage ratio is negative and statistically significant ($\beta = -0.098$, $p < 0.05$). A higher wage for the wife relative to the husband is therefore associated with a shift in relative production work away from the wife and toward the husband, consistent with an income effect.

Both measures of non-labor income are positively associated with the wife's relative production burden. Government welfare transfers have a positive own-covariate coefficient ($\beta = 0.046$, $p < 0.01$), as do private transfers ($\beta = 0.042$, $p < 0.01$). Higher crop prices are associated with a shift in production work away from the wife ($\beta = -0.075$, $p < 0.01$). By contrast, the recently harvested crop indicator has a large positive coefficient ($\beta = 0.553$, $p < 0.01$), indicating that the wife's relative production burden is substantially higher in couple-months associated with a recently harvested crop.

The endogenous peer-effects parameter is again positive and precisely estimated ($\rho = 0.540$, $p < 0.01$). Although it is somewhat smaller than the corresponding domestic-sharing estimate, it still indicates substantial dependence between a couple's relative production allocation and the production allocations of couples to whom it is connected in the estimated network. As in the domestic-sharing equation, the contextual female-to-male wage ratio has the opposite sign from its own-covariate counterpart ($\gamma = 0.404$, $p < 0.01$). A higher relative wage within the focal couple is associated with a lower relative production burden for the wife, whereas a higher relative wage among connected couples is associated with a higher relative production burden for the focal wife. The contextual coefficients on welfare ($\gamma = -0.110$, $p < 0.01$), private transfers ($\gamma = -0.088$, $p < 0.01$), and crop price ($\gamma = -0.121$, $p < 0.01$) are also opposite in sign to their corresponding own-covariate coefficients. The contextual cultivation coefficient is large, positive, and precisely estimated ($\gamma = 1.515$, $p < 0.01$).

The reversal between own and contextual wage-ratio coefficients may be consistent with competition for labor in a common village labor market. However, the present specification does not separately identify this explanation from other channels through which the economic circumstances of connected couples affect the focal couple's labor allocation.

A policy or economic change may affect only some couples directly, but its consequences can propagate through the estimated network. When directly affected couples change their labor-sharing arrangements, connected couples may respond, generating further responses among their own connections.

The spatial estimates are largely robust in sign and significance to how the outcome is built and how the model is estimated. The main specification uses an inverse-hyperbolic-sine of spousal labor; as a robustness check, I re-estimate on the reference spouse's labor share, a bounded outcome, by Poisson pseudo-maximum-likelihood (PPML), using the estimated **W** matrix. Across

both specifications, the peer parameter ρ stays significant, and the neighbor (contextual) terms keep their signs and significance. Magnitudes are not comparable across the two, since PPML uses a different representation of the outcome, but the pattern of results is stable. A separate placebo check strengthens the argument that the peer effect comes from the recovered network itself and not merely from couples being linked within a village: when the tie structure of W is scrambled while its row sums and weights are preserved, ρ collapses, and the true value lies beyond every scrambled draw. Full estimates and both checks are in Appendix C.

5.3 Exploring network structure

Table 5 reports the density of each estimated network by village. Densities vary considerably across communities. Production-norm network density ranges from 0.015 in Shirapur to 0.079 in Kapanimbargi; domestic-norm network density ranges from 0.018 in Markabbinahalli to 0.077 in Tharati, averaging 0.043 and 0.046, respectively, across the sixteen villages. Caste fractionalization ranges from 0.111 in near-homogeneous Karamdi Chingariya to 0.595 in Kalman. The estimated social structures associated with productive and domestic norms appear to be distinct, even within the same village. Details on the construction of entropy and caste fractionalization are given in Appendix A..

[Insert Table 5]

Table 6 regresses network density on caste diversity and village size. Neither entropy nor fractionalization predicts network density at the village level. Village size is the only strong predictor of density: log(N) is statistically significant in both specifications, with a consistently negative coefficient, ranging from −0.038 to −0.043. Density therefore declines as villages grow, consistent with couples maintaining a roughly constant number of ties rather than forming ties in proportion to the expanding pool of potential connections. Details are given in Appendix A.

[Insert Table 6]

Table 7 asks whether couples take cues on labor-sharing norms disproportionately from couples of their own caste, religion, or landholding class, beyond what the composition of their village would predict on its own. I measure this using graph assortativity (Newman 2003), which ranges from −1 to 1. A value of zero indicates mixing independent of the attribute, while larger positive values indicate greater same-attribute sorting. Because a village's caste, religion, or landholding composition mechanically creates some same-attribute ties, I benchmark each observed assortativity coefficient against a null distribution generated by shuffling attribute labels within village. The difference between the observed coefficient and this benchmark captures sorting not explained by village composition alone. Appendix B details the construction. Caste and landholding are the only attributes that exceed their null benchmarks, and only in the production network; religion does not exhibit excess sorting in either network. Thus, the production network

shows excess same-caste and same-landholding connections, while the domestic network does not show excess sorting on caste, religion, or landholding.

[Insert Table 7]

Table 8 reports correlates of a couple's influence in each network. The outcome is the total weight that other couples place on a focal couple(the column sum of W)standardized within village. The model is estimated by OLS with village fixed effects and standard errors clustered at the village level. Because there are only sixteen village clusters, marginal statistical significance should be interpreted cautiously. Non-Hindu couples are significantly less central in the production network, by 0.48 standard deviations ($p < 0.01$). This result is notable given the absence of excess religious assortativity in tie formation in Table 7: religion does not predict excess same-religion connections, but it does predict how much influence a couple accumulates once connected. Forward-caste couples have somewhat higher domestic centrality, by 0.23 standard deviations ($p < 0.10$), a marginal result with no equivalent in the production network. Women's SHG participation and landholding, including landlessness, do not predict influence in either network at conventional significance levels.

[Insert Table 8]

6. Conclusions

The estimated network carries implications that go beyond documenting dependence in labor-sharing outcomes. Because the model recovers the structure of the network itself, it speaks to how interventions may be designed, how their effects may propagate, and how we should think about the household as the unit of decision. A number of implications follow.

First, the own-covariate and contextual channels of a policy lever can agree or oppose, and this distinction matters for deployment. Each observed characteristic enters a couple's outcome twice: through the couple's own value and through the network-weighted values of couples to whom it is connected. When these channels have the same sign, a change affecting both the focal couple and its connected couples reinforces the initial effect. When they have opposite signs, as they do for the wage ratio and some transfer measures in the estimates of this paper, broad changes may produce own and contextual effects that offset one another. For example, a village-wide policy that raises women's wages relative to men's changes both a focal couple's relative wage and the relative wages of its connected couples. In the domestic-sharing equation, the own wage-ratio coefficient is positive while the contextual coefficient is negative; in the production-sharing equation, the signs reverse. In both cases the two channels offset one another, potentially through a competition channel. A lever with reinforcing channels may therefore suit broad rollout, whereas a lever with offsetting channels may generate larger effects when targeted to particular couples or parts of the network.

Second, endogenous network feedback is a separate channel from own- and contextual-covariate effects. Because ρ is positive and precisely estimated in both domains, a change in one

couple's outcome propagates to connected couples and sets off further responses through the network. Because ties are directed and unevenly weighted, a shock that starts at a well-connected couple travels further than the same shock at the periphery, so the magnitude of the total effect depends on which couples are hit first and where they sit. This feedback multiplier is not the same as the total effect of a broad wage or resource policy, since such policies also act directly through the own- and contextual-covariate coefficients. The two channels should be kept distinct.

Third, the results bear on how intra-household bargaining is modeled. Bargaining is often treated as resolved between two spouses, conditional on their preferences, resources, and outside options. The estimates suggest the division of labor is not determined within the household alone: a couple's labor-sharing outcome is associated with the outcomes of couples to whom it is connected, and a couple's network position predicts the influence it receives and exerts. A model that treats couples' preferences and labor-allocation choices as entirely internal therefore omits a social channel. The peer environment enters the decision problem alongside spouses' relative resources and bargaining positions. This matters for interpretation, since an observed change in household labor sharing may reflect a shift in the surrounding social environment rather than only a change in bargaining power within the couple. It also matters for policy, since an intervention directed at one couple may alter the reference points facing connected couples..

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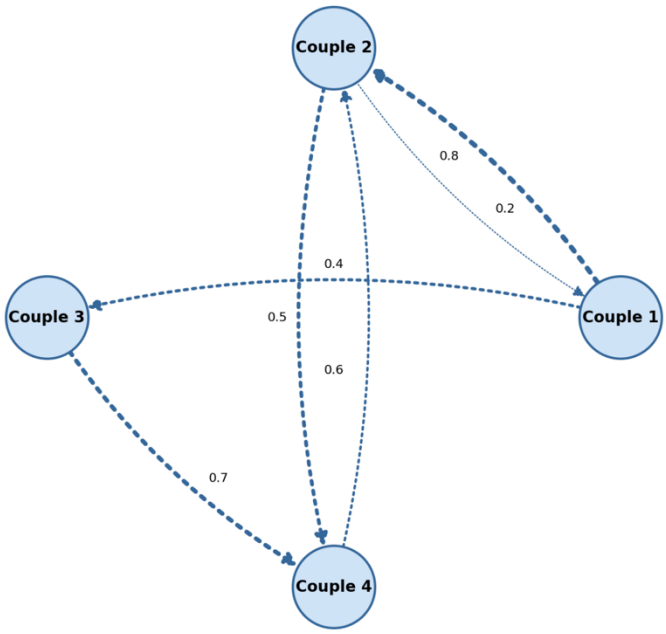
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Figures and Tables

Figure 1: llustration of a directed, weighted couple network



Notes: *Each node represents a couple. A directed edge from couple i to couple j indicates that couple ii influences couple j. Arrow direction therefore identifies the direction of influence. Edge labels denote the weight of the influence tie, with larger values indicating stronger influence. The figure is illustrative and does not depict an observed village network.*

Table 1: Definitions and construction of couple-month outcomes and regressors

VARIABLE	LABEL	UNITS	CONSTRUCTION
Outcomes			
ihs_prod_ratio	Relative production burden	Difference in IHS-transformed days	Productive days are the sum of market wage, own-farm, and livestock work days for each spouse. The outcome is arcsinh(f_prod) − arcsinh(m_prod).
ihs_dome_ratio	Relative domestic burden	Difference in IHS-transformed days	Domestic days are each spouse's own household work days. The outcome is arcsinh(m_dome) − arcsinh(f_dome), with the difference reversed so that a positive value indicates a greater share of domestic work undertaken by the male spouse.
Regresors			
ln_wage_ratio	Log female-to-male opportunity wage ratio	Log Rs/day	ln(female_opp_wage) − ln(male_opp_wage). Each spouse's opportunity wage is assigned by main occupation: farm workers receive the village-level gender-specific daily farm wage; non-farm workers receive the non-farm wage. Remaining gaps are filled with the village average of farm

			and non-farm wages for that gender and month. State × month medians serve as a further fallback.
ihs_welfare_hh	IHS government welfare, couple	IHS Rs/month	Couple-level welfare transfers, winsorised at the 99th percentile before arcsinh transformation. Zero where no transfer was received in that month.
ihs_transfers_hh	IHS private transfers received, couple	IHS Rs/month	Couple-level gifts and remittances received, winsorised at the 99th percentile before arcsinh transformation. Zero where no transfer was received in that month.
has_crop_price	'Recently harvested' crop indicator.	Binary	Equal to one if recent_main_crop is non-missing for that couple-month, and zero otherwise.
ihs_crop_price	IHS recent crop price	IHS Rs per quintal	Village-level price of the most recently harvested crop matched to recent_main_crop and recent_harvest_season. Zero-filled for non-cultivating couple-months before arcsinh transformation.

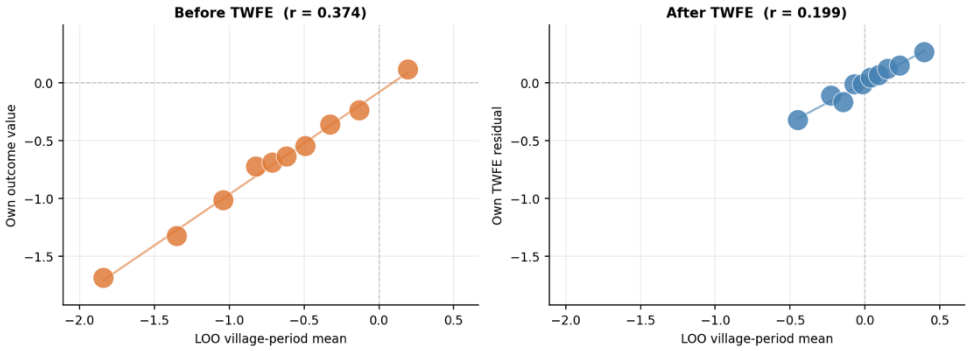
Notes: *This table defines the couple-month outcomes and regressors used in the analysis. IHS denotes the inverse hyperbolic sine transformation. Monetary variables are measured in nominal Indian rupees. Female and male subscripts denote the wife and husband, respectively. Variables labelled "couple" are constructed by aggregating spouses' reports within a couple-month. Crop-price measures are assigned at the village level using the household's most recently harvested main crop and harvest season. Opportunity wages are village-level, gender-specific daily wages assigned according to each spouse's main occupation and imputed as described in the Construction column.*

Table 2: Data descriptives

Variable	Unit	N	Mean	SD
Outcomes				
IHS relative production burden (F–M)	IHS	37,740	−0.7125	1.3421
IHS relative domestic burden (M–F)	IHS	37,740	−1.6594	1.1396
Regressors				
Log female-to-male opportunity-wage ratio	log Rs/day	37,740	−0.5131	0.3931
IHS welfare transfer (couple)	IHS Rs	37,740	5.5597	2.1166
IHS private transfers (couple)	IHS Rs	37,740	1.8199	2.9608
IHS crop price (0-fill)	IHS Rs	37,740	4.9056	4.1287
Recently harvested crop indicator	0/1	37,740	0.5900	0.4918

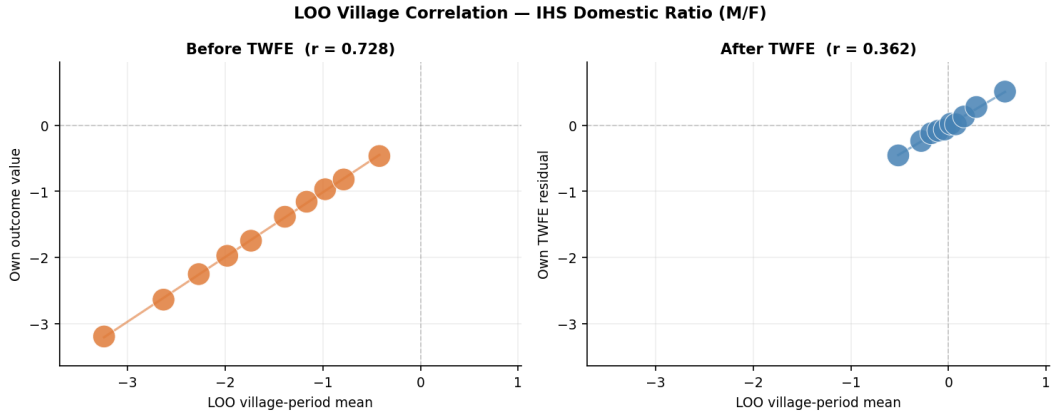
Notes: *The unit of observation is a couple-month. N reports the number of couple-month observations and is identical across variables because the estimation sample is balanced after construction and imputation of the regressors. IHS denotes the inverse hyperbolic sine transformation. In the production-burden outcome, positive values indicate relatively more production work by the wife; in the domestic-burden outcome, positive values indicate relatively more domestic work by the husband. Monetary values are measured in nominal Indian rupees. Welfare and private transfers are winsorized at the 99th percentile before IHS transformation. The crop-price variable is set to zero for couple-months without a recently harvested main crop.*

Figure 2: Leave-one-out binscatter plots of relative production burden



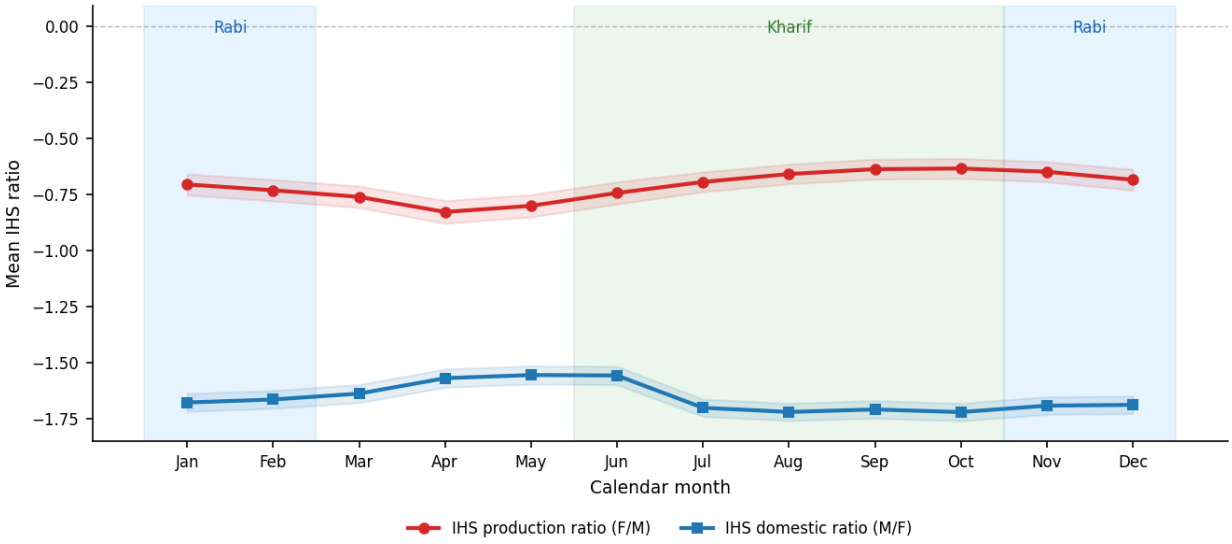
Notes: *The figure plots the relationship between a couple's leave-one-out (LOO) network exposure and its relative production burden. For each focal couple, LOO exposure is calculated using the relevant outcome measure among connected couples, excluding the focal couple's own outcome from the calculation. Each point represents the mean outcome and mean LOO exposure within a bin of the LOO exposure distribution. The solid line shows the fitted linear relationship. The unit of observation is a couple-month. The production-burden outcome is* $arcsinh(fprod) - arcsinh(mprod)$; *positive values indicate relatively more production work by the wife.*

Figure 3: Leave-one-out binscatter plots of network exposure and relative domestic burden



Notes: *The figure plots the relationship between a couple's leave-one-out (LOO) network exposure and its relative domestic burden. For each focal couple, LOO exposure is calculated using the relevant outcome measure among connected couples, excluding the focal couple's own outcome from the calculation. Each point represents the mean outcome and mean LOO exposure within a bin of the LOO exposure distribution. The solid line shows the fitted linear relationship. The unit of observation is a couple-month. The production-burden outcome is* $arcsinh(fprod) - arcsinh(mprod)$; *positive values indicate relatively more production work by the wife.*

Figure 4: Monthly mean relative production and domestic burdens across the agricultural year



Notes: *The figure plots mean couple-month relative production and domestic burdens by calendar month. Relative production burden is measured as* $\text{arcsinh}(fprod) - \text{arcsinh}(mprod)$ *such that positive values indicate relatively more production work by the wife. Relative domestic burden is measured as* $\text{arcsinh}(mdome) - \text{arcsinh}(fdome)$*, such that positive values indicate relatively more domestic work by the husband. The unit of observation is a couple-month. IHS denotes the inverse hyperbolic sine transformation.*

Table 3: Results for baseline TWFE specification (without network structure)

	Domestic Sharing (ihs_dome_ratio)	**Production Sharing (ihs_prod_ratio)**
ln(F/M wage ratio)	−0.0087	0.0347
	(0.0831)	(0.0464)
IHS(Government welfare)	−0.0022	−0.0022
	(0.0110)	(0.0067)
IHS private transfers (w., couple)	0.0024	−0.0102**
	(0.0046)	(0.0046)
IHS(Crop price)	0.0051	−0.0119
	(0.0178)	(0.0255)
Has crop price	0.0006	0.1303
	(0.1436)	(0.2183)
N (obs)	37,740	37,740
N (couples)	629	629
R² within	0.0013	0.0012
Couple FE	Yes	Yes
Year × Month FE	Yes (60)	Yes (60)
SE cluster	Village	Village

Notes *The dependent variables are relative domestic burden and relative production burden. Relative domestic burden is defined as the inverse hyperbolic sine of the husband's household-work days minus the inverse hyperbolic sine of the wife's household-work days. Relative production burden is defined as the inverse hyperbolic sine of the wife's production-work days minus the inverse hyperbolic sine of the husband's production-work days, where production work includes market wage work, own-farm work, and livestock work. All specifications include couple fixed effects and month-by-year fixed effects. Standard errors, reported in parentheses, are clustered at*

*the village level. The estimation sample is a balanced panel of 629 couples observed in each of 60 monthly periods from 2010 to 2014, yielding 37,740 couple-month observations. ** $p < 0.05$.*

Table 4: Results for SAR specification

Parameter	Domestic Sharing (ihs_dome_ratio)	Production Sharing (ihs_prod_ratio)
Spatial term		
ρ	0.5816***	0.5396***
	(0.0154)	(0.0180)
β (own-outcome equation)		
ln(wage ratio)	0.1581***	-0.0980**
	(0.0257)	(0.0388)
IHS welfare transfers (hh)	0.0190***	0.0459***
	(0.0063)	(0.0063)
IHS private transfers (hh)	-0.0118***	0.0420***
	(0.0036)	(0.0037)
IHS crop price	-0.0430***	-0.0752***
	(0.0159)	(0.0153)
Has crop price (indicator)	0.2624**	0.5525***
	(0.1318)	(0.1283)
γ (cross-outcome equation)		
ln(wage ratio)	-0.1978***	0.4040***
	(0.0319)	(0.0368)
IHS welfare transfers (hh)	-0.0389***	-0.1102***
	(0.0072)	(0.0059)
IHS private transfers (hh)	0.0281***	-0.0880***
	(0.0049)	(0.0054)
IHS crop price	0.0047	-0.1209***
	(0.0204)	(0.0200)
Has crop price (indicator)	0.6536***	1.5151***
	(0.1621)	(0.1709)
N (couples)	629	629
Couple FE	Yes	Yes
Year × Month FE	Yes (60)	Yes (60)
SE cluster	Village	Village

Notes: *The dependent variables are relative domestic burden and relative production burden. Relative domestic burden is defined as the inverse hyperbolic sine of the husband's household-work days minus the inverse hyperbolic sine of the wife's household-work days. Relative production burden is defined as the inverse hyperbolic sine of the wife's production-work days minus the inverse hyperbolic sine of the husband's production-work days, where production work includes market wage work, own-farm work, and livestock work. The reported coefficients are structural parameters from the SAR specification. All specifications include couple fixed effects and month-by-year fixed effects. Standard errors, reported in parentheses, are clustered at the village level. The estimation sample is a balanced panel of 629 couples observed in each of 60 monthly periods from 2010 to 2014, yielding 37,740 couple-month observations. ** $p < 0.05$, *** $p < 0.01$.*

Table 5. Village-level network density and caste composition.

Village	N	Fractionalization	Entropy	Density (Prod.)	Density (Dom.)
Karamdi Chingariya	51	0.111	0.323	0.032	0.029

Babrol	34	0.161	0.431	0.032	0.042
Tharati	34	0.208	0.523	0.043	0.077
Kapanimbargi	23	0.227	0.559	0.079	0.075
Markabbinahalli	29	0.238	0.579	0.078	0.018
Makhiyala	32	0.305	0.696	0.045	0.064
Belladamadugu	31	0.437	0.907	0.040	0.048
JC Agraharam	32	0.443	0.717	0.055	0.071
Dokur	35	0.451	0.928	0.050	0.046
Chatha	36	0.475	0.964	0.040	0.021
Aurepalle	42	0.490	0.761	0.036	0.041
Shirapur	83	0.499	0.732	0.015	0.019
Kinkhed	26	0.536	0.820	0.040	0.063
Kanzara	56	0.554	0.856	0.028	0.026
Pamidipadu	30	0.584	0.863	0.048	0.064
Kalman	55	0.595	0.906	0.028	0.025

Notes: *N is the number of couples in the balanced estimation sample in each village. Fractionalization and entropy summarize the village-level distribution of caste categories. Density is the share of all possible directed within-village ties assigned a nonzero weight in the estimated network. Production and domestic densities are calculated separately from the corresponding estimated networks. Details on the construction of caste fractionalization and entropy are provided in Appendix A.*

Table 6. Association between village network density, caste diversity, and village size

Panel A. Production network

	Entropy	**Fractionalization**
Diversity	−0.011	−0.015
	(0.485)	(0.428)
log(N)	−0.040***	−0.038***
	(0.001)	(0.001)
R^2	0.627	0.631

Panel B. Domestic network

	Entropy	**Fractionalization**
Diversity	−0.010	+0.004
	(0.671)	(0.903)
log(N)	−0.042***	−0.043***
	(0.007)	(0.008)
R^2	0.452	0.445

Notes: *OLS coefficients with p-values in parentheses below. Each column reports a separate regression using the indicated caste-diversity measure. The dependent variable is the density of the estimated village network. N = 16 villages. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.*

Table 7. Attribute assortativity against a within-village permutation null

Network	**Attribute**	**r (assortativity)**	**Null mean**	**Null SD**	**Excess**	**p**
Production	Caste (FC/OBC/SC-ST)	0.409	0.319	0.031	+0.091	0.005***
	Religion	0.018	0.075	0.068	−0.056	0.417
	Land quartile	0.085	−0.010	0.040	+0.095	0.013**
Domestic	Caste (FC/OBC/SC-ST)	0.323	0.330	0.031	−0.007	0.826
	Religion	−0.015	0.069	0.066	−0.084	0.233
	Land quartile	−0.008	−0.026	0.043	+0.018	0.932

Notes: *Assortativity is calculated separately for the estimated production and domestic networks. For each attribute, the observed assortativity coefficient is compared with a within-village permutation distribution obtained by randomly shuffling attribute labels within village while holding the estimated network fixed. Excess assortativity equals observed assortativity minus the mean of the permutation distribution. Reported p-values are based on 200 draws. Positive excess values indicate more same-attribute sorting than implied by village composition alone.*

Table 8. Associations with network influence: OLS with Village-Clustered SE

Predictor	Production	Domestic
Age gap (M−F yrs)	−0.015 (0.011)	+0.003 (0.018)
Woman edu >8 yrs	+0.055 (0.117)	+0.026 (0.136)
Man edu >8 yrs	−0.032 (0.120)	+0.033 (0.105)
Non-Hindu	−0.476 (0.152)***	−0.080 (0.197)
Caste FC (vs SC/ST)	+0.104 (0.128)	+0.228 (0.126)*
Caste OBC (vs SC/ST)	+0.155 (0.102)	−0.029 (0.145)
Woman in SHG (ever)	+0.003 (0.088)	+0.090 (0.081)
No Land (vs Q4)	−0.199 (0.195)	+0.306 (0.216)
Land Q1 (vs Q4)	−0.139 (0.136)	+0.178 (0.146)
Land Q2 (vs Q4)	−0.139 (0.144)	+0.079 (0.131)
Land Q3 (vs Q4)	+0.064 (0.127)	+0.202 (0.123)
N	629	629

Notes*: The dependent variable is a couple's network influence, measured as the column sum of the estimated directed weight matrix W, that is, the total weight other couples place on the focal couple, and standardized within village. Regressions include village fixed effects. Standard errors are clustered by village and reported in parentheses. Omitted categories are Hindu, SC/ST, and land quartile 4, respectively, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$*

Appendix A – Estimated network structures

Figure A1 – Estimated structure for production-labor sharing influence network

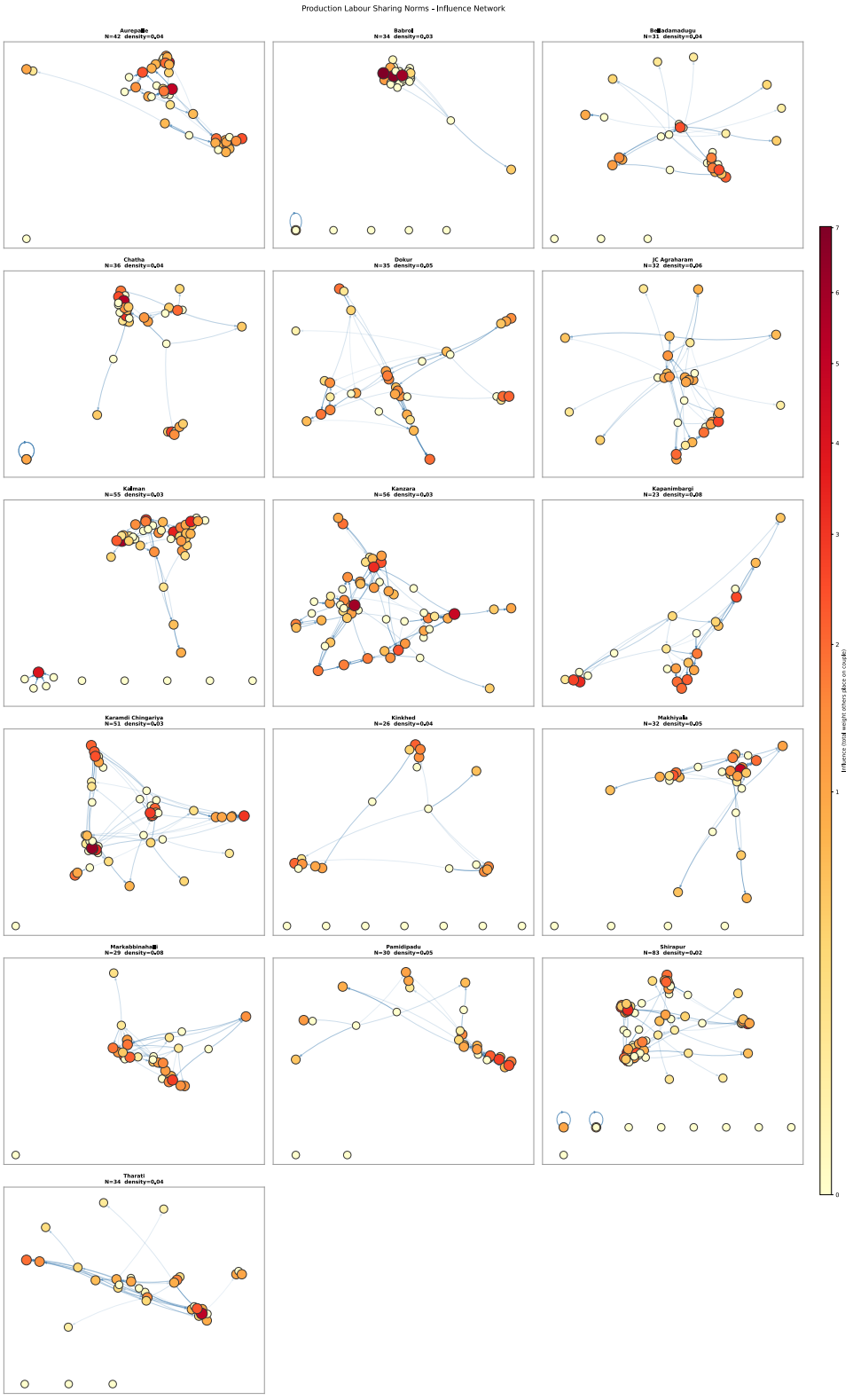
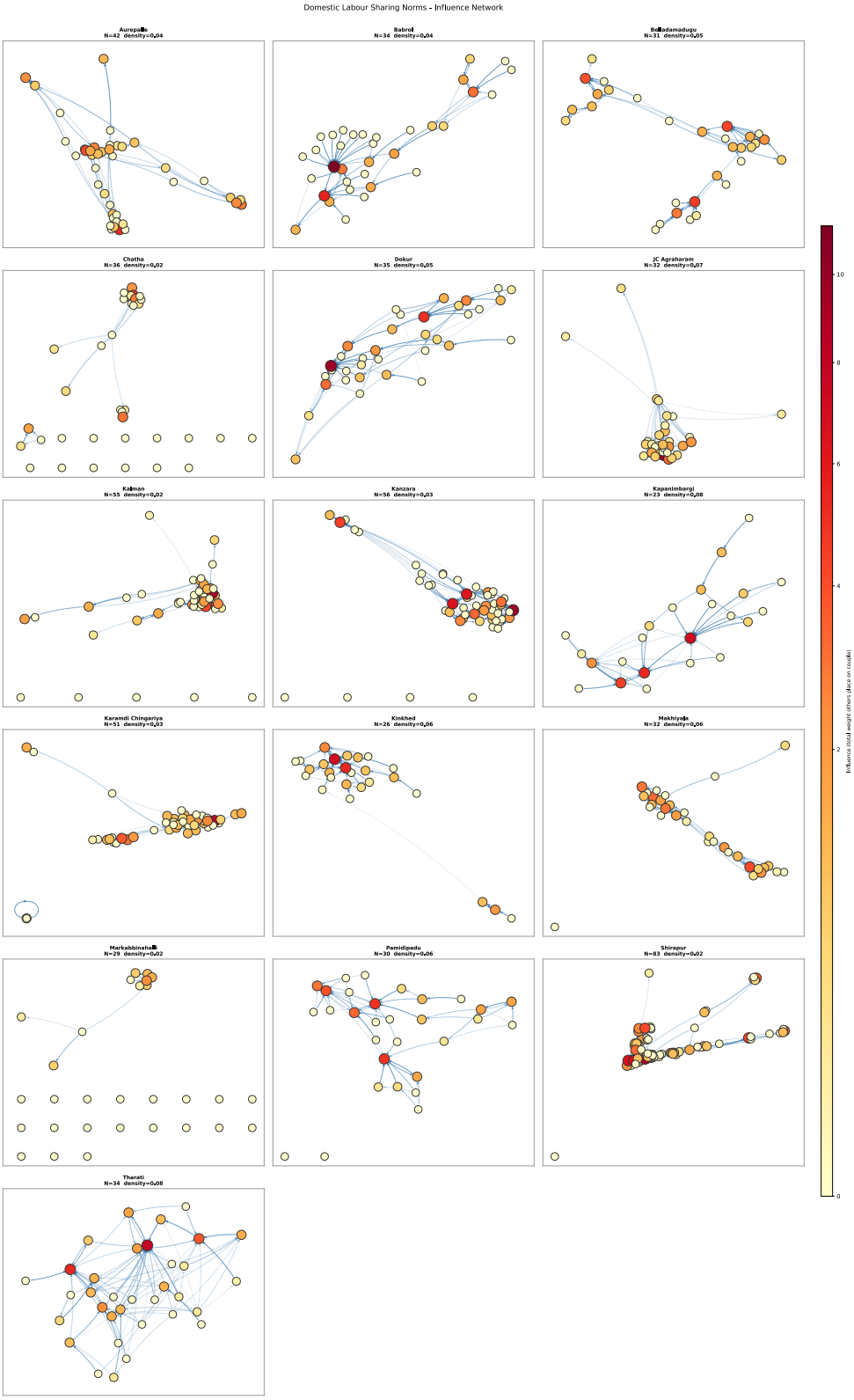


Figure A2 – Estimated structure for domestic-labor sharing influence network



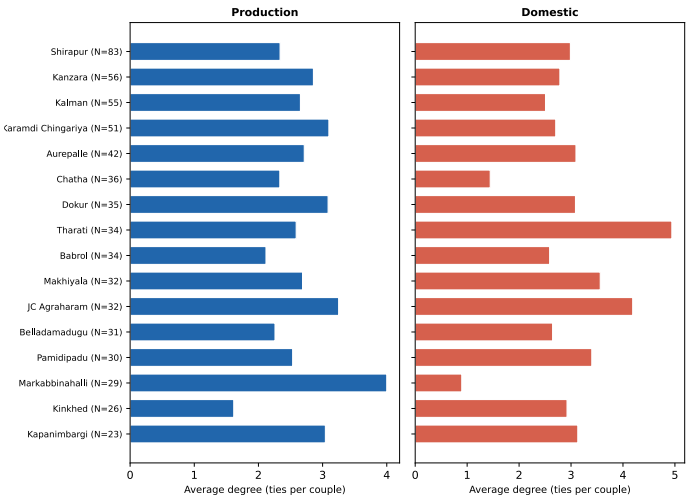
Prior to the elastic-net and adaptive elastic-net fit, a preliminary filter evaluates the full N×(N−1) universe of directed ties starting from the empty network, with no ties assumed. For each potential tie *ij*, it computes the derivative of the GMM moment condition with respect to that single weight. It checks the marginal improvement in fit for couple i from admitting an infinitesimal amount of j's influence into i's equation. Ties whose derivative falls below a small threshold (0.01) are judged to contribute essentially nothing and are fixed to zero, dropping out of consideration. It prunes the N×(N−1) universe down to the reduced candidate set the penalized model searches over. In **Figure A1** and **A2** above, a node floats when every one of its potential peers fails this derivative test, leaving an empty row with no admissible incoming edge.

The average number of undirected ties per couple (i.e. a tie in either direction, whether the couple influences or is influenced by a peer couple), is the couple's degree. Mean degree is shown in **Table A1**, and its distribution across villages in Figure A3.

Table A1 – Features of ties across both types of networks

Feature of ties	Production-labor norm network	Domestic-labor norm network
Undirected degree (a tie going in either direction – either influencing or being influenced by), mean	2.68	2.91
Undirected degree, median	2	2
Couples with zero ties	6.0%	7.2%

Figure A3 – Distribution of average ties across villages



This is consistent with couples maintaining ties with a small number of others (roughly two to three) rather than forming ties in proportion to the number of potential peers in the village. If average undirected degree, d, remains approximately constant as village size increases, the number of realized ties grows approximately linearly in *N,* whereas the number of possible directed ties grows as *N(N−1).* Network density is then approximately proportional to d/(N−1) and declines with village.

I examine additional village-level factors that might account for variation in network density: two measures of caste heterogeneity, fractionalization and entropy. Each specification regresses density on one heterogeneity measure and log village size, so the reported coefficients are partial associations.

Fractionalization F measures the probability that two couples drawn at random from the village belong to different castes. Let the percentage of a caste be p_c . Then F is given by:

$$F = 1 - \sum p_c^2$$

The summation term is the Herfindahl–Hirschman index (HHI), a standard measure of concentration, and fractionalization is its complement. The measure is driven mainly by the size of the largest castes: a caste holding 60% of couples contributes 0.36 to the HHI, while one holding 5% contributes 0.0025. Fractionalization equals 0 when a single caste is present. Its maximum is 1 − 1/K, attained when all K castes are equally represented , so villages with more castes can reach higher values.

Normalized entropy measures how evenly couples are distributed across the castes present, relative to the most even split that village could achieve. Given K castes in a village, and percentage of caste c p_c

$$Entropy = {-\sum p_c \log p_c}\Big/{\log K}$$

Relative to fractionalization, the logarithm in the entropy measure gives more weight to small categories, so the presence of minor castes registers more strongly here. Castes with zero share are dropped before computing K; villages with K = 1 are assigned 0 directly, since $\log_2(1) = 0$ would otherwise make the denominator zero. Dividing by $\log_2 K$ places the measure on [0, 1]: 0 indicates a single caste, 1 indicates a perfectly even split given however many castes are present. A village split 50/50 between two castes and one split 33/33/33 across three both score 1.0 on entropy, since each is perfectly even relative to its own maximum. On fractionalization they score 0.50 and 0.6

Appendix B - Constructing the assortativity coefficient

The weighted assortativity coefficient, following Newman (2003), measures the extent to which directed influence ties connect couples from the same caste more frequently than expected under random mixing. Let $wij \geq 0$ denote the weight of the directed influence tie from couple *i* to couple *j*, where $i \rightarrow j$ indicates that couple i influences couple j. Let c_i denote the caste of couple *i.*

$$e_{gh} = \frac{\sum\sum w_{ij}.\ 1[c_i = g, c_{j=h}]}{\sum\sum w_{ij}}$$

where e_{gh} is the share of total influence-tie weight directed from couples in caste g to couples in caste h. By construction, $\sum\sum e_{gh} = 1$. The observed weighted share of same-caste influence ties is therefore $\sum e_{gg}$.

Let.

$$a_g = \sum e_{gh} \text{ and}$$

$$b_g = \sum e_{hg}$$

Under independent mixing of source and target caste, the expected weighted share of same-caste ties is.

$$\sum a_g . b_g$$

where a_g is caste g's share of total outgoing influence-tie weight and b_g is caste g's share of total incoming influence-tie weight.

Weighted caste assortativity is then defined as

$$\frac{\sum e_{gg}. - \sum a_g . b_g}{1 - \sum a_g . b_g}$$

A value of $r = 1$ indicates perfect same-caste assortative mixing: all influence-tie weight lies on within-caste ties. A value of $r = 0$ indicates that the observed weighted mixing pattern is consistent with independent source and target caste assignment, conditional on caste-specific incoming and outgoing influence-weight shares. Negative values indicate that same-caste influence ties are under-represented relative to this benchmark.

To assess whether observed caste assortativity exceeds that generated mechanically by village caste composition, I randomly permute caste labels among couples within each village 2,000 times, holding the directed weighted network fixed. The statistic of interest therefore measures excess within-village caste assortativity beyond that implied by the observed network structure, edge weights, and village-level caste composition.

Appendix C – Robustness and placebo checks

Table C1 checks whether the spatial results depend on how the outcome is measured or how the model is fit. The main analysis uses an inverse-hyperbolic-sine form of the labor each spouse performs, estimated by OLS. Here I instead use the share of labor done by the reference spouse (the female share in production, the male share in domestic labor, matching the orientation of the main outcome). This is bounded between 0 and 1 and estimated by PPML. PPML accommodates nonnegative outcomes, including zeros, and avoids log-transforming the outcome(Santos Silva and Tenreyro 2006). This specification instruments the endogenous peer term with W^2X. The two columns are not meant to match in size. What should carry over is the pattern of signs and significance, and it does: ρ is positive and significant in every column, and the neighbor (γ) terms are especially stable, keeping their sign and significance throughout. The direct (β) terms are less stable: a few shrink in significance under PPML, but these are cases where the PPML estimate is close to zero, so they reflect weaker confirmation of those specific channels rather than a conflict with the OLS results.

Table C1. - Robustness of the spatial model to outcome construction and estimator

Panel A. Production norm network

Parameter	OLS	PPML
ρ (peer_y)	+0.5396(0.0180)***	+1.3121(0.1242)***
β ln(wage ratio)	-0.0980(0.0388)*	-0.0306(0.0162)†
β IHS welfare (hh)	+0.0459(0.0063)***	+0.0071(0.0031)*
β IHS transfers (hh)	+0.0420(0.0037)***	-0.0005(0.0012)
β IHS crop price	-0.0752(0.0153)***	-0.0094(0.0045)*
β has crop price (ind.)	+0.5525(0.1283)***	+0.0486(0.0379)
γ ln(wage ratio)	+0.4040(0.0368)***	+0.1150(0.0208)***
γ IHS welfare (hh)	-0.1102(0.0059)***	-0.0326(0.0035)***
γ IHS transfers (hh)	-0.0880(0.0054)***	-0.0151(0.0016)***
γ IHS crop price	-0.1209(0.0200)***	-0.0084(0.0065)
γ has crop price (ind.)	+1.5151(0.1709)***	+0.2499(0.0539)***

Panel B. Domestic norm network

Parameter	OLS	PPML
ρ (peer_y)	+0.5816(0.0154)***	+2.0865(0.2114)***
β ln(wage ratio)	+0.1581(0.0257)***	+0.0717(0.0246)**
β IHS welfare (hh)	+0.0190(0.0063)**	-0.0006(0.0045)
β IHS transfers (hh)	-0.0118(0.0036)***	+0.0033(0.0016)*
β IHS crop price	-0.0430(0.0159)**	-0.0046(0.0099)
β has crop price (ind.)	+0.2624(0.1318)*	-0.0221(0.0831)
γ ln(wage ratio)	-0.1978(0.0319)***	-0.2034(0.0283)***
γ IHS welfare (hh)	-0.0389(0.0072)***	-0.0285(0.0041)***
γ IHS transfers (hh)	+0.0281(0.0049)***	+0.0115(0.0021)***
γ IHS crop price	+0.0047(0.0204)	+0.0035(0.0102)
γ has crop price (ind.)	+0.6536(0.1621)***	+0.4482(0.0879)***

Notes: Entries are coefficient estimates; standard errors are reported in parentheses. ρ denotes the endogenous peer-effect parameter, β denotes the coefficient on the focal couple's covariate, and γ denotes the coefficient on the network-weighted neighbor covariate. OLS estimates use the IHS-transformed relative labor-burden outcomes used in the main analysis. PPML estimates use the reference spouse's labor share: the wife's share of production labor in Panel A and the husband's share of domestic labor in Panel B. The endogenous peer term is instrumented using $\boldsymbol{W^2X}$. All specifications use the main estimation sample and the same controls and fixed effects as the baseline model.

As a placebo check, I test whether any random within-village matrix connecting couples would produce the same estimated peer effect. The idea is to destroy the network's structure while preserving its mathematical properties, re-estimate the peer parameter ρ on the destroyed version, and check whether it collapses. I scramble W as follows. Within each village block, each row's existing edge weights are permuted independently across the other couples in that village, with the diagonal held out. This keeps everything about the matrix except who is connected to whom: each row remains non-negative, sums to one, has a zero diagonal, and retains its own set of weight values. What is destroyed is the assignment of those weights to specific couples, and all higher-order structure that depends on it, since each row is shuffled on its own rather than through a single shared relabeling of nodes. In-degree concentration, reciprocity, and degree correlation are generally disrupted. If the estimated peer effect comes from the genuine tie pattern, the value ρ should fall sharply when the matrix is scrambled; if it comes merely from the fact that couples in a village are linked by some row-stochastic matrix, ρ should survive. For each outcome I re-estimate ρ by GMM on 200 independently scrambled draws of W and compare the true ρ to the resulting null distribution.

Table C2 reports the comparison. In both networks the true ρ lies far outside the scrambled null: no scrambled draw out of 200 reaches the true value in either outcome ($p < 0.005$). For production the scrambled ρ collapses to near zero (mean 0.057, true 0.540), so essentially the entire peer effect derives from the specific network structure. For domestic the scrambled mean is higher (0.234, true 0.582), meaning some within-village common variation survives any row-stochastic matrix with the same marginals; even so, the true ρ sits far above this baseline. In both cases the recovered tie structure, not merely the existence of a within-village row-stochastic matrix, is what generates the estimated peer effect.

Table C2. Scramble placebo test

	Production (ihs_prod_ratio)	**Domestic (ihs_dome_ratio)**
True ρ	0.540	0.582
Scrambled ρ, mean (SD)	0.057 (0.031)	0.234 (0.029)
Scrambled ρ, median	0.058	0.234
Scrambled ρ, [5%, 95%]	[0.004, 0.110]	[0.186, 0.279]

Figure C.3 plots the null distribution of ρ across the 200 scrambled draws, with the true ρ marked. In both networks the true value lies beyond every scrambled draw (0 of 200, $p < 0.005$). For production the scrambled ρ collapses toward zero (mean 0.057, true 0.540), so almost the

entire peer effect derives from the specific network structure. For domestic the scrambled distribution sits higher (mean 0.234, true 0.582), indicating that some within-village common variation survives any row-stochastic matrix with the same marginals; even so, the true ρ lies far above this baseline. In both cases it is the recovered tie structure, not the mere existence of a within-village network, that generates the estimated peer effect.

Figure C3. Scramble placebo test

