Beyond Bargaining: Social Networks and Women's Economic Empowerment

Abstract

Mainstream economic models of women's economic empowerment have historically been limited by a rigid adherence to husband-wife comparisons in bargaining models and a misplaced belief that employment is a universal proxy for economic agency. Such analysis fails to incorporate foundational principles, deeply rooted in fields such as sociology, gender studies, and psychology, that women's economic power is multidimensional and emerges through broad social networks and peer relationships.

Using original survey and social network data from 209 married women in two rural villages in Tamil Nadu, India, this study expands traditional models in two ways: (1) by incorporating social network dynamics beyond spousal comparisons and (2) by measuring household decision-making power directly rather than inferring agency from employment alone. We find that social effects consistently outperform traditional bargaining metrics like education or employment status in modelling economic empowerment outcomes, and that household economic decision-making power (EDMP) and female labour force participation (FLFP) have markedly different predictors, demonstrating that employment-based measures fail to account for important dimensions of women's economic agency. Our findings provide empirical support for socially embedded and multidimensional models of empowerment, suggesting that effective interventions aiming to support women's economic power must consider more than labour force participation as their key indicators and move beyond individual capacity-building to designing interventions that account for the importance of social dynamics.

Keywords: Women's economic empowerment, social networks, household bargaining, economic decision-making, social capital, peer effects, female labour force participation, India.

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1 Introduction

Women's economic agency is both an intrinsic right and cornerstone of inclusive growth and development worldwide. When women gain economic power, they experience higher levels of autonomy and wellbeing, which also yields wider benefits to others, including improved child health and education outcomes, enhanced household welfare, and long-run economic growth (Quisumbing et al., 2003; Duflo, 2012; Jayachandran, 2015).

Recognising the benefits of women's economic agency, diverse institutions invest heavily in women's empowerment and rights interventions. Recent examples include Melinda French Gates' $1 billion commitment to support global initiatives for women's equity through Pivotal Philanthropies, the African Development Bank's $1.7 billion investment in women entrepreneurs, and government initiatives like India's ₹4.49 lakh crore 2025-26 gender budget allocation (Blasey, 2024; UN Women Africa and African Development Bank Group, 2024; Choudhary and Choudhury, 2025). However, significant investment in these interventions and rising global female education levels have failed to consistently translate into material increases in female economic agency. This suggests fundamental limitations in current methods of understanding and measuring women's agency (Jayachandran and Voena, 2025).

These limitations are twofold. First, the current reliance on employment-based measures may systematically overlook crucial dimensions of women's economic agency. While female labour force participation (FLFP) is used as the dominant proxy for empowerment, mounting evidence suggests this approach fails to capture women's actual influence over key economic decisions (Pimkina and de La Flor, 2020). Second, standard household bargaining theory, a common modelling approach for women's empowerment, is limited in its scope. While this framework recognises power as relational, it constrains analysis to dyadic comparisons between spouses and therefore misses the broader social context which can shape how women convert individual resources into household influence. These models predict that women with higher relative education levels, employment, or resources wield greater economic power through negotiations with husbands (McElroy and Horney, 1981), but extended literature has found that further social and situational support is required for women to translate these resource advantages into increased agency (Chang et al., 2020). Without addressing this combination of inadequate measurement and incomplete theoretical models, our evaluation and design of empowerment initiatives will continue to be systematically limited and misled.

Using original data from 209 married women across two rural villages in Tamil Nadu[1], India, we address these limitations by expanding traditional household bargaining models to include social network characteristics - peer empowerment levels, network composition,

[1]Villages are referred to by their pseudonyms "A̲lakāpuram" and "Te̲npaṭṭi" used by Power (2017).

and social capital. We test whether this expanded framework improves our ability to explain women's economic decision-making power (EDMP), then apply this approach to FLFP to compare predictors across empowerment domains.

Our findings demonstrate that social network characteristics significantly outperform traditional bargaining variables in explaining women's empowerment outcomes, while our new decision-making metric captures a unique and historically overlooked dimension of women's agency. This reflects that social networks provide crucial missing context for understanding how individual resources translate into actual agency. Women's positions within, and the compositions of, their social support networks emerge as robust predictors of economic empowerment outcomes, while relative education, employment status, and age differences between spouses show negligible effects. We also find that cross-caste network ties are more closely associated with employment participation than EDMP. This indicates that different types of social connections are associated with different empowerment outcomes and that power is multidimensional, operating through multiple social pathways.

Additionally, our exploratory analysis across villages indicates that these social mechanisms may operate differently across communities. While requiring validation in larger samples, this variation suggests that empowerment processes may be embedded in and heavily influenced by local social structures.

Our results make significant contributions to our understanding of women's economic empowerment, with this study being the first to provide a simultaneous quantitative exploration of the multidimensionality and social dynamics of women's economic agency using behavioural science insights. We also provide a novel household economic decision-making power index that captures dimensions of women's actual agency, revealing patterns that would otherwise remain invisible using FLFP. These insights have important implications for policy and intervention design.

Ultimately, our results suggest that household bargaining models require expansion rather than replacement. Moving forward, both theoretical models and policy interventions should use outcome measures that capture women's actual influence in decision-making, while accounting for the role of larger communal social dynamics in shaping agency.

2 Literature Review

2.1 Why Focus on Women's Economic Empowerment?

There is substantial evidence for the widespread benefits of increased women's economic agency. Beyond the established benefits to the wellbeing of women and the broader commu-

nity, improvements in women's status and resource control also lead to beneficial effects in areas such as increased household savings and proactive purchasing decisions, since women make different spending decisions than men (Quisumbing et al., 2003). Further, economic power can serve as a foundation for broader social and political power by providing women with resources and capabilities that can be leveraged across multiple domains. Reflecting the central role of women's economic agency in supporting broader development goals, The World Bank's Gender Agenda 2024-2030 emphasises "advances in women's participation in decision-making" as a key strategic focus.

Historically, however, women have had limited direct participation and agency in economic decisions compared to men in most societies. While participation rates have increased in some parts of the world, advancements have not been seen equally worldwide (Jayachandran and Voena, 2025). This reinforces persistent inequality and inhibits opportunities for broader inclusive development and the manifestation of aforementioned benefits (Jayachandran, 2015).

Before further analysing and critiquing current approaches to women's economic empowerment, we must first clarify the scope of our concepts, definitions, and proposed measurement.

2.2 Conceptualising Women's Economic Empowerment and Agency

While there is no universal agreement on the definition of women's economic empowerment, agency, and power, most agree that these concepts encompass "women's equal access to, and control over, resources" and "enjoyment of autonomy and capacity to make decisions that shape their life" (OECD, 2022). We build on this definition, following Jayachandran and Voena (2025), in distinguishing empowerment, the dynamic process through which women acquire greater control over their lives and circumstances, from power and agency, which represent the actual authority that women possess at any given time. However, as with their definitions, measuring these metrics remains conceptually challenging and political, with important implications for both theory and application.

2.2.1 The Dynamic, Multidimensional, and Relational Nature of Power

A key way to consider agency is in terms of the ability to make choices. To be disempowered is to be denied choice. Empowerment and agency involve "processes by which those who have been denied the ability to make choices acquire such an ability." through change (Kabeer, 1999). Kabeer further conceptualises empowerment as three interconnected dimensions that operate as a sequential process: resources, agency, then achievements. This progression

provides the foundation for measuring empowerment as a continuum, incorporating the structural parameters of individual choice and evolution of one's agency across contexts and time into the analysis of women's empowerment.

Given empowerment's multidimensional nature, this process operates differently across life domains (Quisumbing et al., 2003). Women may exercise substantial authority in some domains while having limited influence in others, or may participate in economic activities without controlling the resources they generate. Jayachandran and Voena (2025) emphasise this complexity, noting that empowerment interventions must account for these different dimensions in order to be effective, as unidimensional approaches systematically miss the interconnected nature of empowerment processes.

Crucially, this empowerment process operates through relationships and social structures rather than existing as an individual attribute (Rowlands, 1997). This relational understanding explains why identical individual resources may translate into different empowerment outcomes across social contexts, establishing that empowerment cannot be understood separately from the social and institutional contexts that constrain or enable agency. Using this framework, social capital, the resources embedded in social relationships, may prove as important as individual human or financial capital in determining empowerment outcomes.

Therefore, empowerment is not a static state, but an ongoing process of expanding capabilities and challenging constraints. It requires both access to resources and supportive social environments that enable effective action. This implies that empowerment strategies and outcomes may change as women gain experience, build networks, and encounter new opportunities or constraints. This challenges static models that assume fixed relationships between individual characteristics and empowerment outcomes, suggesting that new metrics of social dynamics will improve our understanding and explanatory power of actual pathways.

2.3 Conceptualising Social Capital and Norms

For our purposes we focus on social capital as a resource embedded in social relationships that functions as a bargaining tool independent from individual human or financial capital (Coleman, 1988; Putnam, 1994). One's social capital is a function of their position in a social network, which determines, inter alia, their ability to access support, to influence or be influenced by others, and to receive information. Each component is measured by different network statistics that represent one's level in each dimension (i.e. closeness, degree, betweenness). Depending on the similarities between connections, social capital can also provide "bridging" or "bonding" connections. Bridging capital occurs between different groups and bonding capital occurs between similar groups. These connections likely provide

different kinds of support, information, or influence depending on the type (Putnam, 2000; Gittell and Vidal, 1998).

Social norms are a key type of information spread through social networks. Through norms, social networks shape behavioural expectations and incentives through "social sanctions or rewards" (Benabou and Tirole, 2011; Bursztyn et al., 2020). Individuals spread descriptive and injunctive norms through their relationships, providing information on which behaviours are normal and socially accepted (Benabou and Tirole, 2011). This creates different layers of normative influences and incentives, depending on network structure and composition.

2.4 Current Modeling Approaches and Their Limitations

2.4.1 Traditional Household Bargaining Models

Household economics literature has evolved beyond a purely unitary conception of household decision-making, in which households are treated as single decision-making units. Modern literature also incorporates collective models, which focus on intrahousehold bargaining. This evolution represents a significant theoretical advance, explicitly acknowledging that household members may have conflicting preferences and that decision-making emerges from bargaining processes between spouses.

Popular models include threat point bargaining models, (Manser and Brown, 1980; McElroy and Horney, 1981) which implement Nash bargaining theory, in which each spouse's influence depends on their outside options, i.e. their utility if bargaining fails, and Chiappori's (1988, 1992) collective framework, which allows for diverse bargaining processes through "sharing rules" and distribution factors while maintaining Pareto efficiency.[2]

Though these models provided important progress in our understanding of household dynamics, the focus of household bargaining theory on dyadic comparisons between spouses has proven to be incomplete and limits our understanding of actual empowerment mechanisms. While correctly recognising that power is relational, it is confined to husband-wife negotiations and therefore overlooks how broader social contexts, networks, and norms fundamentally shape bargaining processes and outcomes, alongside providing bargaining resources of their own (Agarwal, 1997; Granovetter, 1985). Agarwal (1997) provides further detail, arguing that bargaining occurs not just between spouses, but within broader social systems that determine which resources can be mobilised, which strategies prove effective, and which outcomes are achievable.

[2]For our purposes, we draw most of our inspiration from threat point models due to the simplicity of our reduced form model.

An Incomplete Understanding of Bargaining Resources

Traditional models focus on individual resources in determining women's bargaining position, treating these as the primary determinants of household negotiating power. This approach generates clear theoretical predictions but has been found to perform poorly in many contexts. Cross-national studies show systematic patterns of weak relationships between traditional bargaining indicators and measures of women's household authority. Bertocchi et al. (2014) find weak relationships between individual resource advantages and empowerment measures across diverse contexts, while experimental evidence from the Philippines shows that spousal control dynamics are more complex than resource-based models predict (Ashraf, 2009). This growing body of evidence suggests that household bargaining theory may be measuring only a subset of the relevant bargaining resources.

Recognising these limitations, researchers have begun to explore broader determinants of bargaining power. Research from the International Food Policy Research Institute (IFPRI) has identified four key determinants that extend beyond individual resources including control over resources and mobilisation of interpersonal networks (Quisumbing et al., 2003; Alkire et al., 2013). Recent empirical studies support this expanded view. Machio et al. (2024) show that social participation and group membership are significant predictors of decision-making power even after controlling for education and employment. Ikhar et al. (2022) find similar patterns in rural India. This highlights the importance of social capital as a potentially crucial missing component in bargaining models.

2.4.2 Female Labour Force Participation as the Dominant Measure

Empirical applications of household bargaining theory have relied heavily on FLFP as the primary measure of women's economic empowerment. This approach assumes that employment provides women with independent economic resources which, according to bargaining theory, should translate into an enhanced household negotiating position and therefore increased household influence.

This theoretical appeal, combined with practical advantages, has driven widespread adoption of employment-based measures. Labour force participation is relatively simple to measure, widely available in survey data, and appears to capture women's economic engagement (Calder et al., 2020). Policy applications have largely embraced this framework, with development institutions focusing interventions on enhancing women's employment opportunities. However, this practical appeal comes at the cost of missing many dimensions of economic power and agency.

Employment May Not Reflect Free Choice or Agency

A fundamental limitation of approaches that use employment-based measures is that they assume labour force participation indicates empowered choice rather than responses to structural and economic pressures. Employment decisions occur within complex environments of household financial pressures, limited alternative opportunities, social expectations, and structural barriers that may affect participation regardless of women's preferences. In many contexts, women enter the labour force when household economic circumstances leave them no alternative. This conflation becomes particularly problematic when employment occurs in exploitative conditions that may actually reduce rather than enhance women's overall economic agency. Importantly for our purposes, the assumption that access to employment automatically translates into access to empowering resources has been proven empirically questionable across many contexts (Pimkina and de La Flor, 2020; Bhattacharjee and Dubey, 2024).

The U-Shaped Relationship: Evidence from India

These structural and economic dynamics become evident when examining employment patterns across economic stages, reinforcing that female employment may reflect labour market constraints rather than empowerment levels. Goldin's (1994) U-shaped hypothesis illustrates that women's labour participation often declines as economies develop before rising again, creating patterns that defy the simple supposition of a direct relationship between employment and household influence.

The U-shaped pattern supports that employment often reflects economic necessity during early stages of development, when women's labour supplements household income rather than signaling greater autonomy. As economies grow and household incomes rise, FLFP frequently declines, not because women become less empowered, but because structural barriers such as limited formal job opportunities or restrictive norms prevent them from continuing to work, even as their education levels or other forms of capital rise (Goldin, 1994). At later stages of development, when these barriers begin to lift, FLFP tends to rise again. Interpreted uncritically, this risks mischaracterising structural economic trends as shifts in empowerment.

India's experience provides a particularly compelling example. Between 2004-2018, FLFP declined by 25 percentage points in rural India and stagnated at 20 percent in urban India, while women's educational attainment increased substantially (Deshpande and Singh, 2021). Even considering recent increases, India's 2022 FLFP remains low compared to countries with similar GDP per capita. Employment-based indicators would suggest women's empowerment declined precisely when their educational capabilities were expanding, reveal-

ing the measure's inability to distinguish structural constraints from actual agency.

Recent research provides additional evidence for the complexity of the employment-empowerment relationship in India. Bhattacharjee and Dubey (2024) find that while employment does correlate with empowerment measures, the relationship varies significantly across contexts. Their results suggest that employment effects operate through improved access to resources and information, consistent with social capital mechanisms rather than simple resource comparison models.

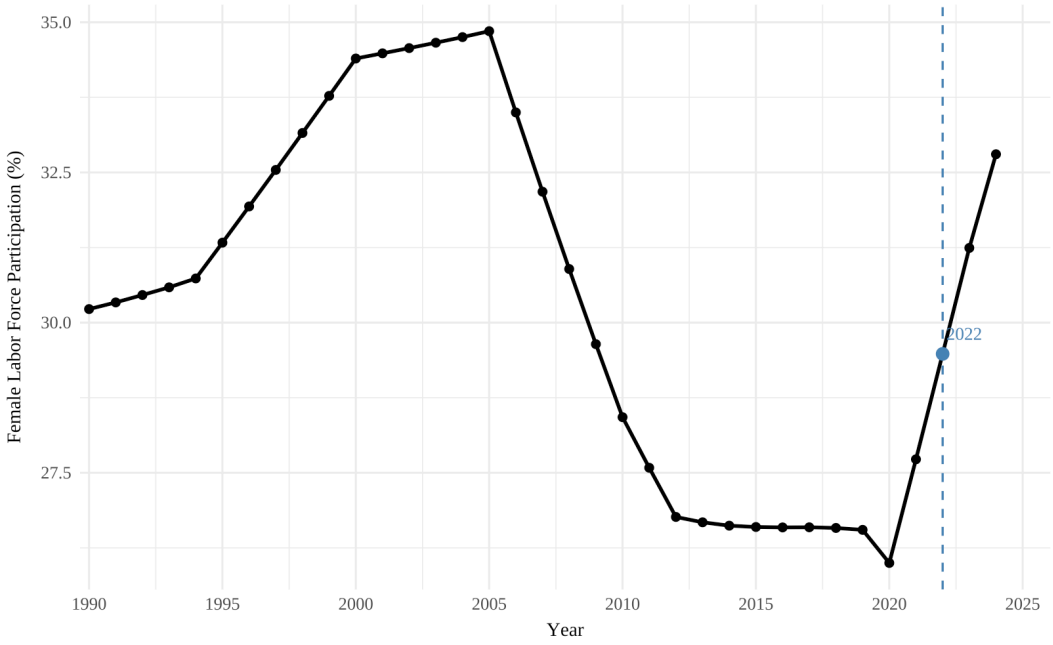
2.4.3 The Need for Complementary Measures: Economic Decision-Making Power

The theoretical and empirical limitations of FLFP as a measure of women's economic empowerment necessitate complementary indicators that capture women's actual authority over economic decisions within households. While employment participation provides valuable information about women's engagement with labour markets, it fails to capture whether women exercise control over economic resources and outcomes, which is an important distinction for considering empowerment as agency rather than mere participation.

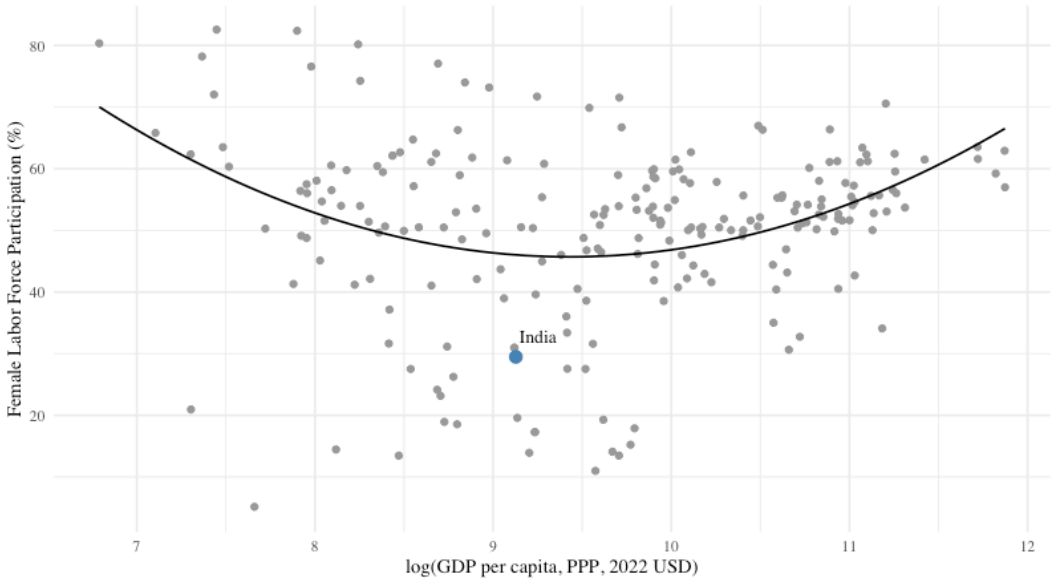
EDMP has emerged as a prominent alternative measure, directing measuring women's reported influence over consequential household financial decisions, including major purchases, savings allocation, and borrowing decisions. This shift reflects growing recognition within economics that employment-based proxies may be inadequate in contexts where social norms, economic necessity, or institutional constraints mediate the relationship between work and empowerment.

The development of EDMP measures builds on influential work by Quisumbing et al. (2003) and subsequent research at IFPRI (2013), which emphasised the importance of measuring women's decision-making authority across multiple domains. Empirical applications have demonstrated that decision-making measures often reveal patterns that diverge significantly from those observed using FLFP, particularly in contexts where women's labour force participation is driven by economic distress rather than expanding opportunities. Recent comprehensive reviews of this literature (Jayachandran and Voena, 2025) document the growing adoption of decision-making indicators as core measures of women's economic empowerment across development programs and academic research.

However, EDMP involves important methodological considerations. Economists traditionally prefer revealed preference indicators over self-reported measures due to concerns about non-classical measurement error (Bertrand and Mullainathan, 2001) and factors like social desirability bias, with respondents potentially reporting what is culturally expected rather than actual household practices (Nederhof, 1985). Yet EDMP offers the advantage of directly measuring agency rather than relying on weak proxies. While more objective



(a) Trends in FLFP in India from 1990 to 2024.



(b) Global FLFP by GDP in 2022.

Figure 1: FLFP in India over time and in international perspective. Panel (a) shows the trajectory of FLFP in India from 1990 to 2024, with the 2022 study year highlighted with a dashed line. Panel (b) shows India's 2022 FLFP relative to other countries, plotted against log(GDP per capita, PPP). While FLFP has recently increased, it remains low compared to global peers at similar income levels.

Source: World Bank World Development Indicators (WDI) 2025

measures like employment status or asset ownership avoid some reporting biases, they carry their own interpretive limitations and may actually have the same limitations depending on how they are collected and measured. These measurement considerations must be acknowledged and interpreted appropriately, but they do not negate the value of decision-making indicators for understanding women's economic empowerment.

2.5 Behavioural Economics: Building on Current Models

Behavioural economics has systematically demonstrated that individuals make decisions through bounded rationality, social heuristics, and context-dependent reference points rather than optimising in isolation (Kahneman & Tversky, 1974, 1991). This has profound implications for household bargaining theory. If women's empowerment decisions are fundamentally shaped by social context - the peers they observe, the networks they access, and the norms they encounter - then models focusing solely on individual resources or dyadic spousal comparisons will systematically miss many determinants of economic agency and opportunities for optimisation. This framework highlights social networks not merely as background contexts, but as active mechanisms that generate empowerment through distinct behavioural pathways.

2.5.1 Social and Psychological Mechanisms of Empowerment

Social networks likely influence women's economic empowerment through two broad complementary mechanisms that operate simultaneously within households and communities. First, networks provide social capital through multiple pathways including bonding and bridging capital. Networks also enable social learning, where women observe and model behaviour from network members, gaining an understanding of what is socially acceptable and information about how to navigate household negotiations and community constraints (Jackson, 2020).

However, the composition of these networks fundamentally determines their empowerment effects. When network members demonstrate empowered behaviours and supportive attitudes, these mechanisms enhance women's agency and household influence. When networks consist of traditionally-minded members, the same mechanisms can reinforce restrictive norms and constrain empowerment efforts. Dense, homogeneous networks amplify shared norms through repeated reinforcement, whether empowering or constraining, while diverse networks expose women to varied strategies and provide multiple reference points that can challenge restrictive constraints (Jackson, 2020).

Second, networks shape empowerment through social comparison processes that alter

how women evaluate their appropriate level of household authority. Social comparison theory (Festinger, 1954) suggests that people assess their position and achievements relative to their self-identified peers. In this context, it follows that women would assess their empowerment opportunities relative their female peers, not just through comparisons with their husbands. When women observe empowered peers in their networks, this shifts their reference points for achievable levels of household authority and provides information about what female behaviour is both typical and socially acceptable within their context. Importantly, the observation of empowered peers may legitimise behaviour that was deemed unobtainable and therefore not previously considered. Reference-dependent preferences (Tversky and Kahneman, 1991) formalise this process. Women's agency expectations and incentives, and therefore relative utility, will reflect the norms of their environment. If exposed to empowered peers, all factors used to determine optimal behaviour could change, potentially motivating aspiration and greater assertion of economic decision-making power.

Social capital and social comparison processes work in tandem. Social capital provides the means to pursue greater agency, while social comparison processes provide the motivation and normative justification for doing so.

2.5.2 Context-Dependent Effects and Local Gender Contracts

Social networks function as normative environments within what Webster and Caretta (2016) term "local gender contracts", place-specific agreements linking gendered power relations and daily practices. Network characteristics such as density, homophily, and the distribution of influence affect how information spreads and which norms are reinforced or challenged, making network structure critical for understanding how traditional gender constraints are maintained or transformed (Jackson, 2014).

As mentioned, network effects are conditional on the characteristics of network members. Connections to empowered women may enhance agency through social support and reduced risk of social sanction, while connections to traditionally-minded women may constrain empowerment through negative sanctioning mechanisms (David, 1980). As David (1980) documents, women can serve as "the most ruthless enforcers of the tradition of female suffering" through homophilous connections that reinforce restrictive norms.

These mechanisms create reinforcing cycles that explain why context-dependence emerges systematically rather than randomly. Communities with different gender contracts, network structures, and solidarity patterns create different environments for these cycles due to differences in normative incentive structures. In contexts where female solidarity is strong and empowered peers are visible, social comparison processes motivate empowerment while social capital provides the means to achieve it. In contexts where women are more isolated or

peers have limited authority, the same individual resources may not translate into successful empowerment.

Recent evidence supports these theories. Kandpal and Baylis (2019) find that networks with restrictive social hierarchies may limit changes in agency because information and norms circulate within homophilous groups, reinforcing rather than challenging existing patterns. However, when increases in peer agency occur through networks with empowered members, they prove substantial, significantly improving women's physical mobility, employment likelihood, and household decision-making authority. While "some norm-driven outcomes appear very difficult to alter" through traditional interventions such as health programs or income increases, they find increasing evidence suggesting that changing social norms or expectations can change these outcomes quickly, indicating that network-based interventions may be particularly effective for addressing empowerment challenges that resist individual-focused approaches (Kandpal and Baylis, 2019; Bursztyn et al., 2020).

2.5.3 Empirical Expectations

Combining insights from across behavioural science, our socially-embedded empowerment framework generates several testable empirical predictions. If empowerment operates through social mechanisms rather than individual resource accumulation alone, social capital should outperform individual resource measures as predictors of women's economic decision-making power. Network composition, peer empowerment levels, and access to social support should prove more powerful predictors than traditional bargaining variables like education, employment, or age differences between spouses.

The conditional nature of network effects suggests that simple measures of network gender composition will be insufficient without considering the empowerment characteristics of female connections. Connections to empowered women should enhance agency while connections to traditionally-minded women may constrain it, generating observable clustering of empowerment within communities that reflects social transmission rather than independent development.

Different agency domains should have different predictors and respond to different social mechanisms, with household decision-making power particularly sensitive to female solidarity through density of female social support, while employment outcomes may depend more on diverse network connections. Finally, context-dependent effects should emerge systematically, with social network variables showing different predictive power across communities with different normative environments and network structures. All effects should be reflected empirically and confirmed descriptively in our network diagrams.

3 Methodology

3.1 Survey Design and Sample Characteristics

To test these theoretical predictions, we use cross-sectional household decision-making and social network survey data collected in two rural villages - A̲lakāpuram and Te̲npaṭṭi - in Tamil Nadu, southern India in 2022 by Dr. Eleanor Power.

The household decision-making questions are adapted from the India Human Development Survey (IHDS; Desai and Vanneman, 2018), while the social network questions build on Power's earlier longitudinal work in these communities and comprise seventeen social layers including support, employment, financial, and kinship ties. All surveys were conducted via face-to-face interviews using paper surveys that were later digitised. Household decision-making questions were typically answered by wives, with social network questions self-reported. In cases where wives were unavailable, husbands or relatives responded; robustness checks excluding these cases show substantively unchanged results.

3.1.1 Sample Characteristics

For our analysis, we restrict the sample to 209 married women[3], who completed both the household decision-making and social network surveys. This allows us to compare women of a similar life stage and construct a measure of 'bargaining' that is consistent with the literature, following suggested approaches by Jayachandran and Voena (2025). Our subsample is broadly representative of the demographic and occupational composition in the region, though our "scheduled" caste composition and female labour force participation rate are higher than the national and regional average (Govindharaj and Elanchezhian, 2023).

Respondents were, on average, 45.4 years old, and had been married for approximately 25 years. Most had arranged marriages and an average of two children. About half of the sample is of a "scheduled" caste. The majority identified as Hindu (76.6%), with the remaining population identifying as Christian. Only 21.5% of wives were native to their current village of residence, reflecting prevailing patrilocal marital norms (Power and Ready, 2019).

Educational attainment among wives was relatively low, though consistent with rural norms in India and other low- and middle-income countries (Local Burden of Disease Educational Attainment Collaborators, 2020). Most women were slightly less educated than their husbands. A majority of respondents (62.7%) were employed outside of the household, primarily in agricultural wage labour, informal day labour, or small business ownership.

[3]In our sample all women are married to men.

The two villages exhibited important differences that provide variation for testing context-dependent peer effects. Aḻakāpuram has higher scheduled caste representation (71.6% vs. 22.6%) and importantly, female employment rate (67.2% vs. 57.0%), suggesting a more normalised women's work environment. Teṉpaṭṭi shows higher decision-making authority across domains (particularly cooking: 88.7% vs. 72.0%) and slightly higher empowerment levels among female peers, though lower average EDMP across wives, indicating that empowered women may be better connected in Teṉpaṭṭi.

3.2 Key Variable Construction

3.2.1 Household EDMP

We construct EDMP as a continuous index to capture each married woman's relative influence in household economic decision-making, drawing on frameworks that treat empowerment as a latent, context-dependent construct.

Latent Construct and Domain Selection

Based on theoretical considerations and prior empirical work, we identified a subset of three indicators as particularly reflective of economic agency: (1) purchasing of expensive items, (2) acquiring land or property, (3) deciding how much to spend on a social function. Through exploratory factor analysis (EFA), we were able to empirically validate this domain classification, as the three theorised "economic" items loaded strongly on a single primary factor (Watkins, 2018). This confirmed their coherence as a distinct dimension of household bargaining power, which we interpret as one's underlying economic household decision-making power.

Scoring Method

To quantify influence within each domain, we assign each individual i a base score equal to $\frac{\delta_{i,q}}{n_q}$, where n_q is the number of decision-makers named for domain q. If an individual is identified as the top decision-maker, m receive a bonus of $\tau_{i,q} \cdot \frac{\gamma}{n_q}$, scaled by γ. Thus, the final score for each domain reflects both inclusion and authority[4], weighted as a composite score using EFA loading weights.

[4]For example, if two individuals. (p and m) are named as decision-makers, but m is further named as the top decision-maker, they would receive a score of 1 (base 0.5 and bonus of 0.5), while p would receive 0.5. This reflects that m has greater overall influence in this decision-domain than p.

Table 1: Summary Statistics by Village

	Pooled	Aḷakāpuram	Teṉpaṭṭi
Demographics			
Age	45.378	44.034	47.054
Education	5.545	5.319	5.828
Social Composition			
Scheduled Caste (%)	49.761	71.552	22.581
Higher Education (%)	11.483	13.793	8.602
Native Village (%)	21.531	25.000	17.204
Economic Power Outcomes			
EDMP	0.378	0.391	0.361
	(0.398)	(0.411)	(0.382)
FLFP (%)	62.679	67.241	56.989
Household Bargaining			
Education Difference	−0.048	−0.078	−0.011
Employment Difference	−0.206	−0.164	−0.258
Age Difference	−5.344	−4.853	−5.957
Closeness Centrality Difference	0.498	0.466	0.538
Social Support Network Composition			
Female (%)	52.953	54.748	50.714
Different Caste (%)	47.847	47.414	48.387
Not Kin (%)	49.761	46.552	53.763
Peer Characteristics – Female Peers			
Average EDMP	0.407	0.373	0.449
	(0.294)	(0.265)	(0.324)
Average FLFP (%)	55.855	60.505	50.055
	(0.378)	(0.372)	(0.380)
Decision-Making Authority (%)			
Daily Cooking	79.904	71.983	89.785
Child Illness	56.380	54.598	58.602
Children's Marriage	39.474	39.655	39.247
Observations	209	116	93

Notes: Values represent sample mean, with additional standard deviations for EDMP, Average EDMP of female peers and Average FLFP of female peer noted in parentheses. Household bargaining metrics - education, employment, and closeness centrality differences - represent the average trichotomised value for the domain. See Appendix Table A1 for full metric definitions and scales.

An individual i's composite EDMP score is a weighted sum across their applicable domains q:

$$\text{EDMP Score}_i = \sum_{q \in A_i} w_q \left(\frac{\delta_{i,q}}{n_q} + \frac{\gamma \cdot \tau_{i,q}}{n_q} \right)$$

Where:

$Q =$ Set of all decision domains

$q \in Q$ Index for a decision-making domain, where Q is the set of all domains

$A_i \subseteq Q$ Set of domains applicable in individual i's household

$$\delta_{i,q} = \begin{cases} 1 & \text{if individual } i \text{ is named as a decision-maker for domain } q \\ 0 & \text{otherwise} \end{cases}$$

$$\tau_{i,q} = \begin{cases} 1 & \text{if individual } i \text{ is listed as the top decision-maker for domain } q \\ 0 & \text{otherwise} \end{cases}$$

$n_q =$ Total number of individuals named as decision-makers for domain q

$w_q =$ Normalised weight for domain q derived from EFA loadings, where $\sum_{q \in A_i} w_q = 1$

$\gamma \in \mathbb{R}$ Scaling parameter for top decision-maker bonus (default $\gamma = 1$)

Only individuals alive in 2022 are included in the scoring process. Domains in which no decision was made in the household are excluded from the calculation for that family. If a decision was made but an individual was not named, they receive a score of zero for that domain.

Initial Validation

The resulting EDMP index distribution is right-skewed ($\mu = 0.378$, $\sigma = 0.398$), with most women reporting limited, and even no, influence, though a subset is highly empowered. This distribution is theoretically expected given traditional gender norms in rural contexts (Nayak and Mahanta, 2012). Construct validity is supported by association patterns with other household decision-making domains. EDMP shows modest correlation with routine decisions like daily cooking (r = 0.21) but stronger correlations with major family decisions regarding child illness (r = 0.52) and marriage (r = 0.53), suggesting that economic decision-making authority aligns with other consequential household choices rather than general domestic control. This indicates that EDMP captures meaningful household authority over high-

stakes decisions. Importantly, our variance inflation factors are below 3.1 for these metrics, confirming that major multicollinearity does not compromise our regression analyses with the inclusion of these metrics (James et al., 2011).

Compared to IHDS 2011-2012 data for Tamil Nadu, respondents in our sample report greater average involvement in economic decisions, potentially reflecting either methodological differences or evolving gender norms over the past decade (Desai and Vanneman, 2018).

3.2.2 Bargaining Measures

To measure intra-household spousal bargaining dynamics, we construct variables capturing a wife's relative position vis-à-vis her husband across observable characteristics associated with outside fallback utility. Following standard household bargaining approaches, we calculate $R_i^{(k)}$ as the relative advantage of individual i over their spouse j for factor k, given by:

$$R_{i,j}^{(k)} = z_i^{(k)} - z_j^{(k)}$$

We compare wives and husbands across four dimensions: years of education, employment status, age, and social support network access (closeness centrality). We use closeness centrality as opposed to other centrality measures as it directly captures one's access to others within their support networks. This aligns with household bargaining theory's emphasis on the relative strength of outside options and fallback utility, as women with higher closeness centrality can more easily access social support, information, and alternative resources that strengthen their bargaining position within the household.

Our approach focuses on identifying whether wives hold a meaningful categorical advantage in these bargaining resources, rather than measuring precise numerical differences. To capture these relative bargaining positions, we trichotomise education, employment, and social support variables to {–1, 0, 1}, where 1 indicates a relative advantage for the wife, 0 indicates parity, and –1 an advantage for the husband. Age difference is retained as a continuous measure to preserve meaningful variation, as trichotomisation would collapse variation and amplify rare cases. This is due to the extreme right-skew in age differences, where nearly all wives are younger than their husbands.

While education and employment can be trichotomised using more straightforward comparisons of attainment and status, closeness centrality requires a different approach due to measurement noise. As small differences in centrality scores are relatively meaningless due to the nature of network metrics, we use the sample mean difference between spouses as a threshold for trichotomisation, where 1 indicates that the difference in closeness centrality is larger than the sample mean.

These indicators are included individually to assess how specific bargaining asymmetries relate to EDMP and FLFP, enabling a multidimensional interpretation of power within the household.

3.2.3 Social Support Network Composition

We include measures of a wife's support network composition, independent of comparison with her spouse. We construct three measures: female homophily as the proportion of individuals in the support network who are women, non-kin composition as the proportion who are not family members, and caste heterophily as the proportion from different castes. These variables proxy access to female social support, non-familial support, norm-divergent information, and overall potential social autonomy.

3.2.4 Peer Network Measure

To assess peer influence, we calculate the average EDMP and employment levels of each wife's friendship network. Peer networks are defined as the union of two directed layers: confidants and individuals with whom the respondent happily and casually has conversations with.

We calculate the average EDMP and employment levels both among each woman's female friends and among all of her friends, weighted by tie strength. We measure tie strength as the frequency with which someone is mutually nominated across network layers, ensuring that more frequently mentioned friends carry greater weight in determining potential influence. These metrics reflect the normative and informational environment of each wife, which may shape her reference group or expectations regarding empowerment and employment.

3.2.5 Additional Controls

We include supplementary household decision-making measures - daily cooking, child illness, children's marriages - to assess whether EDMP reflects broader patterns of household authority or represents a distinct empowerment dimension. While these domains are not included in the EDMP index, they provide complementary insight into broader patterns of women's authority within the household.

We also include age, caste, education level, native village status, and village fixed-effects as additional demographic controls to control for unobserved contextual factors.

3.2.6 Approach to Missing Data

Nine women (three in A̲lakāpuram, six in Te̲npaṭṭi) lacked any female friends with EDMP data in their support network. These respondents are retained in the sample and assigned

a value of zero for the network peer average and working variables. They do not differ systematically in age, caste, or education level, although we note that some are relatively young and are likely more socially isolated. We additionally impute missing values for husband education (N = 3) using predictive mean matching based on education, employment, caste, marriage type, age, and occupation.

3.2.7 Econometric Models

We estimate two main empirical models examining the determinants of women's economic empowerment in the following theoretical blocks:

EDMP OLS Model:[5]

$$\begin{aligned}\text{EDMP}_i = \beta_0 &+ \beta_1 \cdot \text{BargainingPower}_{i,j} + \beta_2 \cdot \text{SocialSupportComposition}_i \\ &+ \beta_3 \cdot \text{PeerEffects}_i + \beta_4 \cdot \text{DemographicControls}_i \\ &+ \beta_5 \cdot \text{HouseholdDecisionMaking}_i + \epsilon_i\end{aligned}$$

FLFP Logit Model:[6]

$$\begin{aligned}\text{logit}(\text{P(Working=1)})_i = \alpha_0 &+ \alpha_1 \cdot \text{BargainingPower}_{i,j} + \alpha_2 \cdot \text{SocialSupportComposition}_i \\ &+ \alpha_3 \cdot \text{PeerEffects}_i + \alpha_4 \cdot \text{DemographicControls}_i \\ &+ \alpha_5 \cdot \text{EDMP}_i + \alpha_6 \cdot \text{HouseholdDecisionMaking}_i + \epsilon_i\end{aligned}$$

[5] Full EDMP construction:

$$\begin{aligned}\text{EDMP}_i = \beta_0 &+ \beta_1 \text{ Rel. Education}_{i,j} + \beta_2 \text{ Rel. Employment}_{i,j} + \beta_3 \text{ Rel. Age}_{i,j} + \beta_4 \text{ Rel. Social Support Closeness}_{i,j} + \beta_5 \text{ \%Female}_i \\ &+ \beta_6 \text{ \%Diff. Caste}_i + \beta_7 \text{ \%Not Kin}_i + \beta_8 \text{ Avg. Female Peer EDMP}_i + \beta_9 \text{ Has Confidant}_i + \beta_{10} \text{ Daily Cooking}_i + \beta_{11} \text{ Child Illness}_i \\ &+ \beta_{12} \text{ Marriage of Child}_i + \beta_{13} \text{ Higher Educ.}_i + \beta_{14} \text{ Working Status}_i + \beta_{15} \text{ Caste (SC)}_i + \beta_{16} \text{ Native Village}_i + \beta_{17} \text{ Village (Tenpaṭṭi)}_i + \beta_{18} \text{ Age}_i + \epsilon_i.\end{aligned}$$

[6] Full FLFP construction:

$$\begin{aligned}\text{logit}\big(P(\text{Working} = 1)\big)_i = \alpha_0 &+ \alpha_1 \text{ Rel. Education}_{i,j} + \alpha_2 \text{ Rel. Age}_{i,j} + \alpha_3 \text{ Rel. Social Support Closeness}_{i,j} \\ &+ \alpha_4 \text{ \%Female}_i + \alpha_5 \text{ \%Diff. Caste}_i + \alpha_6 \text{ \%Not Kin}_i + \alpha_7 \text{ Avg. Female Peer EDMP}_i + \alpha_8 \text{ Has Confidant}_i + \alpha_9 \text{ Daily Cooking}_i \\ &+ \alpha_{10} \text{ Child Illness}_i + \alpha_{11} \text{ Marriage of Children}_i + \alpha_{12} \text{ Higher Educ.}_i + \alpha_{13} \text{ Caste (SC)}_i + \alpha_{15} \text{ Native Village}_i \\ &+ \alpha_{16} \text{ Village (Tenpaṭṭi)}_i + \alpha_{17} \text{ Age}_i + \alpha_{18} \text{ EDMP}_i + \epsilon_i.\end{aligned}$$

Theoretical Foundation

Following household bargaining theory, we assume that observed economic decision-making power reflects the outcome of intrahousehold negotiations, but we do not observe individual preferences, utility functions, or the bargaining process itself. Instead, we estimate a reduced-form relationship between empowerment outcomes and variables that theory suggests should influence bargaining strength, both traditional threat point variables - relative levels of education, age, and employment status - and social network characteristics that may provide additional bargaining resources.

Our empirical approach tests whether expanding the set of variables beyond traditional dyadic comparisons improves our ability to predict observed empowerment patterns (both EDMP and FLFP), without requiring assumptions about specific utility functions or bargaining rules.

Empirical Implementation

Given confirmed heteroskedasticity (Breusch-Pagan test, $p < 0.001$), we use robust standard errors throughout. For pooled specifications, standard errors are clustered by village and include village fixed effects to control for unobserved community-level factors.

Our identification relies on cross-sectional variation in economic empowerment outcome variables (EDMP and FLFP) and our key predictors of interest, social dynamics and traditional bargaining variables. We exploit variation in EDMP, FLFP, network position, peer empowerment levels, and network composition to identify social effects on empowerment outcomes.

We estimate pooled, village-stratified, and caste-stratified specifications to test for contextual variation in empowerment mechanisms. Our stratified analyses examine whether peer effects and social network mechanisms operate differently under varying normative contexts. Due to space limitations, caste-stratified results are reported in the appendix.

To address concerns of multicollinearity and overfitting, we employed a systematic model building approach. Starting with a baseline of demographic controls, we sequentially added groups of theoretically related predictors (e.g., bargaining indicators, network composition, peer norms, other household characteristics), assessing model fit and retaining variable groups that improved explanatory power. This approach preserved theoretical structure while reducing redundancy and successfully addressed multicollinearity concerns (mean VIF = 1.5, maximum VIF = 3.1)(James et al., 2011).

We attempted to instrument peer empowerment using friends-of-friends' empowerment, but likely due to sample size, the instrument was weak and failed first-stage diagnostics. However, our OLS and IV estimates are not significantly different (Wu-Hausman $p = 0.84$),

suggesting that endogeneity may not substantially bias our estimates. We therefore interpret our results as documenting robust associations between social network characteristics and empowerment outcomes, but do not make strong causal claims.

4 Results

4.1 Determinants of Economic Decision-Making Power

4.1.1 Pooled Results

Table 2 presents pooled results for EDMP using the full sample (N = 209). The model explains substantial variation in economic decision-making power (Adjusted $R^2 = 0.396$). We use standardised coefficients (Table A2) in addition to our initial model to compare effect-sizes across different predictor categories.

Social network characteristics show consistent associations that systematically exceed traditional bargaining metrics. Network centrality demonstrates the most robust network effect ($\beta = 0.026$, $p < 0.001$; standardised $\beta = 0.071$), providing statistical significance and larger effect sizes than traditional bargaining predictors. Female peer empowerment levels ($\beta = 0.135$, $p > 0.10$; standardised $\beta = 0.098$) and female peer composition ($\beta = 0.286$, $p < 0.05$; standardised $\beta = 0.092$) show similarly sized standardised effects, though with limited statistical precision that may reflect sample size constraints.

Traditional bargaining variables demonstrate minimal and non-significant associations that support critiques of dyadic bargaining approaches. Education differences between spouses ($\beta = 0.011$, $p > 0.10$; standardised $\beta = 0.030$), employment differences ($\beta = -0.002$, $p > 0.10$; standardised $\beta = -0.022$), and age differences ($\beta = 0.001$, $p > 0.10$; standardised $\beta = 0.019$) all show negligible effects, confirming that these metrics poorly predict women's economic decision-making power.

Individual-level characteristics also show substantial effects. Higher education shows the second largest coefficient in the model ($\beta = 0.142$, $p > 0.10$; standardised $\beta = 0.307$), followed by employment status ($\beta = 0.065$, $p > 0.10$; standardised $\beta = 0.230$) and residence in natal village ($\beta = 0.081$, $p < 0.05$; standardised $\beta = 0.210$). The importance of these metrics suggests that empowerment operates through both individual capabilities and social network mechanisms working in tandem.

Decision-making authority in other household domains have some of the largest standardised effects in the model. Child illness authority shows the strongest association ($\beta = 0.293$, $p < 0.001$; standardised $\beta = 0.373$), followed by children's marriage decisions ($\beta = 0.307$,

$p < 0.001$; standardised $\beta = 0.358$) and daily cooking decisions ($beta = 0.087$, $p < 0.05$; standardised $\beta = 0.118$). These strong associations, combined with substantial correlations between EDMP and other household decision-making domains ($r = 0.21$-0.53), suggest that economic decision-making authority may be part of a broader pattern of household empowerment.

Analysis of individual EDMP domains (Appendix Table A11) suggests that network effects vary across decision types. Network centrality most strongly associates with expensive purchase decisions ($\beta = 0.034$, $p < 0.05$), while female peer composition shows strongest effects for social function spending ($\beta = 0.422$, $p < 0.05$). Meanwhile land purchasing decisions are most associated with higher education ($\beta = 0.122$, $p < 0.05$), illustrating how different mechanisms operate across various economic decision domains.

4.1.2 Village-Stratified Results

Village-stratified analyses (Table 3) provide robust support for network-based empowerment mechanisms across both study communities, though the specific pathways through which networks operate vary between villages. Though, Sample sizes within villages are limited (N = 93 in Teṉpaṭṭi, N = 116 in Aḷakāpuram), requiring cautious interpretation of village-specific effects.

As with our pooled model, network variables consistently outperform traditional bargaining predictors across both communities, confirming the robustness of our core finding. However, specific social mechanisms differ by village, indicating context-dependent empowerment pathways. In Teṉpaṭṭi, peer empowerment effects are strong ($\beta = 0.285$, $p < 0.001$), while this relationship is absent in Aḷakāpuram ($\beta = -0.044$, $p > 0.10$), where female network composition shows stronger associations ($\beta = 0.605$, $p < 0.10$). This variation supports our theoretical framework that empowerment processes are embedded within local gender contracts.

Traditional bargaining variables remain negligible in both villages, strengthening the critique of dyadic bargaining approaches. Individual characteristics also reveal village-specific patterns: higher education associates with EDMP in Teṉpaṭṭi ($\beta = 0.253$, $p < 0.10$) but not in Aḷakāpuram ($\beta = 0.058$, $p > 0.10$), suggesting that human capital conversion depends on local contexts. The village-specific models achieve different explanatory power (Teṉpaṭṭi $R^2 = 0.514$; Aḷakāpuram $R^2 = 0.313$), indicating that empowerment processes may be more systematic in some community contexts than others.

Table 2: Determinants of Economic Decision-Making Power (OLS)

	(1) EDMP
Bargaining Metrics (Wife - Husband)	
Education	0.011
	(0.021)
Employment Status	−0.002
	(0.056)
Age	0.001
	(0.004)
Social Support Closeness Centrality	0.026***
	(0.007)
Social Support Composition	
Percent Female	0.286**
	(0.140)
Percent of Different Caste	0.038
	(0.095)
Peer Norms (Female Friends)	
Average EDMP	0.135
	(0.147)
Other Household Decision-Making	
Daily Cooking	0.087**
	(0.033)
Child Illness	0.293***
	(0.010)
Marriage of Children	0.307***
	(0.044)
Controls	
Higher Education	0.142
	(0.086)
Working	0.065
	(0.045)
Native Village	0.081**
	(0.033)
Village Fixed Effect (Tenpaṭṭi)	−0.046***
	(0.009)
Constant	−0.251
	(0.248)
Observations	209
Adjusted R-squared	0.396

Notes: Values are coefficient estimates from OLS regressions with village fixed effects and robust standard errors clustered by village, shown in parentheses. Additional controls include age and caste, which are not reported due to limited coefficients and p-values. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.001$.

Table 3: Determinants of EDMP by Village

	(1) Aḷakāpuram	(2) Teṉpaṭṭi
Bargaining Metrics (Wife – Husband)		
Education	0.011	−0.038
	(0.045)	(0.046)
Employment Status	−0.017	0.092
	(0.095)	(0.099)
Age	−0.005	0.005
	(0.010)	(0.006)
Social Support Closeness Centrality	0.016	0.029
	(0.073)	(0.061)
Social Support Composition		
Percent Female	0.605*	0.410
	(0.354)	(0.290)
Percent Different Caste	0.130	−0.047
	(0.147)	(0.133)
Percent Not Kin	−0.380	0.236
	(0.366)	(0.196)
Peer Norms (Female Friends)		
Average EDMP	−0.044	0.285***
	(0.134)	(0.093)
Other Household Decision-Making		
Daily Cooking	0.136*	0.570
	(0.076)	(0.088)
Child Illness	0.298***	0.309***
	(0.076)	(0.054)
Marriage of Children	0.250**	0.349***
	(0.096)	(0.085)
Controls		
Higher Education	0.058	0.253*
	(0.091)	(0.149)
Working	−0.030	0.078
	(0.121)	(0.095)
Caste (SC)	0.019	−0.080
	(0.083)	(0.068)
Constant	0.064	−0.510
	(0.403)	(0.431)
Observations	116	93
Adjusted R-squared	0.313	0.514

Notes: Values are village stratified OLS regression estimates using robust standard errors, provided in parentheses. Column (1) displays results for Aḷakāpuram, while column (2) displays results for Teṉpaṭṭi. Additional controls include age and native village, which are not reported due to limited coefficients and p-values. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.001$.

4.2 Determinants of Female Labour Force Participation

Table 4 presents marginal effects for the probability of employment, displaying predictions for how different factors affect the likelihood of labour participation in percentage points. The patterns differ notably from EDMP results, with standardised effects revealing different effect-size hierarchies compared to household decision-making outcomes.

Network variables show meaningful associations with employment, but through different patterns compared to EDMP. Network centrality demonstrates the largest network effect (standardised $\beta = 0.068$), followed by peer employment levels (standardised $\beta = 0.056$), which is very statistically significant ($p < 0.001$). Cross-caste network connections show strong statistical significance ($\beta = 0.077$, $p < 0.001$) despite smaller standardised magnitude ($\beta = 0.026$). Female peer composition, which showed meaningful associations with EDMP (standardised $\beta = 0.092$), demonstrates negligible employment effects (standardised $\beta = -0.031$).

Traditional spousal bargaining metrics demonstrate minimal associations with employment probability, consistent with EDMP findings. Educational differences between spouses show negligible effects (standardised $\beta = -0.038$), and age differences show minimal associations (standardised $\beta = -0.029$). This consistency across both empowerment domains reinforces that individual resource advantages within marriage provide limited explanatory power regardless of the outcome measured.

Individual variables demonstrate the strongest standardised associations with employment probability, but in patterns that directly oppose their relationships with household authority. Higher education has the largest negative magnitude ($\beta = -0.208$, $p > 0.10$; standardised $\beta = -0.175$), representing a substantial negative association with employment. This contrasts sharply with education's positive association with EDMP (standardised $\beta = 0.307$).

EDMP demonstrates the strongest positive standardised association with employment probability ($\beta = 0.159$, $p > 0.10$; standardised $\beta = 0.073$) among all predictors. However, this relationship remains statistically imprecise and smaller than the cross-domain household authority effects observed for EDMP.

Non-economic household authority variables demonstrate negligible associations with employment probability. Daily cooking authority shows small negative effects (standardised $\beta = -0.061$), child illness authority shows minimal association (standardised $\beta = -0.026$), and children's marriage authority demonstrates negligible effects (standardised $\beta = -0.006$). This absence of cross-domain relationships contrasts starkly with the strong coherence observed across household decision-making domains for EDMP.

Table 4: Determinants of Female Labour Force Participation (FLFP)

	(1) FLFP
Economic Decision-Making Power (EDMP)	0.159
	(0.264)
Bargaining Metrics (Wife – Husband)	
Education	−0.020
	(0.120)
Age	−0.005
	(0.004)
Social Support Closeness Centrality	0.081
	(0.066)
Social Support Composition	
Percent Female	0.093
	(0.874)
Percent of Different Caste	0.077***
	(0.006)
Peer Norms (Female Friends)	
Average FLFP	0.193**
	(0.083)
Other Household Decision-Making	
Daily Cooking	−0.069
	(0.066)
Child Illness	−0.005
	(0.126)
Marriage of Children	0.021
	(0.023)
Controls	
Higher Education	−0.208
	(0.194)
Native Village	−0.006
	(0.098)
Village Fixed Effect (Tenpaṭṭi)	−0.119**
	(0.056)
Constant	0.603**
	(0.253)
Observations	209
Log Likelihood	−127.515
AIC	291.031

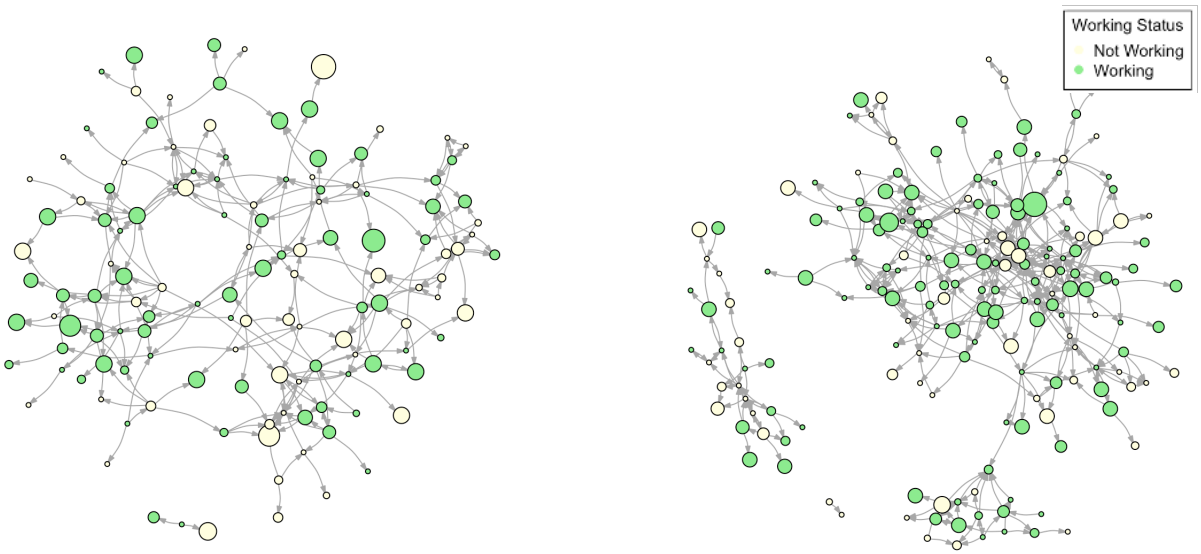
Notes: Values are logistic regression estimates, reporting marginal effects using robust standard errors clustered by village, provided in parentheses. Additional controls include age and caste, which are not reported due to limited coefficients and p-values. Employment status (working) and relative employment status are not included due to concerns of collinearity. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.001$.

4.3 Visualising Network Structure

Figures 2 and 3 provide visual confirmation of the social network mechanisms identified in our regression analyses. The female friendship networks (Figure 2) exhibit clustering patterns that support our theoretical predictions about peer influence. Women with similar EDMP levels cluster together in connected groups, while employed women (shown in green) predominantly connect to other employed women, illustrating how empowered individuals seem to reinforce each other's authority through social connections.

The network visualisations reveal village-specific differences that correspond to our regression findings. In Teṉpaṭṭi (Panel a), those with larger nodes (have higher EDMP) are predominantly green (are employed) and form clusters, illustrating how empowered, employed women seem to reinforce each other's authority through social connections. This clustering pattern aligns with the significant peer EDMP effects ($\beta = 0.285$, $p < 0.001$) found in our regression analyses. Aḷakāpuram's network (Panel b) shows weaker clustering by empowerment level and more dispersed employment patterns, mirroring the absence of peer EDMP effects ($\beta = -0.044$, $p > 0.10$) and suggesting that different social dynamics may affect empowerment social effects.

The social support network (Figure 3) illustrates centrality mechanisms, with women having larger nodes (have higher EDMP) occupying more central positions in the support network. This provides visual confirmation of significant network centrality effects (standardised $\beta = 0.071$, $p < 0.001$)), demonstrating that network position serves as a crucial empowerment resource.



(a) Teṉpaṭṭi (b) Aḷakāpuram

Figure 2: Female friendship networks in Teṉpaṭṭi and Aḷakāpuram. Node size indicates EDMP, node colour indicates employment status. Networks show clustering by empowerment level and employment status, supporting peer influence mechanisms.

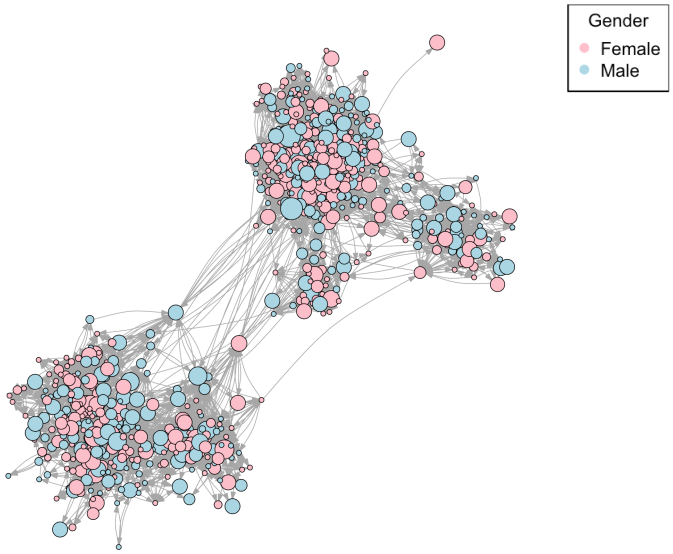


Figure 3: Combined social support network for Teṉpaṭṭi and Aḷakāpuram. Node size indicates EDMP, node colour indicates gender. Higher EDMP women occupy more central network positions, supporting network centrality effects.

4.4 Robustness Checks

To assess robustness, we conducted a series of specification checks examining measurement of EDMP, bargaining metrics, and social capital metrics and the stability of estimated coefficients across alternative modelling approaches (Appendix Tables A6–A13 and Figure A1).

To test measurement robustness of EDMP, we re-estimated the index using alternative scoring rules (binary, "top only," and "base only"), equal domain weights, and by varying the top-decision-maker bonus parameter $\gamma \in [0, 2]$. Across all constructions, network coefficients remain positive and comparable in magnitude, while bargaining indicators remain weak predictors. We additionally disaggregated EDMP into its three domains. This showed that network effects persist within each, though effect sizes vary. For bargaining variables, recoding relative differences in education, age, and social closeness as continuous produced qualitatively unchanged results. Additionally, substituting alternative centrality measures (degree and betweenness) instead of closeness centrality also yielded similar patterns.

To test model specification robustness, we repeated all models excluding household decision-making surveys where the wife was not the primary respondent; results were substantively unchanged. We re-estimated all models with standard errors clustered at the individual rather than village level, which also did not alter patterns of statistical significance. We additionally compared pooled, village-stratified, and caste-stratified specifications to assess contextual heterogeneity; core social network findings were consistent across contexts. Across all specifications, the magnitude and direction of coefficients on social network variables were stable, while traditional bargaining variables continued to explain little of the variation in economic empowerment outcomes.

5 Discussion

Our analysis demonstrates strong evidence of the limitations of traditional approaches for modelling women's economic empowerment. We find that social network dynamics significantly outperform traditional household bargaining variables in explaining women's economic decision-making power and that EDMP captures an important, unique dimension of women's agency. Network characteristics emerge as robust and statistically significant predictors, while spousal resource comparisons show negligible effects across all specifications.

These findings suggest that women's bargaining positions depend more heavily on broader social contexts than on individual resource advantages relative to their husbands. Women's economic agency appears to operate through social mechanisms involving social support, reference point formation, and norm dynamics within local gender contracts rather than

through dyadic spousal negotiations alone.

5.1 Potential Mechanisms: Social Dynamics and Networks Effects

Our findings are consistent with several behavioural mechanisms operating through social comparison and peer effects, as predicted by our theoretical framework. While we do not establish these mechanisms causally, our results suggest for how they might operate.

The positive association between network centrality and household decision-making power ($\beta = 0.071$, $p < 0.001$) suggests that women in central network positions may be better able to mobilise social capital as a bargaining resource. This represents a potential fundamental expansion of household bargaining theory. Women appear to negotiate with husbands from positions determined not only by individual resource comparisons, but by their access to social capital through network relationships. Additionally, the positive association between female peer connections and household empowerment provides evidence for what Tamil women describe as "the strength engendered by gathering together" (David, 1980). This suggests that when women coordinate empowerment efforts through peer networks, they may be able to overcome social sanctions that deter individual attempts at increased autonomy.

The relatively strong performance of female peer empowerment variables is consistent with social comparison theory, suggesting that women may evaluate their appropriate level of household authority relative to their female peers, rather than just through comparisons with husbands. The gender-specificity of these effects - female peer agency shows modest but meaningful associations ($\beta = 0.098$, $p < 0.10$) while analysis using all peers shows weaker effects (Appendix Table A6) - indicates that same-gender peer groups may serve as primary reference points for empowerment decisions.

This pattern could reflect reference-dependent preferences where exposure to empowered peers may shift women's reference points about achievable household authority, creating aspirational effects that operate independently of individual resource advantages. These social comparison processes could operate within peer networks, with evidence for social learning or social sorting with peers in both empowerment domains (EDMP standardised $\beta = 0.098$, $p < 0.10$; FLFP standardised $\beta = 0.0.056$, $p < 0.05$). This could include the transmission of positive empowerment norms between female peers that make agency more feasible and socially acceptable through insulated local norms and incentive structures.

5.2 FLFP & EDMP: Distinct Dimensions

The contrasting predictive patterns across multiple predictors provide compelling evidence for distinct empowerment mechanisms, supporting our theoretical argument that empowerment is fundamentally multidimensional. Network characteristics, individual resources, and peer influences show markedly different effects across household authority and employment outcomes.

Social network effects demonstrate clear divergent patterns. Female peer composition is a modest but robust predictor of EDMP (standardised $\beta = 0.092$) but has virtually no relationship with employment (standardised $\beta = -0.031$). In contrast, cross-caste connections are particularly important for FLFP (standardised $\beta = 0.026$, $p < 0.001$) while having minimal impact on household decision-making. Network centrality is associated with both metrics but likely operates through different mechanisms, potentially facilitating household empowerment via solidarity while enabling employment access through alternative pathways.

Individual characteristics reveal the most dramatic reversals across empowerment dimensions. Education has a large positive relationship with EDMP (standardised $\beta = 0.307$) but a substantial negative relationship with employment (standardised $\beta = -0.175$), likely due to limited appropriate work opportunities for educated women in rural areas. This highlights how employment-based measures may miss important determinants of household authority, potentially leading to incomplete assessments of empowerment interventions and undervaluing certain mechanisms.

Diverging patterns in agency domains further illuminate these distinct pathways. EDMP maintains a modest positive connection with employment (standardised $\beta = 0.073$), but other household authority measures show limited relationships with employment (all standardised $\beta < -0.006$). This suggests that economic decision-making authority operates differently from general domestic authority.

Crucially, traditional bargaining variables remain weak predictors across both empowerment measures, confirming that spousal resource comparisons have limited explanatory power regardless of the outcome examined. This consistent pattern reinforces our conclusion that social network factors constitute the primary drivers of women's empowerment.

This divergence has important methodological implications that extend beyond our study. Employment-based measures may systematically overlook dimensions of economic agency, leading to incorrect assessments of empowerment levels and intervention effectiveness. Our findings also suggest that exclusive reliance on labour force participation indicators provides incomplete assessments of women's economic power, particularly missing the household authority dimensions that likely operate through alternative social pathways.

5.3 Exploratory Evidence for Context-Dependence

The exploratory village-stratified analyses provide suggestive evidence consistent with our theoretical framework predicting that social network variables would have different predictive power across communities with different normative environments. The two villages exhibit distinct patterns of effect sizes across social mechanisms, though the limited sample sizes require cautious interpretation of whether this reflects systematic or random variation.

These differences coincide with variation in village composition and social structures. While there are likely many unobservable differences between communities that we do not capture, the differences in scheduled caste representation and female employment rates across villages would certainly contribute to different normative environments, which directly affect the likelihood of women's work and the prevalence of caste norms.

While these patterns are consistent with empowerment processes being embedded within local social structures and normative environments, establishing systematic context-dependence would require larger samples across more diverse communities. The observed variation suggests that different communities may offer different pathways to women's agency depending on existing network structures, employment norms, and connectivity patterns.

This potential context-dependency has important implications for intervention design and scaling. If confirmed in larger studies, the variation in social mechanisms for empowerment suggests that practitioners should assess community characteristics such as employment norms, empowered women's connectivity, and social group composition, before designing interventions. Rather than universal approaches, this evidence points toward context-specific programming that optimises strategies to local empowerment pathways.

5.4 Network Effects Within Broader Structural Change

While the mean EDMP score of 0.378 ($\sigma = 0.398$) suggests moderate economic empowerment on average, the right-skewed distribution conceals that almost 38% (79 women) report zero economic decision-making power. These women likely face deeper structural barriers that extend beyond what social networks alone can address, requiring targeted interventions and attention alongside network-based approaches.

However, this exists in a period of active transformation. Our measures exceed those from the 2011-2012 IHDS wave for Tamil Nadu, coinciding with rising educational attainment and renewed female labour force participation growth across India (The World Bank, 2025). Within this changing context, network mechanisms become vital for helping women convert expanding opportunities into household influence, accelerating positive trends already underway.

Social networks amplify structural change rather than replace it. As barriers shift, networks provide pathways for translating individual gains into empowerment, while empowered women reshape norms for others. This suggests that effective strategies must combine network approaches with broader structural interventions, paying special attention to those currently excluded from decision-making entirely.

5.5 Limitations and Causal Interpretation

Several limitations constrain our interpretation of these findings. While we observe strong associations between network characteristics and empowerment outcomes, our cross-sectional design and limited sample size prevent establishing clear causality.

Reverse causality poses a particular challenge for interpreting peer effects. More empowered women may seek out friends that are more empowered, creating spurious associations between peer and individual empowerment levels. This could bias our peer effect estimates upward. The self-reported nature of our empowerment measure complicates our estimate further. If empowered women face social sanctions that lead them to underreport their influence, our estimates might be biased downward, while social desirability bias could lead to overreporting, biasing in the other direction. Separately, unobserved characteristics could simulataneously affect network formation and empowerment outcomes, or be a true causal link between the two. We have no direct evidence of any of these points, but must note the possibility of their existence and potential to bias our outcomes.

We are likely underpowered to detect many important effects, due to our sample size, particularly interaction effects and heterogeneity across subgroups. This includes our ability to explore age cohort interactions, caste-specific effects, and other sources of heterogeneity that theory suggests should affect empowerment mechanisms and social norms. This could be biasing our estimates toward zero, potentially missing significant relationships that would emerge with larger samples. We see evidence of this in our low and statistically insignificant coefficient estimates for age and caste controls.

Our study also provides limited causal insight into the specific social and psychological mechanisms that drive the social dynamics, including peer effects, that we observe. We do not directly measure transmission channels, and therefore cannot distinguish whether our associations reflect genuine peer influence (whether one's influence on their friends or vice versa), selection effects, nor which channel they may operate by in the case of genuine influence, whether through social support, norms, reference-points, etc.

The village-stratified results should be interpreted with particular caution given small sample sizes. While the patterns are suggestive, they could reflect sampling variation rather

than genuine contextual differences. External validity is also limited by our focus on two Tamil Nadu villages and married women, though the underlying mechanisms we identify are likely generalisable across contexts and for unmarried women.

5.6 Policy Implications

Our findings suggest that effective empowerment interventions must address social network dynamics alongside individual capacity-building. Programmes that focus exclusively on human capital development, education, or skills training may have limited effectiveness without addressing the social contexts that determine how these resources translate into actual influence.

The differential mechanisms underlying household authority versus labour market participation have specific design implications. Interventions aimed at increasing women's household decision-making power should prioritise building social capital through women's groups, peer support networks, and community-based programming that create a supportive environment for women to come together. Employment-focused interventions should additionally emphasise bridging social capital by facilitating cross-group connections and information sharing about labour market opportunities.

5.6.1 Network-Informed Programme Design

The robust effects of peer empowerment levels suggest that interventions should consider network selection and peer influence dynamics. Programmes that bring together women with varying empowerment levels may generate spillover effects that amplify individual treatment effects by creating normative expectations about increased appropriate female behaviour. However, the finding that women can also reinforce traditional constraints necessitates close attention to group composition and peer characteristics, as not all women may have a positive effect.

Network centrality effects indicate that identifying and supporting women in central network positions may generate broader community impacts through their influence on connected peers. This approach leverages existing social structures rather than attempting to create entirely new networks, potentially improving programme sustainability and reach.

The village-stratified results for both EDMP and FLFP underscore that effective interventions must be tailored to local contexts. The strong positive relationship between household authority and employment in Teṉpaṭṭi suggests that interventions promoting either outcome may have spillover effects in communities where women's agency is emerging. Conversely, the weak relationship in Aḷakāpuram indicates that different strategies may be

needed where employment is normalised but disconnected from household empowerment. These patterns suggest that successful programmes should assess local empowerment landscapes to inform intervention design.

The divergent predictors of different empowerment dimensions indicate that evaluation strategies must move beyond employment-based indicators to capture multiple facets of economic agency. Programmes evaluated solely on labour force participation may fail to address substantial empowerment effects in household decision-making domains, leading to incorrect assessments of intervention effectiveness.

Comprehensive evaluation frameworks should incorporate measures of household authority, community participation, and social network characteristics alongside traditional employment outcomes. This multidimensional approach would provide more accurate assessments of programme impacts and inform more effective intervention design, particularly for addressing the dimensions of empowerment that appear most responsive to social network interventions.

5.7 Future Research Directions

This study opens several important avenues for future research that can address current study limitations while advancing understanding of network-based empowerment mechanisms. Establishing causality should be one of the highest priorities moving forward. This can be pursued through many complementary approaches that will provide clearer information on pathways and context-dependency.

Longitudinal studies tracking empowerment and network evolution over time, can be used identify how peer influence operates dynamically. Such designs could distinguish network mechanisms such peer selection effects, influence effects, and the effects of different types of social capital while examining how empowerment spreads through networks over time.

Experimental interventions that manipulate peer exposure or network composition could test specific pathways and mechanisms for empowerment diffusion while generating policy-relevant evidence about optimal intervention design. Quasi-experimental designs exploiting natural variation in network exposure, such as the introduction of new local programmes or policy changes that affect network composition, could provide causal identification while preserving external validity.

Future work should also integrate multiple empowerment measures to better understand how different dimensions of agency, household authority, labour market participation, mobility, and political engagement, relate to each other and respond differently to social influences. This could help develop more comprehensive theories of empowerment that capture

its multidimensional and context-dependent nature.

Research expanding across diverse contexts is additionally promising for identifying the structural and social factors that determine when and how social capital mechanisms operate. This expansion is soon to be realised, with collaborative work in Uttar Pradesh, India and Nepal under discussion using similar network and survey data that would test the generalisability of our findings across different cultural, economic, and institutional settings with varying normative environments and social structures.

Finally, research incorporating direct measures of social and psychological mechanisms could illuminate the processes underlying peer influence. Studies measuring normative beliefs, aspirations, social comparison processes, and reference point effects could distinguish between information sharing, emotional support, social norms, and other influence channels that drive empowerment diffusion through social networks.

Importantly, the network-based mechanisms identified in this study should not remain unexplored due to data collection constraints. As traditional network mapping can be prohibitively expensive, proposed methods like network elicitation through Aggregated Relational Data (ARD) can be used to collect key network parameters at a potentially 80% lower cost than traditional full network surveys[7], allowing for similar analyses regarding social composition (Breza et al., 2017). This approach could enable broader investigation of how network composition shapes women's empowerment across diverse contexts and larger samples where network samples are not available or able to be feasibly collected, further advancing this work.

6 Conclusion

This study challenges the conventional understanding of women's economic empowerment by demonstrating the importance of social networks relative to traditional household bargaining dynamics and the multidimensional nature of economic power, which are overlooked in current models. We find that women's social network characteristics are substantially more predictive of economic decision-making power than traditional bargaining variables, and that our EDMP measure captures important dimensions of agency that standard employment-based proxies overlook.

Traditional household bargaining theory predicts that women with greater individual resources relative to their husbands should exercise more economic power. However, we find that standard bargaining predictors, relative education, employment, and age differences between spouses, show negligible and statistically insignificant effects. In contrast, multiple

[7]Calculated from J-PAL fieldwork (Breza et al., 2017).

dimensions of social network characteristics emerge as robust and significant predictors of women's empowerment outcomes.

This suggests that traditional bargaining models overlook a critical bargaining resource: social capital. Women's negotiating positions depend not only on individual resources like education and age relative to their husbands, but also on their social capital accessed through network relationships. Social networks provide bargaining resources that current models fail to capture, including information, emotional support, collective coordination, and social validation for asserting household authority. Rather than requiring fundamental replacement, household bargaining theory needs to be expanded to incorporate this missing dimension of bargaining power.

Additionally, we confirm that empowerment is a multidimensional rather than a unitary phenomenon. Our economic decision-making power index captures patterns of household authority that diverge substantially from employment outcomes, demonstrating that different empowerment dimensions are associated with different social mechanisms and individual predictors. Bonding social capital among women appears particularly important for household decision-making authority, while bridging social capital across different castes shows stronger associations with labour force participation. Individual resources like education show opposing relationships across empowerment domains, positively associated with household decision-making power, but negatively associated with employment participation. This reveals that relying on employment indicators may overlook important empowerment effects, including positive impacts of education on household authority that would otherwise go undetected. Interventions therefore need to account for these distinct pathways and comprehensive measurement frameworks are essential for accurate evaluation.

Finally, our findings suggest that social networks serve as important pathways within this period of broader structural transformation. While 38% of women in our sample remain entirely excluded from economic decisions, rising educational attainment and labour force participation in India create an environment where network-mediated empowerment becomes increasingly relevant. Social connections may help translate expanding opportunities into household influence, suggesting that empowerment interventions should harness both structural changes and network approaches to amplify social benefits.

The policy implications are significant. Interventions should recognise that individual resources require supportive social contexts to translate into increased agency. The multidimensional nature of empowerment suggests that programmes must be designed with specific outcomes in mind, those aimed at enhancing household decision-making power should prioritise building bonding social capital through women's groups and peer support networks, while employment-focused interventions should also consider bridging social capital by facilitating

connections between different social groups. Additionally, the opposing effects of education across empowerment dimensions further highlight that programmes may have different impacts on different types of agency. This requires moving beyond employment-based evaluation to comprehensive frameworks that capture multiple empowerment outcomes. Given our context-dependent findings, effective empowerment strategies must be tailored to local social and incentive structures, with different approaches needed in different normative environments.

While our cross-sectional design and sample size limit causal inference, these findings contribute to reconceptualising empowerment as a fundamentally social and multidimensional process. Future longitudinal research across diverse contexts can build on these findings to establish causal mechanisms and develop more effective network-informed interventions that recognise women's agency as embedded within their social relationships. In the near future, the collaborative work planned in Uttar Pradesh, India and Nepal will test whether our findings generalise across different cultural and institutional settings, adding to the growing momentum in both academic research and policy practice toward recognising the social foundations of women's economic empowerment.

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Appendix A

Table A1: Variable Definitions and Conceptual Blocks

Variable	**Definition**	**Range / Unit**	**Conceptual Block**
EDMP	Economic Decision-Making Power index constructed using EFA-weighted domain scores from household decision-making responses (see Methods). Represents the influence one has in the economic decisions for their household. There is a maximum of 1 for your own household. If EDMP $>$ 1, you are involved in economic decisions in other households as well as your own	0 – 2	Outcome variable
FLFP	Female Labour Force Participation; indicator for whether the respondent was currently employed at the time of the survey (equals 1 if externally employed)	Binary {0, 1}	Outcome variable
Relative Education	Trichotomised bargaining indicator for a wife's categorical advantage in years of education attained. -1 indicates disadvantage (fewer years attained), 0 parity, 1 indicates advantage (more years attained)	{–1, 0, 1}	Bargaining Metrics

Continued on next page

Table A1 (continued). Variable Definitions and Conceptual Blocks

Variable	**Definition**	**Range / Unit**	**Conceptual Block**
Relative Employment Status	Trichotomised bargaining indicator for a wife's categorical advantage in employment status. -1 indicates disadvantage (wife is not employed while husband is), 0 (either both unemployed or employed), 1 (wife is employed but husband is now)	{–1, 0, 1}	Bargaining Metrics
Relative Age	Continuous bargaining indicator for a wife's advantage in age. Wife's age minus husband's age	-23 to 10 years	Bargaining Metrics
Relative Social Support Closeness	Trichotomised bargaining indicator for a wife's categorical advantage in social support closeness centrality. This can be interpreted as access to social support. Threshold for indicator is the sample mean -1 indicates disadvantage (difference between wife and husband in social support centrality is below the sample mean), 0 (differ between wife and husband is the sample mean), 1 indicates advantage (difference is above the sample mean)	{–1, 0, 1}	Bargaining Metrics
% Female in Support Network	Proportion of alters in wife's support network who are female	0 – 100%	Social Support Composition
% Different Caste in Support Network	Proportion of alters of a different caste than the wife	0 – 100%	Social Support Composition

Continued on next page

Table A1 (continued). Variable Definitions and Conceptual Blocks

Variable	Definition	Range / Unit	Conceptual Block
% Not Kin in Support Network	Proportion of alters who are not kin. Kin are defined as those with a kinship value >= 0.0625, equivalent to third-degree relatives	0 – 100%	Social Support Composition
Average Female Peer EDMP	Mean EDMP among female alters in wife's support network	0 – 1.68	Peer Effects
Average Female Peer FLFP	The percentage of female alters in wife's support network that work	0 – 100%	Peer Effects
Has Confidant	Indicator for whether the respondent reports having at least one confidant	Binary {0, 1}	Social Support Composition
Daily Cooking	Represents the influence one has in the daily cooking decisions for their household using the EDMP scoring method with a weight of 1 for the domain. If greater than 1, indicates they make this decision in more than one household	0 – 2	Household Decision-Making Controls
Child Illness	Represents the influence one has in the decisions regarding their child when they are ill for their household using the EDMP scoring method with a weight of 1 for the domain. If greater than 1, indicates they make this decision in more than one household	0 – 2	Household Decision-Making Controls

Continued on next page

Table A1 (continued). Variable Definitions and Conceptual Blocks

Variable	**Definition**	**Range / Unit**	**Conceptual Block**
Marriage of Children	Represents the influence one has in the decisions regarding who their children marry for their household using the EDMP scoring method with a weight of 1 for the domain. If greater than 1, indicates they make this decision in more than one household	0 – 2	Household Decision-Making Controls
Higher Education	Indicator for whether the respondent has completed education past secondary school	0/1	Demographic Controls
Working	Indicator for whether the respondent was working when the survey was conducted in 2022. Similar to FLFP but used as a control measure for EDMP models	Binary {0, 1}	Demographic Controls
Caste (SC)	Indicator for whether the respondent is a member of a scheduled caste	Binary {0, 1}	Demographic Controls
Native Village	Indicator for whether the respondent was born in the village they currently reside in	Binary {0, 1}	Demographic Controls
Village (Teṉpaṭṭi)	Indicator for residence in Teṉpaṭṭi (vs. Aḷakāpuram)	Binary {0, 1}	Demographic Controls
Age	Age of respondent in years	19 to 80 years	Demographic Controls

Notes: Variables constructed from household survey data (2022) in two villages in Tamil Nadu. Conceptual blocks match grouped categories in regression tables and equations. Binary variables are coded 1 if condition met, 0 otherwise. Percentages range from 0 to 100.

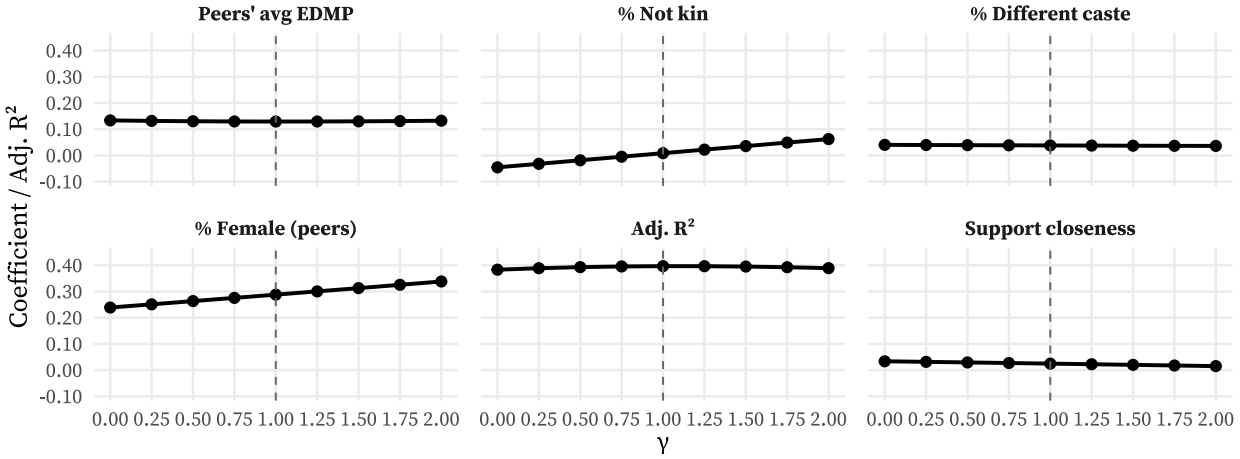

Figure A1: Robustness of coefficient estimates and adjusted R^2 across scaling parameter $\gamma \in [0, 2]$ for weighting of "top" decision-making bonus relative to base score for EDMP scoring. Each panel shows results for a given network composition measure or model fit statistic. Dashed vertical line indicates $\gamma = 1$, the baseline specification reported across models. Coefficients are plotted with a shared y-axis to facilitate comparison.

Table A2: Determinants of EDMP and FLFP Using Standardised Estimates

	EDMP (OLS) (1)	FLFP (Logit) (2)
Economic Decision-Making Power (EDMP)		0.073
		(0.089)
Bargaining Metrics (Wife – Husband)		
Education	0.030	-0.038
	(0.060)	(0.088)
Employment Status	-0.022	
	(0.183)	
Age	0.019	-0.029
	(0.034)	(0.042)
Social Support Closeness Centrality	0.071***	0.068
	(0.018)	(0.033)
Social Support Composition		
Percent Female	0.092*	-0.031
	(0.054)	(0.075)
Percent of Different Caste	0.022	0.026***
	(0.045)	(0.008)
Peer Norms (Female Friends)		
Average EDMP	0.098*	
	(0.106)	
Average FLFP		0.056**
		(0.026)
Other Household Decision-Making		
Daily Cooking	0.118**	-0.061
	(0.127)	(0.051)
Child Illness	0.373***	-0.026
	(0.008)	(0.034)
Marriage of Children	0.358***	-0.006
	(0.047)	(0.012)
Controls		
Higher Education	0.307	-0.175
	(0.190)	(0.091)
Working	0.230**	
	(0.097)	
Native Village	0.210***	-0.082
	(0.073)	(0.126)
Village (Teṉpaṭṭi)	−0.115***	-0.099**
	(0.025)	(0.082)
Constant	-0.184	
	(0.214)	
Adjusted R-squared	0.399	
Log Likelihood		-127.707
AIC		291.414

Notes: Column (1) reports standardised coefficients from OLS regressions for EDMP; Column (2) reports standardised marginal effects from logistic regressions for FLFP. N = 209 across both models. Standard errors are clustered by village, provided in parentheses. Additional controls include caste and age, which are not reported due to limited coefficients and p-values. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.001$.

Table A3: Determinants of FLFP by Village

	(1) Aḷakāpuram	(2) Teṉpaṭṭi
EDMP	−0.0737	0.4882***
	(0.1198)	(0.1587)
Bargaining Metrics (Wife – Husband)		
Education	−0.1248**	0.1519**
	(0.0566)	(0.0695)
Age	−0.0088	−0.0036
	(0.0140)	(0.0127)
Social Support Closeness Centrality	−0.0385	0.0686
	(0.0928)	(0.1068)
Social Support Composition		
Percent Female	0.8766**	−1.0733*
	(0.3538)	(0.5588)
Percent Different Caste	0.0682	0.1014
	(0.3325)	(0.2497)
Percent Not Kin	−0.8349**	0.0500
	(0.3844)	(0.3988)
Peer Norms (Female Friends)		
Average FLFP	0.2443*	0.0191
	(0.1283)	(0.1497)
Other Household Decision-Making		
Daily Cooking	−0.0201	−0.1589
	(0.0822)	(0.1102)
Child Illness	0.1449	−0.1104
	(0.0921)	(0.1261)
Marriage of Children	−0.0047	−0.0344
	(0.1010)	(0.1293)
Controls		
Higher Education	−0.0073	−0.4609*
	(0.1557)	(0.2609)
Caste (SC)	−0.0874	0.2921*
	(0.0982)	(0.1597)
Native Village	0.0795	−0.0958
	(0.1035)	(0.1275)
Wife's Age	0.0081*	−0.0003
	(0.0044)	(0.0059)
Observations	93	116
Log Likelihood	−53.305	−55.413
AIC	140.609	144.826

Notes: Values are village stratified logistic regression estimates, reporting marginal effects using robust standard effects, provided in parentheses. Column (1) displays results for Aḷakāpuram, while column (2) displays results for Teṉpaṭṭi. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.001$.

Table A4: Determinants of EDMP by Caste

	(1) Scheduled Caste	(2) Other Backward Class
Bargaining Metrics (Wife – Husband)		
Education	0.008	0.005
	(0.049)	(0.045)
Employment Status	−0.022	0.022
	(0.099)	(0.102)
Age	0.005	−0.0004
	(0.007)	(0.007)
Social Support Closeness Centrality	0.004	0.008
	(0.083)	(0.070)
Social Support Composition		
Percent Female	0.376	0.140
	(0.347)	(0.348)
Percent Different Caste	−0.132	0.133
	(0.167)	(0.156)
Percent Not Kin	−0.050	0.068
	(0.343)	(0.269)
Peer Norms (Female Friends)		
Average EDMP	0.077	0.152
	(0.133)	(0.112)
Other Household Decision-Making		
Daily Cooking	0.036	0.124
	(0.081)	(0.082)
Child Illness	0.264***	0.334***
	(0.079)	(0.070)
Marriage of Children	0.391***	0.229**
	(0.094)	(0.093)
Controls		
Higher Education	0.256*	0.055
	(0.149)	(0.091)
Working	0.090	0.060
	(0.111)	(0.112)
Village (Tenpaṭṭi)	−0.006	0.049
	(0.083)	(0.082)
Constant	−0.348	−0.203
	(0.471)	(0.417)
Observations	104	105
Adjusted R-squared	0.394	0.312

Notes: Values are OLS regression estimates stratified by caste, using robust standard errors, provided in parentheses. Column (1) displays results for Scheduled Castes, while column (2) displays results for Other Backward Classes. Additional controls include age and native village, which are not reported due to limited coefficients and p-values. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.001$.

Table A5: Determinants of FLFP by Caste

	(1) Scheduled Caste	(2) Other Backward Class
EDMP	0.112	0.212*
	(0.125)	(0.124)
Bargaining Metrics (Wife – Husband)		
Education	0.131**	0.087
	(0.063)	(0.058)
Age	−0.005	−0.013
	(0.012)	(0.013)
Social Support Closeness Centrality	0.081	0.091
	(0.101)	(0.101)
Social Support Composition		
Percent Female	0.656	−0.812*
	(0.416)	(0.480)
Percent Different Caste	0.380	−0.246
	(0.296)	(0.236)
Percent Not Kin	−0.577	0.384
	(0.392)	(0.470)
Peer Norms (Female Friends)		
Average FLFP	0.167	0.227
	(0.132)	(0.140)
Other Household Decision-Making		
Daily Cooking	0.053	−0.301***
	(0.086)	(0.093)
Child Illness	0. − 0.119	0.144
	(0.127)	(0.093)
Marriage of Children	0.096	−0.100
	(0.094)	(0.117)
Controls		
Higher Education	−0.051	−0.345
	(0.148)	(0.241)
Village (Tenpaṭṭi)	−0.103	−0.156
	(0.122)	(0.118)
Constant	0.382	1.186*
	(0.545)	(0.688)
Observations	104	105
Log Likelihood	−49.612	−58.278
AIC	133.224	150.556

Notes: Values are logistic regression estimates, reporting marginal effects, stratified by caste using robust standard errors, provided in parentheses. Column (1) displays results for Scheduled Castes, while column (2) displays results for Other Backward Classes. Additional controls include age and caste, which are not reported due to limited coefficients and p-values. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.001$.

Table A6: Determinants of EDMP and FLFP Including All Peers

	EDMP (OLS) (1)	FLFP (Logit) (2)
Economic Decision-Making Power (EDMP)		0.166
		(0.262)
Bargaining Metrics (Wife – Husband)		
Education	0.010	-0.020
	(0.015)	(0.122)
Employment Status	-0.007	
	(0.046)	
Age	0.001	-0.004
	(0.004)	(0.004)
Social Support Closeness Centrality	0.036*	0.080
	(0.022)	(0.066)
Social Support Composition		
Percent Female	0.261	0.118
	(0.208)	(0.886)
Percent of Different Caste	0.036	0.062
	(0.083)	(0.039)
Peer Norms (All Peers)		
Average EDMP	0.064	
	(0.265)	
Average FLFP		0.191
		(0.125)
Other Household Decision-Making		
Daily Cooking	0.089***	-0.073
	(0.033)	(0.067)
Child Illness	0.290***	-0.016
	(0.010)	(0.121)
Marriage of Children	0.316***	0.030
	(0.056)	(0.027)
Controls		
Higher Education	0.129	-0.243
	(0.092)	(0.184)
Working	0.076	
	(0.064)	
Native Village	0.080***	-0.021
	(0.015)	(0.102)
Village FE (Tenpaṭṭi)	−0.037***	−0.132**
	(0.005)	(0.067)
Constant	-0.257	0.647***
	(0.294)	(0.212)
Observations	209	209
Adjusted R-squared	0.388	
Log Likelihood		-128.367
AIC		292.473

Notes: Column (1) reports OLS coefficients for EDMP; Column (2) reports marginal effects from a logistic regression for FLFP. Peer norms are computed using all peers instead of strictly female peers as in the main regression. Robust standard errors clustered by village are included in parentheses. Additional controls include caste and age, which are not reported due to limited coefficients and p-values. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.001$.

Table A7: Determinants of EDMP and FLFP RSE Clustered by Individual

	EDMP (OLS) (1)	FLFP (Logit) (2)
Economic Decision-Making Power (EDMP)		0.159
		(0.102)
Bargaining Metrics (Wife – Husband)		
Education	0.011	-0.020
	(0.030)	(0.042)
Employment Status	-0.002	
	(0.064)	
Age	0.001	-0.005
	(0.005)	(0.009)
Social Support Closeness Centrality	0.026	0.081
	(0.047)	(0.071)
Social Support Composition		
Percent Female	0.286	0.093
	(0.208)	(0.310)
Percent of Different Caste	0.038	0.079
	(0.106)	(0.188)
Peer Norms (Female Friends)		
Average EDMP	0.135*	
	(0.082)	
Average FLFP		0.193*
		(0.099)
Other Household Decision-Making		
Daily Cooking	0.087	-0.069
	(0.055)	(0.071)
Child Illness	0.293***	-0.005
	(0.049)	(0.078)
Marriage of Children	0.307***	0.021
	(0.060)	(0.084)
Controls		
Higher Education	0.142**	-0.208
	(0.071)	(0.146)
Working	0.065	
	(0.071)	
Native Village	0.081	-0.006
	(0.052)	(0.081)
Village (Tenpaṭṭi)	-0.046	-0.119
	(0.055)	(0.083)
Constant	-0.251	0.603
	(0.253)	(0.450)
Observations	209	209
Adjusted R-squared	0.398	
Log Likelihood		-127.707
AIC		291.414

Notes: Column (1) reports OLS coefficients predicting EDMP; Column (2) reports marginal effects from logistic regressions predicting FLFP. Standard errors are clustered by individual and appear in parentheses. Results include village fixed effects. Additional controls include caste and age, which are not reported due to limited coefficients and p-values. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.001$.

Table A8: Determinants of EDMP and FLFP Using Wife Only Respondents

	EDMP (OLS) (1)	FLFP (Logit) (2)
Economic Decision-Making Power (EDMP)		0.146
		(0.248)
Bargaining Metrics (Wife – Husband)		
Education	0.015	-0.015
	(0.021)	(0.116)
Employment Status	0.011	
	(0.056)	
Age	0.002	-0.004
	(0.004)	(0.003)
Social Support Closeness Centrality	0.030***	0.082*
	(0.003)	(0.042)
Social Support Composition		
Percent Female	0.277*	0.136
	(0.161)	(0.845)
Percent of Different Caste	0.052	0.088***
	(0.065)	(0.016)
Peer Norms (Female Friends)		
Average EDMP	0.134	
	(0.138)	
Average FLFP		0.123
		(0.110)
Other Household Decision-Making		
Daily Cooking	0.058	-0.074
	(0.066)	(0.052)
Child Illness	0.304***	-0.0001
	(0.006)	(0.110)
Marriage of Children	0.285***	0.029
	(0.038)	(0.021)
Controls		
Higher Education	0.138*	-0.252*
	(0.079)	(0.134)
Working	0.054	
	(0.040)	
Native Village	0.064*	-0.018
	(0.034)	(0.115)
Village FE (Tenpaṭṭi)	-0.052***	-0.146***
	(0.009)	(0.068)
Constant	-0.204	0.616**
	(0.275)	(0.217)
Observations	209	209
Adjusted R-squared	0.382	
Log Likelihood		-129.169
AIC		293.276

Notes: Column (1) reports OLS coefficients predicting EDMP; Column (2) reports marginal effects from logistic regressions predicting FLFP. Robust standard errors clustered by village are in parentheses. EDMP scores are calculated only from wife-respondent surveys. Results are robust to main results with larger sample. Additional controls include caste and age, which are not reported due to limited coefficients and p-values. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.001$.

Table A9: Determinants of EDMP Using Equal EFA Weighting

	(1) EDMP - Equal Weights
Bargaining Metrics (Wife – Husband)	
Education	0.019
	(0.019)
Employment Status	0.001
	(0.055)
Age	0.003
	(0.005)
Social Support Closeness Centrality	0.026***
	(0.007)
Social Support Composition	
Percent Female	0.299*
	(0.114)
Percent of Different Caste	−0.026
	(0.345)
Peer Norms (Female Friends)	
Average EDMP	0.143
	(0.114)
Other Household Decision-Making	
Daily Cooking	0.051
	(0.065)
Child Illness	0.303***
	(0.005)
Marriage of Children	0.288***
	(0.042)
Controls	
Higher Education	0.136*
	(0.076)
Working	0.062
	(0.038)
Native Village	0.053
	(0.041)
Village Fixed Effect (Teṉpaṭṭi)	−0.052***
	(0.010)
Constant	−0.192
	(0.273)
Observations	209
Adjusted R-squared	0.385

Notes: Coefficient estimates are from OLS regressions with village fixed effects and robust standard errors clustered by village. EDMP scores calculated using equal weights across domains instead of EFA determined weights. Results do not differ largely from EFA weights. Additional controls include age and caste, which are not reported due to limited coefficients and p-values. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.001$.

Table A10: Determinants of EDMP Using Alternative Scoring

	(1) Binary	(2) Base Only	(3) Top Only
Bargaining Metrics (Wife – Husband)			
Education	0.035***	−0.035	0.043*
	(0.008)	(0.045)	(0.025)
Employment Status	0.019	0.058	−0.075
	(0.027)	(0.076)	(0.103)
Social Support Closeness Centrality	0.045***	0.053***	−0.025
	(0.006)	(0.007)	(0.024)
Social Support Composition			
Percent Female	0.120	0.222	0.505
	(0.393)	(0.292)	(0.405)
Percent Different Caste	0.079***	0.020	0.049
	(0.026)	(0.087)	(0.129)
Percent Not Kin	−0.075	0.237	−0.280
	(0.341)	(0.172)	(0.321)
Peer Norms (Female Friends)			
Average EDMP	0.134***	0.078	0.210*
	(0.042)	(0.324)	(0.118)
Other Household Decision-Making			
Daily Cooking	0.036*	0.194***	0.003
	(0.019)	(0.025)	(0.088)
Child Illness	0.259***	0.314***	0.293***
	(0.043)	(0.014)	(0.037)
Marriage of Children	0.260***	0.317***	0.349***
	(0.082)	(0.014)	(0.042)
Controls			
Higher Education	0.072***	0.200*	0.099
	(0.024)	(0.117)	(0.064)
Working	0.073***	0.005	0.119***
	(0.025)	(0.090)	(0.036)
Caste (SC)	0.014**	0.011	−0.017
	(0.007)	(0.038)	(0.094)
Village (Tenpaṭṭi)	−0.080***	−0.036***	−0.024**
	(0.012)	(0.011)	(0.012)
Constant	−0.051	−0.544**	0.112
	(0.293)	(0.262)	(0.092)
Adjusted R-squared	0.332	0.397	0.249

Notes: OLS regression estimates using alternative EDMP scoring and weights for robustness checks. Robust standard errors in parentheses, using clustering by village. N = 209 across both models. Additional controls include age and native village, which are not reported due to limited coefficients and p-values. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.001$.

Table A11: Determinants of EDMP by Dimension

	(1) Land	(2) Expensive Items	(3) Functions
Bargaining Metrics (Wife – Husband)			
Education	0.012	0.019*	−0.020*
	(0.014)	(0.012)	(0.011)
Employment Status	−0.003	−0.014	0.022
	(0.078)	(0.055)	(0.019)
Age	−0.001	0.001	0.002**
	(0.004)	(0.004)	(0.001)
Social Support Closeness Centrality	0.029	0.034**	−0.010***
	(0.023)	(0.013)	(0.003)
Social Support Composition			
Percent Female	0.121	0.075	0.422**
	(0.112)	(0.099)	(0.165)
Percent Different Caste	0.014	−0.013	0.101**
	(0.117)	(0.079)	(0.048)
Percent Not Kin	0.053	−0.119	0.223
	(0.152)	(0.244)	(0.171)
Peer Norms (Female Friends)			
Average EDMP	0.131	0.127***	0.0003
	(0.193)	(0.022)	(0.246)
Other Household Decision-Making			
Daily Cooking	0.038*	0.101***	−0.021
	(0.019)	(0.023)	(0.035)
Child Illness	0.260***	0.187***	0.212***
	(0.043)	(0.024)	(0.051)
Marriage of Children	0.292***	0.183***	0.258***
	(0.037)	(0.044)	(0.015)
Controls			
Higher Education	0.122**	0.082**	0.101
	(0.061)	(0.036)	(0.096)
Working	0.076	0.040***	0.056
	(0.059)	(0.012)	(0.098)
Village (Teṉpaṭṭi)	−0.039***	−0.039*	0.002
	(0.010)	(0.021)	(0.013)
Constant	−0.144*	−0.025	−0.418*
	(0.079)	(0.180)	(0.232)
Adjusted R-squared	0.221	0.297	0.268

Notes: OLS regression estimates for each domain of the EDMP index. Robust standard errors in parentheses, using clustering by village. N = 209 across all models. Additional controls include age, and native village, which are not reported due to limited coefficients and p-values. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.001$.

Table A12: Determinants of EDMP Using Alternative Social Capital Measures

	(1) EDMP	(2) EDMP
Bargaining Metrics (Wife – Husband)		
Education	0.009	0.010
	(0.022)	(0.022)
Employment Status	0.006	−0.0004
	(0.045)	(0.053)
Age	0.002	0.001
	(0.003)	(0.004)
PageRank	0.064	
	(0.087)	
Degree		0.029
		(0.036)
Social Support Composition		
Percent Female	0.285***	0.290**
	(0.098)	(0.127)
Percent Different Caste	0.040	0.047
	(0.103)	(0.114)
Percent Not Kin	0.043	0.007
	(0.262)	(0.315)
Peer Norms (Female Friends)		
Average EDMP	0.156	0.133
	(0.119)	(0.157)
Other Household Decision-Making		
Daily Cooking	0.093**	0.090**
	(0.043)	(0.041)
Child Illness	0.297***	0.294***
	(0.008)	(0.011)
Marriage of Children	0.292***	0.301***
	(0.058)	(0.050)
Controls		
Higher Education	0.167***	0.145*
	(0.044)	(0.076)
Working	0.055	0.060
	(0.064)	(0.060)
Village (Tenpaṭṭi)	−0.050**	−0.045***
	(0.022)	(0.013)
Constant	−0.310	−0.261
	(0.201)	(0.250)
Adjusted R-squared	0.401	0.396

Notes: OLS regression estimates using alternative social capital metrics. Robust standard errors in parentheses, clustering by village. N = 209 across both models. Additional controls include age, caste, and native village, which are not reported due to limited coefficients and p-values. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.001$.

Table A13: Determinants of EDMP and FLFP Using Continuous Indicators

	EDMP (OLS) (1)	FLFP (Logit) (2)
EDMP		0.171*
		(0.101)
Bargaining Metrics (Wife – Husband)		
Education	0.005***	-0.009
	(0.002)	(0.009)
Employment Status	-0.006	
	(0.061)	
Age Difference	0.001	-0.005
	(0.005)	(0.009)
Social Support Closeness Centrality	-392.128	2,113.683
	(2,741.081)	(4,096.295)
Social Support Composition		
% Female in Network	0.290**	0.153
	(0.114)	(0.313)
% Different Caste in Network	0.043	0.061
	(0.090)	(0.188)
Peer Norms		
Average EDMP	0.145	
	(0.157)	
Average FLFP		0.198**
		(0.100)
Other Household Decision-Making		
Daily Cooking	0.091**	-0.068
	(0.041)	(0.070)
Child Illness	0.295***	-0.0002
	(0.015)	(0.077)
Marriage of Children	0.305***	0.011
	(0.048)	(0.084)
Controls		
Higher Education	0.127*	-0.198
	(0.067)	(0.146)
Working	0.074	
	(0.045)	
Caste (SC)	0.011	-0.005
	(0.040)	(0.081)
Village (Tenpaṭṭi)	-0.044***	-0.110
	(0.017)	(0.084)
Native Village	0.082	0.004
	(0.053)	(0.085)
Constant	-0.265	0.572
	(0.309)	(0.458)
Adjusted R-squared	0.397	–
Log Likelihood	–	-127.629
AIC	–	291.259

Notes: Column (1) reports OLS estimates predicting EDMP; Column (2) reports marginal effects from logistic regressions predicting FLFP, using continuous variables for bargaining, network, and peer effects. Robust standard errors clustered by village are in parentheses. N = 209 across both models. Additional controls include caste, which is not reported due to limited coefficients and p-values. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.001$.

Table A14: Sequential Model Building Controls for EDMP

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Controls									
Age	0.003	0.003	0.003	0.002	0.001	0.0004	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Caste (SC)		0.055	0.046	0.044	0.047	0.046	0.050	0.050	0.045
		(0.055)	(0.063)	(0.063)	(0.062)	(0.063)	(0.064)	(0.064)	(0.064)
Village (Tenpaṭṭi)			-0.017	0.0002	-0.0004	0.009	0.012	0.009	0.006
			(0.064)	(0.064)	(0.064)	(0.064)	(0.065)	(0.065)	(0.065)
Working				0.135**	0.129**	0.126**	0.129**	0.133**	0.121**
				(0.059)	(0.060)	(0.059)	(0.060)	(0.060)	(0.061)
Higher Education					-0.058	-0.060	-0.076	-0.096	-0.043
					(0.098)	(0.098)	(0.101)	(0.110)	(0.117)
Native Village						0.114*	0.111*	0.109	0.104
						(0.067)	(0.067)	(0.068)	(0.068)
# Children							-0.017	-0.016	-0.018
							(0.029)	(0.029)	(0.029)
Marriage Age								0.004	0.004
								(0.007)	(0.007)
Love Marriage									0.187
									(0.137)
Constant	0.251**	0.223**	0.230**	0.201*	0.239*	0.235*	0.229*	0.158	0.017
	(0.106)	(0.110)	(0.114)	(0.113)	(0.131)	(0.130)	(0.131)	(0.178)	(0.205)
Observations	209	209	209	209	209	209	209	207	207
R-squared	0.007	0.012	0.012	0.038	0.039	0.053	0.055	0.056	0.065
Adjusted R-squared	0.003	0.003	-0.002	0.019	0.016	0.025	0.022	0.018	0.018

Notes: Variables reflect coefficients from OLS regressions of EDMP while progressively added control variables. Models (1)–(9) add controls sequentially to identify the set of variables to be included in final theoretical models. Final set of controls are displayed in (6), where R^2 is the largest. Standard errors clustered at the village level in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.001$.

Table A15: EDMP Sequential Model Building Final Controls & Theoretical Blocks

	(1)	(2)	(3)	(4)	(5)
Controls					
Age	0.0005	-0.0003	0.001	0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
Working	0.129**	0.063	0.053	0.040	0.069
	(0.058)	(0.089)	(0.090)	(0.090)	(0.072)
Higher Education	-0.055	-0.019	0.007	0.034	0.147*
	(0.097)	(0.101)	(0.103)	(0.105)	(0.085)
Native Village	0.116*	0.118*	0.131*	0.125*	0.088
	(0.066)	(0.068)	(0.072)	(0.072)	(0.057)
Bargaining Metrics					
Education Diff.		-0.003	-0.010	-0.007	0.007
		(0.034)	(0.034)	(0.034)	(0.027)
Employment Diff.		0.067	0.074	0.082	0.001
		(0.081)	(0.082)	(0.083)	(0.066)
Age Diff.		-0.006	-0.005	-0.005	0.002
		(0.007)	(0.007)	(0.007)	(0.006)
Closeness Diff.		0.095*	0.073	0.058	0.021
		(0.057)	(0.058)	(0.058)	(0.047)
Composition					
Percent Female			0.429	0.460*	0.317
			(0.262)	(0.262)	(0.208)
Percent Diff. Caste			0.058	0.061	0.003
			(0.127)	(0.127)	(0.100)
Percent Not Kin			0.145	0.139	0.038
			(0.246)	(0.245)	(0.194)
Peer Norms					
Avg. EDMP (Female Peers)				0.174*	0.123
				(0.101)	(0.080)
Decision-Making					
Daily Cooking					0.081*
					(0.046)
Child Illness					0.292***
					(0.049)
Marriage of Children					0.310***
					(0.054)
Constant	0.256**	0.266	-0.131	-0.156	-0.298
	(0.124)	(0.177)	(0.329)	(0.359)	(0.286)
R-squared	0.050	0.069	0.084	0.098	0.446
Adjusted R-squared	0.031	0.031	0.033	0.038	0.400

Notes: Variables reflect coefficients from OLS regressions of EDMP with controls determined from Table A14 (displaying only a set of controls due to space constraints), followed by the sequential addition of theoretical blocks: (2) bargaining metrics, (3) network composition, (4) peer norms, and (5) other decision-making domains. Each model builds on the previous to assess the incremental contribution of each block. N = 209 across all models. Standard errors clustered at the village level in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.001$.

Table A16: EDMP Theoretical Blocks with Clustered SEs

	(1)	(2)	(3)	(4)	(5)	(6)
Bargaining Metrics (Wife - Husband)						
Education	-0.014	-0.008				
	(0.017)	(0.030)				
Employment	0.115*	0.109**				
	(0.063)	(0.055)				
Age Difference	-0.004	-0.004				
	(0.008)	(0.009)				
Social Support Closeness Centrality		0.112***				
		(0.041)				
Network Composition						
Percent Female			0.586***			
			(0.145)			
Percent Different Caste			0.038***			
			(0.015)			
Percent Not Kin			-0.086			
			(0.198)			
Peer Norms (Female Friends)						
Average EDMP				0.225		
				(0.168)		
Other Decision-Making Domains						
Daily Cooking					0.075*	
					(0.039)	
Child Illness					0.284***	
					(0.010)	
Marriage of Children					0.336***	
					(0.070)	
Controls						
Scheduled Caste						0.047**
						(0.023)
Village (Teṉpaṭṭi)						0.011***
						(0.002)
Working						0.128*
						(0.077)
Higher Education						-0.070
						(0.064)
Native Village						0.116
						(0.073)
Age						-0.00000
						(0.00000)
Constant	0.379***	0.321***	0.133	0.343***	0.025	0.257***
	(0.044)	(0.024)	(0.111)	(0.065)	(0.030)	(0.047)
R^2	0.031	0.051	0.026	0.026	0.406	0.053
Adjusted R-squared	0.017	0.032	0.011	0.016	0.398	0.025

Notes: Variables reflect coefficients from OLS regressions of EDMP testing each theoretical block independently, without the sequential build-up. Columns (1)–(6) show the effect of each block on EDMP when entered separately, allowing for comparison of explanatory power across blocks. N = 209 across all models. Standard errors clustered at the village level in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.001$.

Table A17: FLFP Theoretical Blocks with Clustered SEs

	(1)	(2)	(3)	(4)	(5)	(6)
EDMP Index	0.975	0.887				
	(0.693)	(0.661)				
Bargaining Metrics (Wife - Husband)						
Education	-0.266	-0.242				
	(0.557)	(0.494)				
Age	-0.013	-0.015				
	(0.029)	(0.035)				
Social Support Closeness Centrality		0.528***				
		(0.107)				
Network Composition						
Percent Female			1.903			
			(3.050)			
Percent Different Caste			-0.206			
			(0.195)			
Percent Not Kin			-1.382			
			(3.834)			
Peer Norms (Female Friends)						
Average FLFP				1.415***		
				(0.328)		
Other Decision-Making Domains						
Daily Cooking					-0.097	
					(0.368)	
Child Illness					0.292***	
					(0.106)	
Marriage of Children					0.590**	
					(0.277)	
Controls						
Scheduled Caste						0.142
						(0.540)
Village (Teṉpaṭṭi)						-0.523*
						(0.293)
Higher Education						-1.444***
						(0.254)
Native Village						0.203
						(0.674)
Age						0.0002
						(0.0003)
Constant	0.096	-0.134	0.812	0.693	0.215***	0.426
	(0.292)	(0.244)	(1.988)		(0.034)	(0.336)
Log Likelihood	-133.290	-131.717	-136.228	-131.913	-135.361	-128.885
Akaike Inf. Crit.	274.580	273.434	280.457	269.825	278.723	269.771

Notes: Variables reflect coefficients from logistic regressions of FLFP testing each theoretical block independently. Columns (1)–(6) correspond to EDMP index, bargaining metrics, network composition, peer norms, other decision-making domains, and controls, respectively. Models are not sequentially built but estimate the contribution of each block on its own. N = 209 across all models. Standard errors clustered at the village level in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.001$.

Appendix B - Supplemental Materials

Household Decision-Making Survey

FamID: _____

In the last two months…	Never	Rarely	Sometimes	Often
Have your family members eaten a smaller meal than you felt you needed?				
Have your family members eaten fewer meals in a day?				
Have your family members had no food of any kind to eat in your household at least once?				
Have your family members gone to sleep at night hungry?				
Have your family members gone a whole day and night without eating?				

Who makes the decisions in your household for the following:

	Wife	Husband	Senior male	Senior female	Others	Not applicable; no one		Most say
What to cook on a daily basis							⇨	
Whether to buy an expensive item such as a TV or fridge							⇨	
How many children you have							⇨	
What to do if you fall sick							⇨	
Whether to buy land or property							⇨	
How much money to spend on a social function such as marriage							⇨	
What to do if a child falls sick							⇨	
To whom your children should marry							⇨	

(code all responses that are given; if more than one response ask, "Who has the most say in the decision?")

Social Network Survey

IndivID: __ __ __ __ __ Interviewer: _____ தேதி: __/__/___

சமூகம் சார்ந்த கணக்கெடுப்பு

1. If you had an unexpected emergency expense, such as a hospital medical treatment, from whom could you get a loan of 2000 Rs [a weeks wages] or more?

Name	IndivID	M/F	Age	Location	Relation	Work	Caste	Fridge	Vehicle	High Position

2. In the event of an unexpected emergency expense, such as a hospital medical treatment, who would come ask you for a loan of 2000 Rs or more?

Name	IndivID	M/F	Age	Location	Relation	Work	Caste	Fridge	Vehicle	High Position

3. For your basic essentials such as rice, sugar, oil and other groceries and household needs, who could you immediately ask and get?

Name	IndivID	M/F	Age	Location	Relation	Work	Caste	Fridge	Vehicle	High Position

4. For their basic essentials such as rice, sugar, oil and other groceries and household needs, who could immediately ask and get from you?

Name	IndivID	M/F	Age	Location	Relation	Work	Caste	Fridge	Vehicle	High Position

5. For you and/or the other women in your household, who happily helps you with tasks [question in Tamil implies physical assistance]

Name	IndivID	M/F	Age	Location	Relation	Work	Caste	Fridge	Vehicle	High Position

6. For you and/or the other men in your household, who happily helps you with tasks [question in Tamil implies physical assistance]

Name	IndivID	M/F	Age	Location	Relation	Work	Caste	Fridge	Vehicle	High Position

7. For you and/or the other women in your household, who do you happily and casually have conversations with?

Name	IndivID	M/F	Age	Location	Relation	Work	Caste	Fridge	Vehicle	High Position

8. For you and/or the other men in your household, who do you happily and casually have conversations with?

Name	IndivID	M/F	Age	Location	Relation	Work	Caste	Fridge	Vehicle	High Position

9. Among those you know very well, who are those of high office, important people, government or NGO employees of high position? For example those in the police department, in politics, or working as a lawyer?

Name	IndivID	M/F	Age	Location	Relation	Work	Caste	Fridge	Vehicle	High Position

10. Who are the people in Madurai, Chennai, or other outside or overseas places who could get things done for you?

Name	IndivID	M/F	Age	Location	Relation	Work	Caste	Fridge	Vehicle	High Position

11. If you wanted to discuss important and confidential matters, who would you talk to?

Name	IndivID	M/F	Age	Location	Relation	Work	Caste	Fridge	Vehicle	High Position

12. If you needed more or new wage work or a salaried job, who could you ask for help finding it?

Name	IndivID	M/F	Age	Location	Relation	Work	Caste	Fridge	Vehicle	High Position

13. In this village, who is the person with a generous disposition?

Name	IndivID

14. In this village, if some problem happens, who is the person to resolve it? Who has the influence and authority?

Name	IndivID

15. In this village, who do you think is the person with a lot of devotion (bhakti)?

Name	IndivID

16. If you had a sudden need, from whom could you immediately borrow 400 INR?

Name	IndivID	M/F	Age	Location	Relation	Work	Caste	Fridge	Vehicle	High Position

17. Who would borrow 400 INR from you, for a sudden need?

Name	IndivID	M/F	Age	Location	Relation	Work	Caste	Fridge	Vehicle	High Position