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Remittance networks fuel cryptic commercial transition in small-scale fisheries

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Remittance networks fuel cryptic commercial transition in small-scale fisheries

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Abstract:

Remittances inject huge sums of external capital into rural, subsistence economies globally, yet longitudinal evidence on how remittances reshape food production is exceptionally rare. Using complete remittance and fish-sharing networks from a Papua New Guinean island from 2018–2026, we quantified how off-island capital propagated through the entire community. External capital facilitated transitions to commercialized fisheries extraction and sale, revealing how remittances can cryptically but meaningfully transform rural food systems.

Main

Remittances are transfers of money, often from family members who have emigrated, which are surging under global labor migration and increasing access to mobile banking. Remittance flows to low- and middle-income countries now exceed US$700 billion annually; more than three times all public development funding[1]. These growing transfers can reconfigure natural resource use both among recipient households and among the broader networks of households with whom resources are subsequently shared. Illustratively, de Lange et al.[2] estimate that direct, unconditional cash transfers sufficient to offset households' income from biodiversity exploitation in low- and middle-income countries would cost approximately US$478 billion annually—much less than current remittance flows. In some countries, remittances exceed these estimated costs by many times. For example, in Papua New Guinea, offsetting nature loss in 2019 was estimated to cost between US$200,000 and US$4.5 million, whereas personal remittances totaled US$29 million in the same year[1,2].

Despite their transformative potential, we know remarkably little about how remittances affect subsistence livelihoods and how their effects propagate through communities over time[3,4]. Some evidence suggests that in rural economies most environmental damages happen during seasonal periods of low income and food insecurity[5]. This implies that remittances can buffer natural resources by decoupling immediate household needs from environmental exploitation, consistent with evidence of reduced deforestation following out-migration and remittance receipt in Nepal and China[6,7]. Yet in contrast, these Nepali households were also less likely to participate in community forestry management, and in Vietnam, wealthier households invested remittances into environmentally extractive technologies[8,9]. These contrasting effects suggest that remittance flows can simultaneously relieve and intensify pressure on natural resources, complicating efforts to measure and achieve progress toward sustainability.

Understanding these dynamics requires repeated observations of whole communities. Here, we present panel data linking changes in directed household remittance networks to changes in the commercialization of fishing practices on a small coral atoll island of 1,251 people in Papua New Guinea from 2018–2026. Because the island covers just 0.3 km² (Figure 1A), we were able to trace the evolution of the complete remittance network through time and differentiate between individuals living internally (on-island) versus those living externally (off-island) in each sampling period. Residents of the island rely predominantly on fishing, with very few opportunities for livelihood substitution[10]. This setting therefore provides a rare, whole-system

and minimally confounded microcosm of how growing remittance flows are associated with changes in subsistence food production (Figure 1B–D).

We used a series of panel regressions to assess changes in households' market commercialization (i.e., where they sell their catch), fishing gear commercialization (e.g., net type), non-gear asset commercialization (e.g., whether they have access to a motorboat or a fish freezer), and commercial share of catch (i.e., proportion of catch they sell versus consume). While greater commercialization can indicate that fishers more intensively extract and profit from fragile coral reef fisheries, it can also indicate greater access to expansive pelagic fisheries (see [10]), potentially decreasing pressure on the reef while supporting household wellbeing. We explore this dynamic by quantifying the secondary associations with food insecurity and fish sharing. Together, these analyses examine how external capital propagates through remittance networks to reorganize rural food production systems.

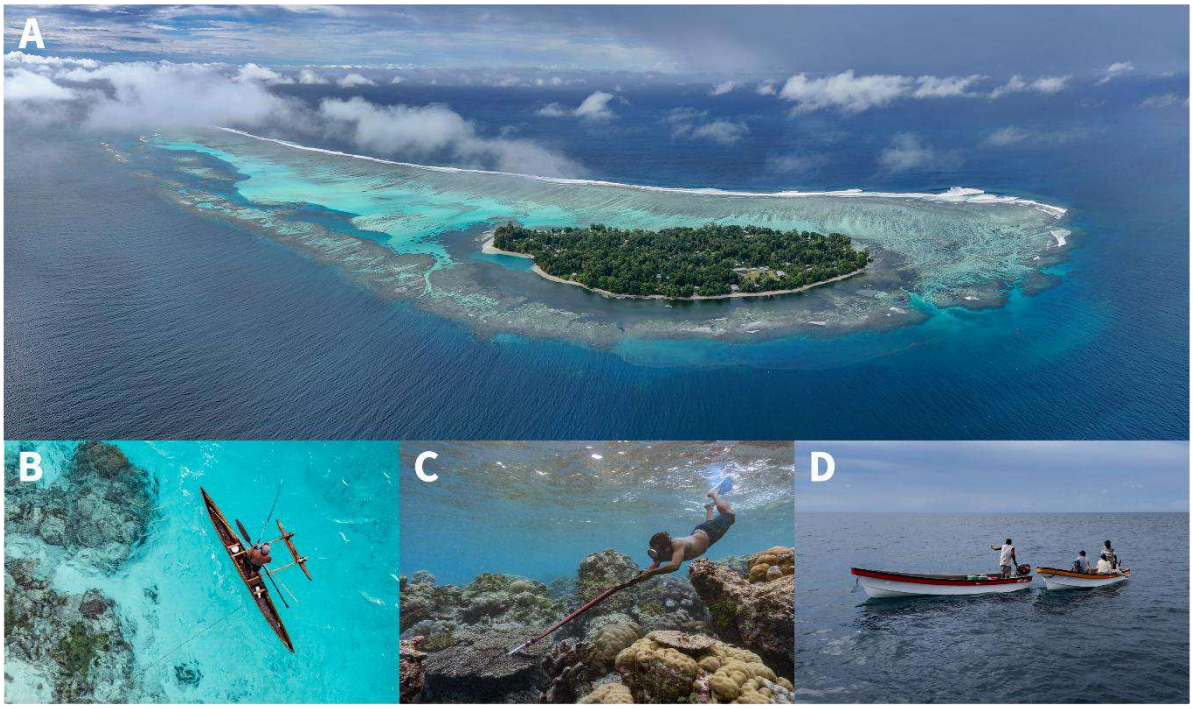

Figure 1: Study system. Panel A shows the 0.3km^2 island in Papua New Guinea where data were collected, including the surrounding coral reef lagoon. Panels B–D show increasing commercialization of fishing practices: near-shore line fishing from a canoe (B), reef spear fishing (C), and motorboat trolling outside the reef for pelagic fishes (D).

Consistent with global remittance trends[1], our data show that average number of people from whom households could request one week's wages in a time of need increased by 53% between 2018 and 2026 (Figure 2A), and 93% of households reported receiving remittances in at least one sampling period. Although the average proportion of internal versus external remittance sources across all households remained stable, there was substantial change in this measure from household to household, including households with sources that changed from fully internal to fully external, and vice versa. Similarly, commercialization indices showed little change on average but varied substantially within households over time (Figure 2B). We also

observed no expansion of livelihood options, with 68.5% of households relying on marine products for their primary livelihood in 2018 and 69.4% in 2026.

To understand how external capital propagated through the community, we first quantified how changes in households' positions within the evolving remittance network were associated with changes in fishing commercialization. We identified two complementary pathways. First, households that directly gained additional external (off-island) remittance sources reliably increased market and gear commercialization (Figure 2C–D). Practically, this means that between 2018 and 2026, households who increased their access to external sources of remittances were likely to simultaneously increase their extractive potential and increase fish sales to provincial markets and fish traders, as opposed to selling fish locally. Second, households that became more central (measured with betweenness centrality; i.e., how often they sit on the shortest path between two other households) in the largely internal remittance network increased their access to commercial fishing assets and the share of catch they reported selling to markets, instead of consuming themselves (Figure 2C–D). This suggests that the restructuring of the internal financial network also had meaningful implications for households' relationships with nature.

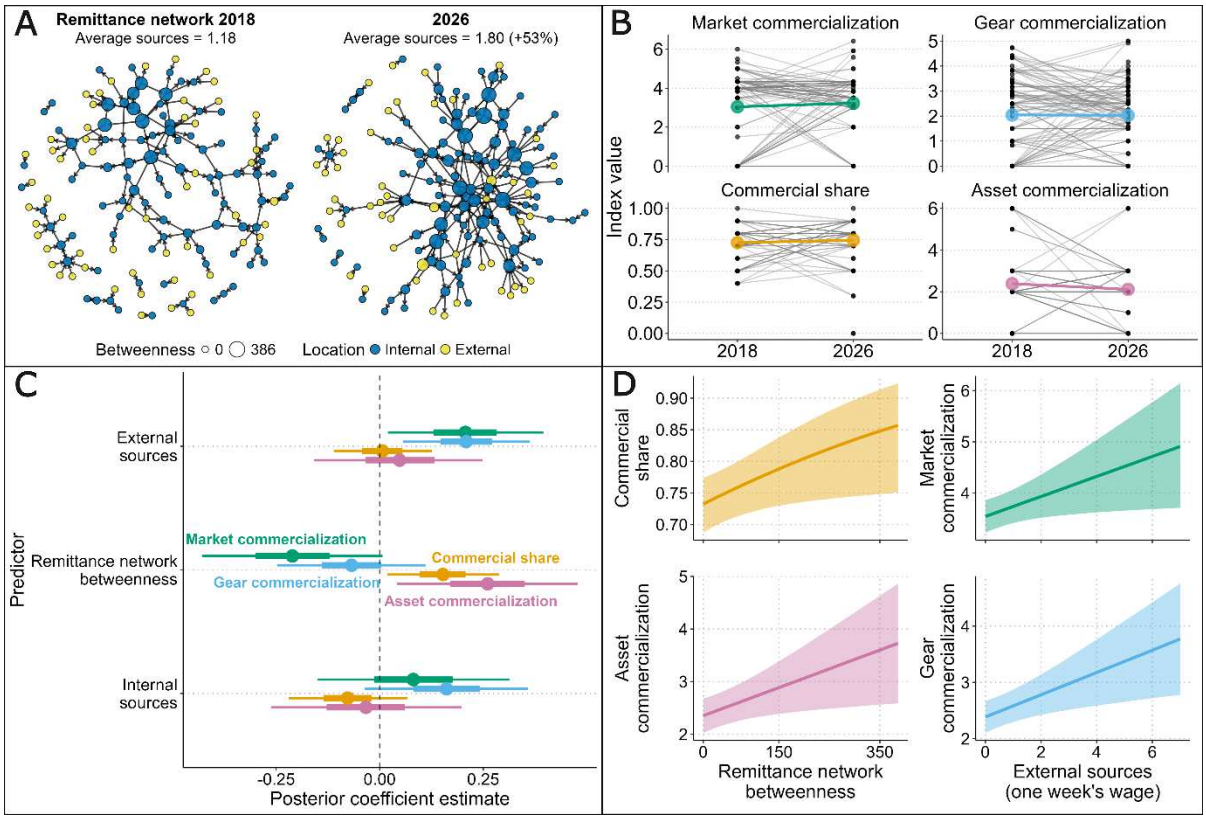

Figure 2: Descriptive (A–B) and statistical (C–D) results. Panel A shows the directed remittance network in 2018 and 2026. Arrows indicate remittance direction. Node color and size represent household location and network betweenness, respectively. Panel B shows household-level changes in indices of market commercialization, gear commercialization, commercial share, and non-gear asset commercialization. Black points and lines show household values; colored points and lines show means. Panel C shows relationships between the remittance network and the primary outcomes. Points show median posterior parameter estimates, thick and thin bars show the inner 50% and 90% of posterior estimates. Panel D

shows the credible conditional expectations from panel C. Lines show median estimates and shading shows the inner 90% of posterior estimates.

Finally, we assessed whether there were credible associations between changes in households' remittance access or fishing commercialization and their food security or fish sharing (measured as their out-degree in the directed sharing network). This analysis showed null effects across all measured relationships aside from remittance network betweenness and fish sharing, likely indicative of general social network position (*Supplementary Figure S1)*. These null effects indicate that while increasing remittance access, particularly from external sources, was associated with increased commercialization of fishing practices, these changes are not translated into changes in food security for focal households nor those in their network.

Because our measure of gear commercialization is highly associated (cor = 0.81) with a focus on pelagic fishing (*Supplementary Methods 1*), these null effects can also be interpreted as showing a transition to more environmentally sustainable fishing without compromising household wellbeing. This is consistent with remittance-based development following an environmental Kuznets curve as seen in country-level aggregate data from across Africa[12] and cross-sectional case studies in Latin America[13]. Hence, fishing commercialization in this case is not clearly good or bad for the coral reef fishery but instead represents a social-ecological transition away from subsistence production. These findings reinforce evidence that sustainability interventions and external capital operate through existing social structures rather than acting on households in isolation[14,15].

Notably, this transition was detectable only through within-household panel observation. At the community level, aggregate measures of fishing practices changed little over the study period (Figure 2B), obscuring the gradual reorganization occurring within households as external remittance access expanded. Had our analyses relied on repeated cross-sectional or community-level observations alone, we would have concluded that little had changed. This demonstrates that growing remittance access can confound evaluations of conservation and climate adaptation interventions by independently reshaping livelihoods, thereby masking or mimicking their effects.

It is important to highlight that while the simple system we study offers advantages in isolating our dynamics of interest and is likely emblematic of many rural economies around the world, it is unique in several ways, potentially limiting the external validity of our findings. Specifically, the coral reef fishery in this system is highly depleted and options for livelihood diversification are extremely limited, pushing fishers toward intensification[10,16]. Increased extraction in this instance is also associated with targeting more sustainable pelagic fish stocks, which may itself be driven by depletion of the coral reef fishery. Moreover, the island's population is relatively well educated, increasing options for worker mobility. Future empirical and theoretical work can build on this foundation to incorporate more complicated dynamics such as livelihood substitution, changing environmental conditions, or competition over resources[17].

In conclusion, the past decade has brought dramatic increases in workers' mobility and ability to send wages back home[18]. These trends are expected to continue in the coming years,

warranting scrutiny of their impacts on people and nature. In this study, we present highly detailed evidence from an entire subsistence food production system, showing that off-island capital facilitated natural resource extraction and export through both direct and indirect pathways. These trends are consistent with a social-ecological transition toward commercial, but possibly more sustainable, production. More broadly, our findings reveal mechanisms through which global economic trends can quietly reshape rural food systems in ways that are both far-reaching and difficult to detect.

Methods

We conducted a household survey in 2018 and 2026, attempting to census each of approximately 120 households on the island using the methodology of Barnes et al.[9] (*Supplementary Methods 2-3*). We gathered demographic information on 1,251 individuals, including their on-island and off-island social networks, accounting for changes in household composition via marriages, births, deaths, immigration, and emigration. Heads of household were asked who they could ask for the equivalent of one week's wages in a time of need, and with whom they would share such an amount (*Supplementary Methods 2*). While this measure differs from conventional measures of remittance volume, it captures the structure and evolution of the networks that confer remittance access; the focus of our study.

Similarly, respondents were asked from whom they received fish and to whom they gave fish during periods of surplus. We also collected information on whether households received remittances in recent memory, their food insecurity, past fortnightly expenditure, and livelihood activities, including a ranking of fishing gear used, markets sold to, proportion of catch retained for consumption, and access to non-gear fishing assets (*Supplementary Methods 3*). Finally, we identified the number of adults and children in each household, as well as the age and leadership status of the household head in each sampling period.

We created four indices summarizing the survey information into independent measures of commercialization in fishers' market use, gear, share of catch sold, and non-gear assets (*Supplementary Methods 1*). We statistically estimated the associations of changes in households' remittance networks with these indices using four fixed-effects panel regressions (*Supplementary Methods 4*). This analytical framework eliminates the influence of unobserved confounding variables that are static within each household between years (e.g., physical location and clan) and those that affect the entire population in each survey year (e.g., season, fishery condition, and survey enumerator), as suggested by Byrnes and Dee[20]. We statistically controlled for known confounding variables that are dynamic across years and between households. These include the age and leadership status of the household head, and the number of adults and children in the house.

Acknowledgments

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Supporting Information

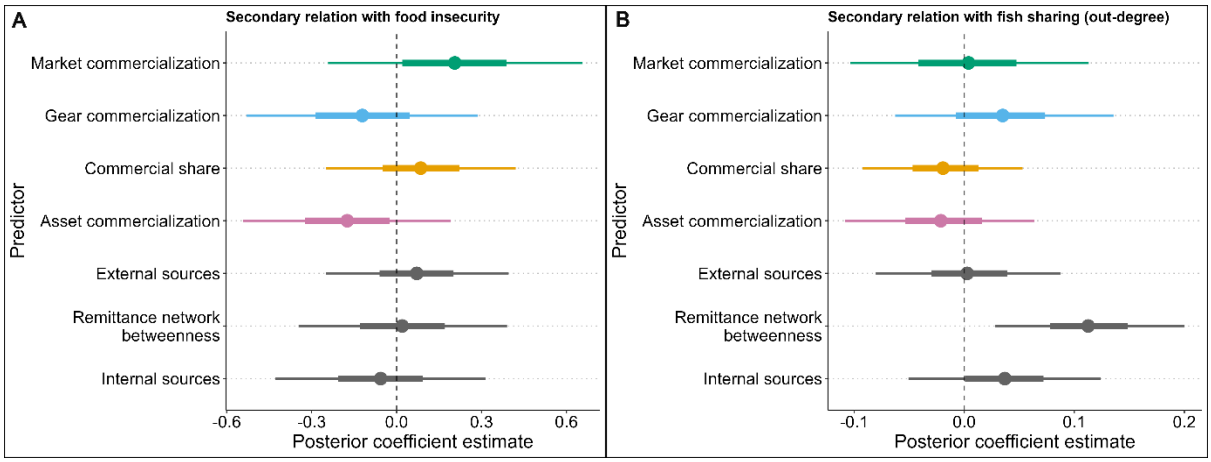

Figure S1: Secondary outcomes. Food insecurity score (panel A) and out-degree in the directed fish-sharing network (panel B). Points show median posterior parameter estimates, while thick and thin bars show the inner 50% and 90% of posterior estimates, respectively. Colors indicate main outcomes from figure 2.

Data and code

Summary data and code used in this analysis can be found at the GitHub: https://github.com/matthewclark1223/PNGRemittanceNetworks

The finalized repository will be archived via Zenodo upon acceptance of this manuscript.

Raw census and social network data are available on request from the corresponding author with reasonable restrictions, as these data contain information that could compromise research participant privacy and consent.

Supplementary Methods

1. Commercialization, pelagic focus, and food insecurity indices

To summarize data collected across numerous related household survey questions, we constructed six composite indices. These measure the four commercialization types (market, gear, commercial share of catch, and asset commercialization), fishers' focus on pelagic fish stocks, and household food insecurity.

Market commercialization index

The market commercialization index measures household participation in commercially oriented fish markets. The four market options available to residents were local village sales, biweekly island markets, off-island provincial markets, and sales to commercial fish traders. These were assigned commercialization weights of 1–4, respectively. Households' reported market importance rankings were then used to calculate their market commercialization score (M), such that markets ranked highly (e.g., as 1 on a ranked list) contributed more strongly. The index was calculated as

$$M_{it} = \sum_{k=1}^{4} \frac{w_k}{r_{ikt}}$$

where M_{it} is the market commercialization score for household i in sampling period (i.e., year) t. The commercialization weight assigned to market type k is given as w_k, and r_{ikt} indicates the rank assigned to a given market type (k) by a household (i) in each sampling period (t).

Gear commercialization index

The gear commercialization index measures household use of fishing gears associated with larger-scale or commercially oriented extraction. The gear options available to residents and their associated weights were manual gleaning (0), handline fishing from a canoe (1) or shore (1), spear fishing (1), harpoon (2), small gillnet (2), pelagic trolling (3), and large gillnet (4). The index was calculated as

$$G_{it} = \sum_{j=1}^{8} \frac{w_j}{r_{ijt}}$$

where G_{it} is the gear commercialization score for household i in sampling period t. The commercialization weight assigned to gear type j is given as w_j and r_{ijt} is reported importance rank of the given gear type for each household (i) in the given sampling period (t).

Commercial share index

The commercial share index measures the proportion of fish allocated to sale rather than household consumption or sharing out of a hypothetical catch of 10 fish. The index was calculated as

$$S_{it} = \frac{\text{Fish sold}_{it}}{10}$$

so that S_{it} is the commercial share score for household i in sampling period t when Fish sold_{it} is the reported number of fish hypothetically allocated for sale.

Asset commercialization index

The capital commercialization index measures household access to production infrastructure and storage technologies associated with commercial fishing activity. The assets available to residents were coolers, motorboats, and fish freezers; these were weighted as 1–3, respectively. The index was calculated as the summed weights of commercial fishing assets such that

$$C_{it} = \sum_{a=1}^{3} w_{ia}$$

where C_{it} is capital commercialization score for household i in sampling period t and w_{ia} is the commercialization weight assigned to asset a.

Pelagic focus index

The pelagic focus index measures the degree to which a household's reported gear use and ranked importance is oriented toward pelagic fishing rather than reef-associated fishing. Fishing gears were assigned pelagic orientation weights ranging from 0 (fully reef-focused) to 1 (fully pelagic). Gleaning, spearfishing, harpooning (from shore), handlining, and small gillnet fishing were assigned weights of 0. Canoe trolling was assigned a weight of 0.5 and pelagic trolling and large gillnet fishing were assigned weights of 1. The index was calculated such that more highly ranked gears (i.e., households ranked them as more important) contributed more strongly to a household's score. This takes the functional form

$$P_{it} = \frac{\sum_{g=1}^{G} \left(\frac{w_g}{r_{igt}}\right)}{\sum_{g=1}^{G} \left(\frac{1}{r_{igt}}\right)}$$

where P_{it} is the pelagic focus score for household i in sampling period t. The pelagic orientation weight assigned to gear g is given by w_g, and r_{igt} is the reported ranked importance of gear g for household i in sampling period t. The resulting index ranges from 0 to 1, where values near 0 indicate a predominantly reef-oriented fishing strategy and values near 1 indicate a predominantly pelagic fishing strategy.

Food insecurity index

We developed our food insecurity index based on the Household Food Insecurity Access Scale Indicator Guide (Coates et al., 2007). This index was constructed from Likert responses to five questions pertaining to different aspect of food insecurity. Specifically, these asked how frequently households skipped meals, ate smaller meals than they felt they needed, went to sleep hungry, went the entire day without eating, or had no food in their house whatsoever. For each question (h), respondents could selected responses (x) from: 'never' (1), 'rarely' (2), 'sometimes' (3), or 'often' (4). These were summed across questions for each household (i) in each sampling period (t) as

$$FI_{it} = \sum_{j=1}^{4} x_{ith}$$

where FI_{it} is the total food insecurity score.

Index covariance

Across all six indices and household estimates of past fortnightly expenditure, the highest covariance of household scores occurred between gear commercialization and pelagic focus (cor = 0.81). This is unsurprising because these are the only two indices that were constructed using the same survey questions data. The next highest coefficient of correlation occurred between the gear and market commercialization indices (cor = 0.70). The third most correlated set of indices was gear and asset commercialization (cor = 0.41), with all other pairwise correlations producing weak coefficients of less than 0.4. While even the most highly correlated indices (gear and market commercialization) appear to be reasonably well-differentiated by the other covariates (Figure 2C), it is possible that in assessing their secondary associations on food insecurity and fish sharing, the covariance of these values inflated our estimated uncertainty.

2. Network statistics

We constructed directed household-level networks describing remittances and fish sharing relationships for each sampling period (2018 and 2026). For remittance networks, directed edges represented the reported access to monetary support equivalent to one week's wages during times of need. Two types of reports were combined to construct each network: (1) ego

reports of receiving from alters and (2) ego reports of giving to alters. Duplicate edges arising from reciprocal reporting were removed. Fish sharing networks were constructed analogously using reported fish receipt and fish giving relationships.

For each household, in each year, we calculated three network statistics: (1) *remittance in-degree* measured the number of incoming remittance ties received by a household and further differentiated by the proportion of incoming ties that were from external (off-island) sources; (2) *out-degree of fish sharing* measured the number of outgoing ties in the fish-sharing network, and; (3) *remittance betweenness centrality* measured as the number of times the shortest path between each pairwise combination of other households traveled through the focal household. Households not observed in a network were assigned values of zero for the corresponding metrics.

3. Survey instrument

<Attached>

4. Statistical model formulation and checking

We estimated the associations between changes in household remittance networks and changes in fishing commercialization using Bayesian fixed-effects panel regression models. Four models were estimated corresponding to the four commercialization outcomes: market commercialization (M), gear commercialization (G), commercial share of catch (S), and asset commercialization (C),

For the approximately continuous commercialization indices (market, gear, and asset commercialization), we specified Gaussian panel regression models of the form

$$M_i \sim Normal(\mu_i, \sigma_M)$$

$$G_i \sim Normal(\mu_i, \sigma_G)$$

$$C_i \sim Normal(\mu_i, \sigma_C)$$

with

$$\mu_i = \alpha_{j[i]} + \delta_{t[i]} + \beta_1 ExtTies_i + \beta_2 IntTies_i + \beta_3 Between_i +$$

$$\beta_4 Adult_i + \beta_5 Child_i + \beta_6 Age_i + \beta_7 Leader_i$$

where μ_i is the deterministic commercialization outcome and σ_M , σ_G , and σ_C are the outcome-specific residual variances. We implemented the household-level fixed effect as $\alpha_{j[i]}$ and the sampling period fixed effect as $\delta_{t[i]}$. Predictor variables of interest included the number of external remittance ties ($ExtTies_i$), internal remittance ties ($IntTies_i$), and remittance network betweenness ($Between_i$); for each model, their relationships with the outcomes were measures as β_1, β_2, and β_3, respectively. The biases introduced by the confounding variables including,

the number of household adults ($Adult_i$), number household children ($Child_i$), age of the household head (Age_i), and leadership status of the household head ($Leader_i$), were controlled by β_4, β_5, β_6, and β_7, respectively.

Because the commercial share index was bounded between 0 and 1 and included exact zeros and ones, we modelled this outcome using a zero-one inflated beta distribution as

$$S_i \sim \text{ZOIB}(\mu_i, \phi, \pi_0, \pi_1)$$

$$logit(\mu_i) = \alpha_{j[i]} + \delta_{t[i]} + \beta_1 ExtTies_i + \beta_2 IntTies_i + \beta_3 Between_i +$$

$$\beta_4 Adult_i + \beta_5 Child_i + \beta_6 Age_i + \beta_7 Leader_i \, .$$

In modelling the secondary associations of fishing commercialization with food insecurity (FI) and fish sharing (FS), we developed panel regression equations similar to those above, but also including the commercialization indices as predictors. We retain the remittance measures as covariates because these affect both fishing commercialization and the secondary outcomes, and therefore need to be controlled for to debias the parameter estimates (Arif & MacNeil, 2023). As with the approximately continuous fishing commercialization indices, we model the food insecurity index as Gaussian, so that

$$FI_i \sim Normal(\mu_i, \sigma_{FI})$$

and

$$\mu_i = \alpha_{j[i]} + \delta_{t[i]} + \beta_1 ExtTies_i + \beta_2 IntTies_i + \beta_3 Between_i +$$

$$\beta_4 Adult_i + \beta_5 Child_i + \beta_6 Age_i + \beta_7 Leader_i +$$

$$\beta_8 M_i + \beta_9 G_i + \beta_{10} C_i + \beta_{11} S_i \, .$$

We estimate the parameter values for the linear association of market commercialization (M_i), gear commercialization (G_i), asset commercialization (C_i), and commercial share of catch (S_i) with food insecurity as β_8, β_9, β_{10}, and β_{11}, respectively.

We estimate the linear relationships between the same set of covariates and the out-degree of fish sharing identically as above but model this outcome as Poisson distributed because it takes only positive integer values. This regression model then takes the function form

$$FS_i \sim Normal(\mu_i, \sigma_{FS})$$

with

$$log(\mu_i) = \alpha_{j[i]} + \delta_{t[i]} + \beta_1 ExtTies_i + \beta_2 IntTies_i + \beta_3 Between_i +$$

$$\beta_4 Adult_i + \beta_5 Child_i + \beta_6 Age_i + \beta_7 Leader_i +$$

$$\beta_8 M_i + \beta_9 G_i + \beta_{10} C_i + \beta_{11} S_i \, .$$

All continuous predictors were standardized prior to estimation to allow for direct comparison of effect sizes (Figure 2 C–D). Models were estimated only for 88 households observed in both years and reporting fishing livelihoods in both sampling periods, ensuring that parameter

estimates reflected within-household temporal change rather than cross-sectional differences between households. We specified weakly regularizing priors for all parameters as suggested by Gelman et al. (2008).

Models were estimated using Hamiltonian Monte Carlo implemented in the 'brms' package with the cmdstanr backend (Bürkner, 2007). Each model used four chains with 10,000 iterations per chain, including 1,500 warmup iterations. To improve sampling efficiency and avoid divergent transitions, models were estimated using an adaptive target acceptance rate of 0.99 and maximum tree depth of 15. We assessed model convergence based on adequate mixing of Markov chains and $\hat{R}$ values equal to one for all parameters. Credible associations were defined as those in which 95% of posterior samples were greater or less than 0. Posterior predictive checks indicated adequate model fit and no major violations of distributional assumptions.

Supporting References

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