Information decay and cooperative entry under risk

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Motivation: Technology Adoption as Network Diffusion

- Adoption rates of potentially welfare-improving technologies remain stubbornly low in many countries (Suri & Udry, 2022).
- These technologies can help producers cope with the effects of climate change (Hultgren et al., 2025).
- Social networks play an important role in technology adoption by alleviating information frictions that inhibit adoption (Munshi, 2014).
- Recent work considers technology adoption using the framework of network diffusion (Akbarpour et al., 2025).
- Both overall network structure and an individual's place in the network affect the diffusion process (Beaman et al., 2021).

Motivation: Identification Challenges

- Bramoullé et al. (2020) gives conditions for causally identifying peer effects.
- Individual farmers' decisions to adopt may be affected by:
  - Unobservable characteristics of those farmers.
  - Adoption decisions of neighbors **(endogenous peer effects)**.
  - Other characteristics of neighbors **(contextual peer effects)**.
- Distinguishing between endogenous peer effects and contextual peer effects is the "reflection problem" (Manski, 1993).
- In addition, unobserved shocks may affect the adoption decision of both a farmer and their neighbors **(correlated effects)**.
- Our solution: geographic exogeneity of networks + drought shocks as exogenous shifters.

This Paper

- 23-year panel of producer entry decisions into a coffee and/or honey cooperative.
- We use two technologies on the same fixed network as mutual placebos.
- We use a linear-in-means model to examine entry over time.
- We interact peer effects with drought shocks.
- **Temporal friction**: compare fixed effects and first differences specifications.
- **Spatial friction**: compare direct and indirect effects using a spatial lag model.
- We interpret asymmetric results in a homophily vs. contagion framework.

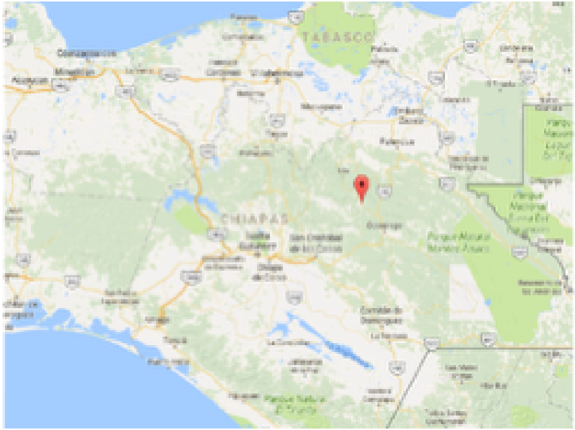
Preview of Findings

- **Key finding**: Coffee and honey show asymmetric drought $\times$ network interactions on the same fixed network — consistent with contagion, not homophily.
- **LiM**: A 10% increase in village entry rate $\rightarrow$ 5% higher entry probability for both cooperatives; effect drops $\sim$75–80% with first differences, suggesting long-run adaptation.
- **LiM (coffee only)**: Severe drought $\rightarrow$ entry $\uparrow$, but network effect offsets this; extreme drought $\rightarrow$ entry $\downarrow$.
- **Spatial lag**: For coffee, indirect network and drought effects exceed direct effects; for honey, only direct network effects — no drought interactions.

Contribution

- We use two technologies on the same fixed network as mutual placebos to separate homophily from contagion in technology adoption.
- We show how comparing fixed effects and first differences specifications reveals temporal frictions in information diffusion.
- We show how comparing direct and indirect spatial lag effects reveals spatial frictions in information diffusion.
- We provide a 23-year panel of producer entry decisions from an indigenous community in Chiapas, Mexico.

Study Area



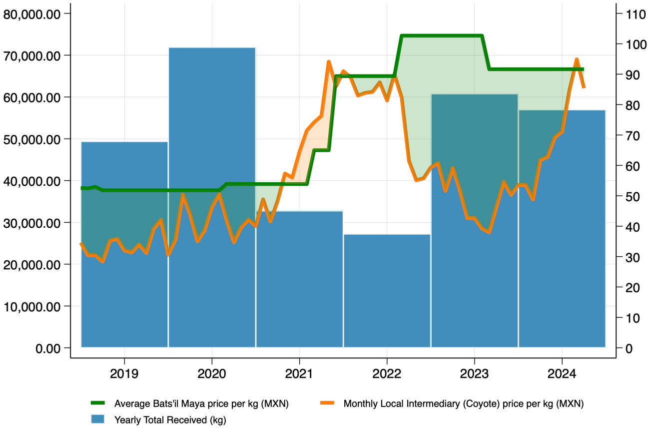
Indigenous Community

- Tzeltal Maya communities in the highlands of Chiapas, Mexico.
- Producers are organized into villages with stable social networks rooted in geography and culture.
- Coffee and honey production are both non-native technologies introduced during the 20th century.
- Two cooperatives — one for coffee, one for honey — serve the same producer population.

Coffee Cooperative

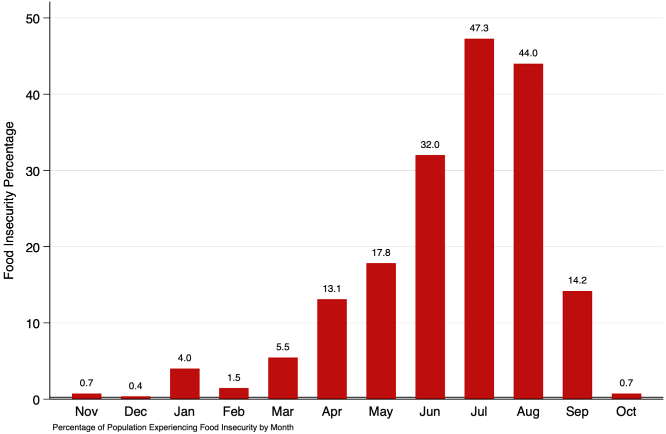
- **Price volatility** $\rightarrow$ **price insurance**: The cooperative guarantees a floor price for coffee, insuring producers against global market fluctuations.
- **Coffee rust shock** $\rightarrow$ **better plants and techniques**: The cooperative provides access to disease-resistant varieties and technical training in response to coffee leaf rust outbreaks.
- **Consumption smoothing** $\rightarrow$ **emergency microloans**: The cooperative offers small emergency loans to help producers bridge income gaps between harvests.

Price Insurance



Better Plants and Techniques

Food Insecurity Exposure

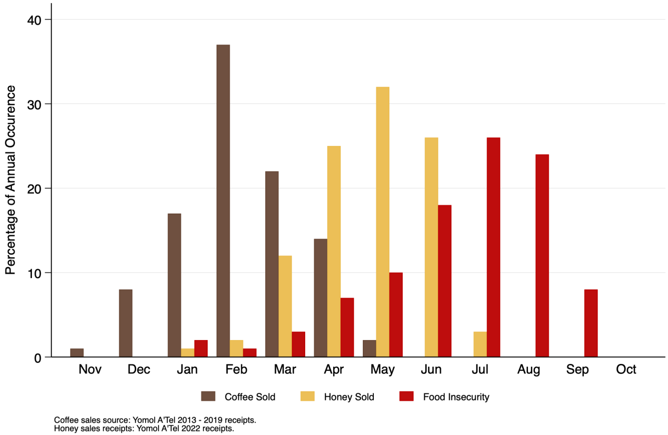


Honey Cooperative

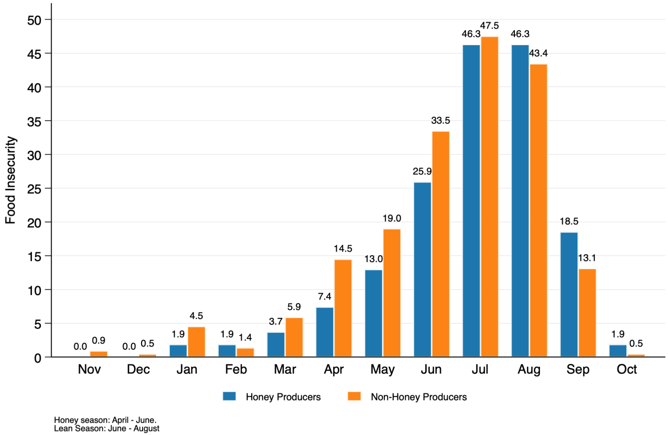
- **Income at another time of year**: Honey harvest arrives at a different point in the agricultural calendar, smoothing consumption across the year.
- **A sweet and timely form of insurance**: turn on and off with small capital and labor investment.
- **Differential food insecurity**: Producers who adopt honey production experience less food insecurity than those who rely on coffee alone.

A Sweet and Timely Form of Insurance

Coffee and Honey Seasonality



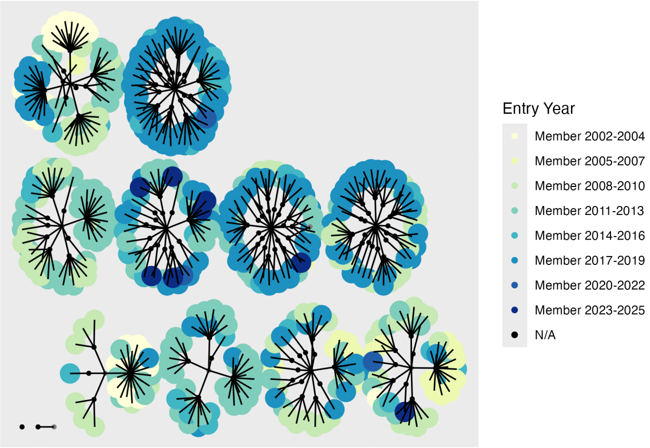
Differential Food Insecurity



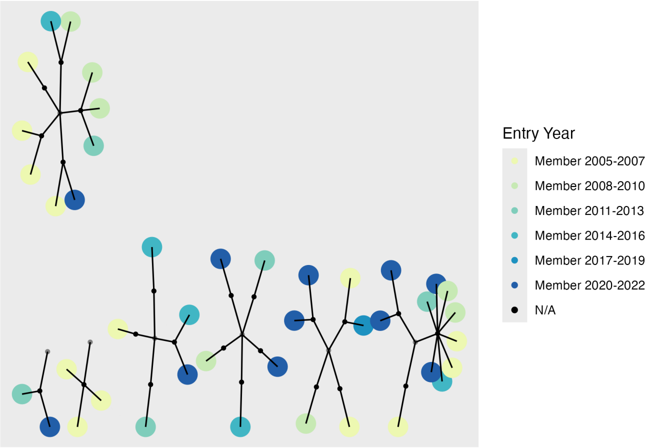
Producers and Villages

- Universe of 498 producers who adopt into the coffee cooperative, the honey cooperative, or both.
- Spatial variation: eleven regions divided into 124 total villages.
- Network definition: producers in the same village share a direct link; producers in the same region but different village share an indirect link.
- Temporal variation: 23 years
  - 2002–2012: self-reported date of entrance
  - 2013–2025: deliveries to both cooperatives

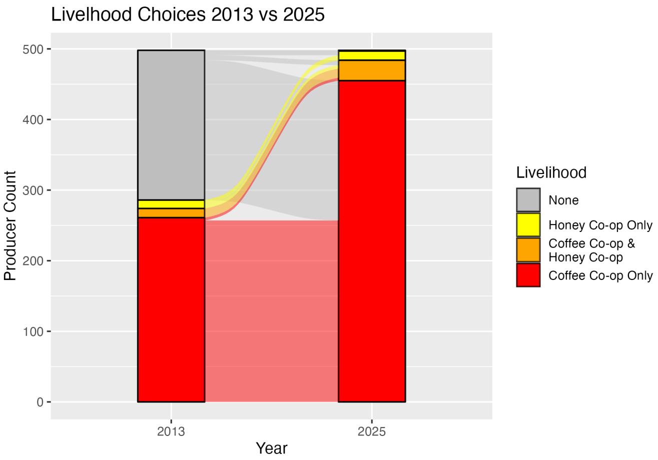
Network Structure of Coffee Cooperative Entry



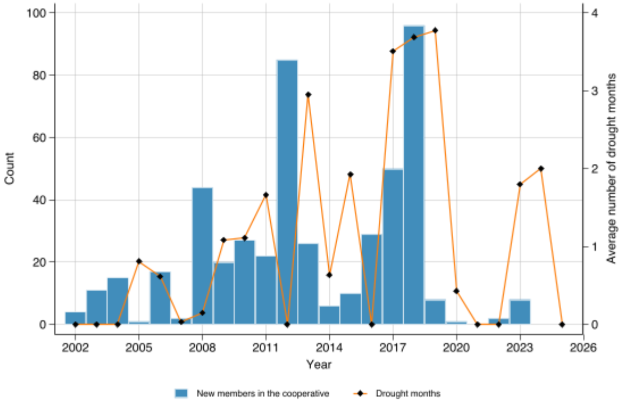
Network Structure of Honey Cooperative Entry



Livelihood Choices 2013 vs. 2025

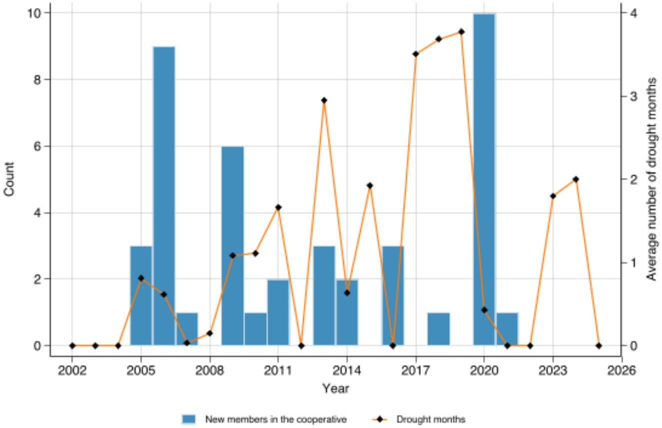


Coffee Cooperative Entry and Drought



▸ Entry/Exit Detail

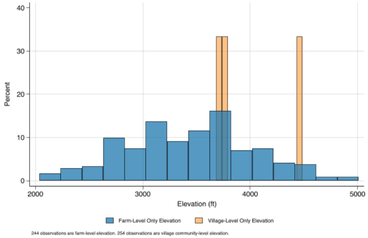
Honey Cooperative Entry and Drought



Remote Sensing

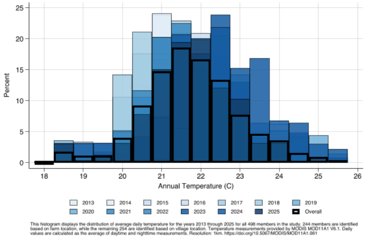
- Geolocated coffee parcels for 244 producers (collected during the pandemic).
- Remaining 254 producers: village coordinates from the Mexican census (fuzzy match).
- We use Google Earth Engine to match coordinates with elevation, temperature, and rainfall data.
- Drought data from the Standardized Precipitation-Evapotranspiration Index (Vicente-Serrano et al., 2010).
  - **Severe drought**: SPEI ≤ -1.5
  - **Extreme drought**: SPEI ≤ -2.0

Climate Characteristics



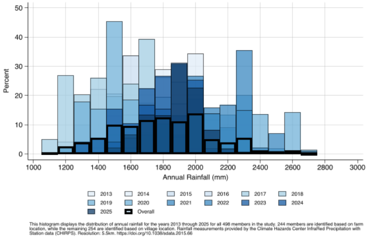
Elevation

▸ Elevation



Temperature

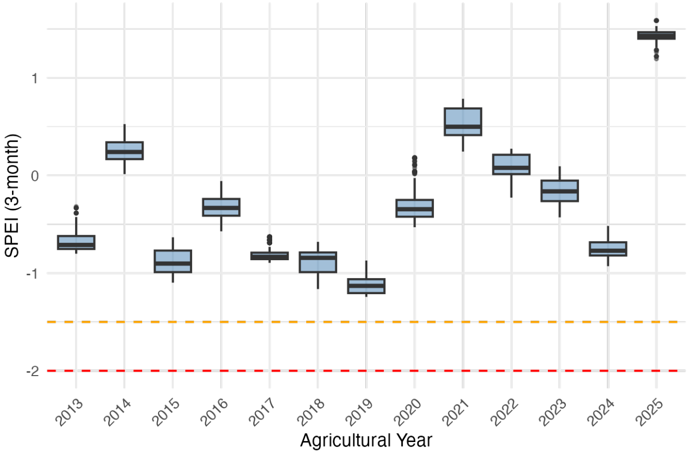
▸ Temperature



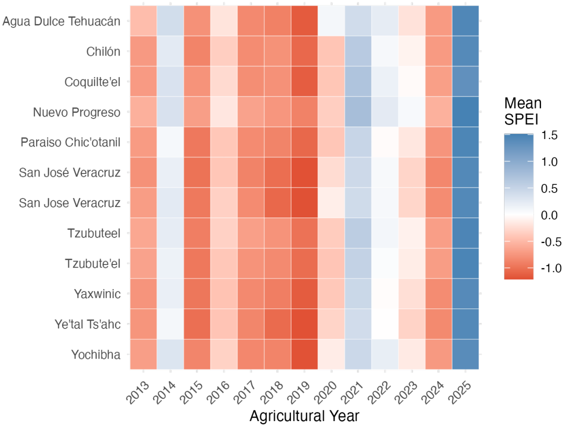
Rainfall

▸ Rainfall

SPEI Distribution by Year



Mean SPEI by Region and Year



Within-Year ICC

Empirical Strategy - Linear-in-Means Model

- We use a linear-in-means model to examine the peer effects of producers in the same village on adoption (Bramoullé et al., 2009).
- The outcome is y_{ijt}^{z}: whether producer i in village j adopts cooperative z in time t.
- N_{ijt}^{z} in Equation (1) is network strength; D_{ijt} is number of periods of drought.
- Following Millimet and Bellemare (2025), we augment our producer fixed-effect specification in Equation (2) with a first-difference one in Equation (3).

$$N_{ijt}^{z} = \frac{1}{n_j - 1} \sum_{k=1, k \neq i}^{n_j} y_{kjt}^{z} \tag{1}$$

$$y_{ijt}^{z} = \alpha_1^{z} + \beta_1^{z} N_{ijt-1}^{z} + \delta_{\mathbf{1}}^{\mathbf{z}} \mathbf{D}_{\mathbf{ijt-1}} + \gamma_{\mathbf{1}}^{\mathbf{z}} \mathbf{D}_{\mathbf{ijt-1}} N_{ijt-1}^{z} + \phi_{1i}^{z} + \xi_{1t}^{z} + \epsilon_{1ijt}^{z} \tag{2}$$

$$\Delta y_{ijt}^{z} = \alpha_2^{z} + \beta_2^{z} \Delta N_{ijt-1}^{z} + \delta_{\mathbf{2}}^{\mathbf{z}} \mathbf{\Delta D}_{\mathbf{ijt-1}} + \gamma_{\mathbf{2}}^{\mathbf{z}} \mathbf{\Delta D}_{\mathbf{ijt-1}} N_{ijt-1}^{z} + \xi_{2t}^{z} + \Delta \epsilon_{2ijt}^{z} \tag{3}$$

Empirical Strategy - Spatial Lag Model

- We use a spatial lag model to examine additional indirect effects of adoption decisions in other villages in the same region or all other villages in addition to the direct effects of peer effects in a producer's own village (Halleck Vega & Elhorst, 2015).

$$y_{ijt}^{z} = \alpha_3^z + \beta_3^z N_{ijt-1}^{z} + \delta_3^{\mathbf{z}} \mathbf{D_{ijt-1}} + \mathbf{WN_{t-1}^{z}} \theta_3 + \mathbf{WD_{t-1}} \lambda_3 + \epsilon_{3ijt}^{z} \quad (4)$$

- Network strength N and drought D are defined as above.
- We build three weighting matrices $\mathbf{W}$. Diagonal elements are 0. Off diagonal elements are as follows for producer j and k.
  1. **Binary Contiguity**: $w_{jk}^1 = 1$ iff j and k are in the same region; 0 otherwise.
  2. **Inverse Distance - Region**: $w_{jk}^2 = \frac{1}{d_{jk}}$ iff j and k are in the same region; 0 otherwise.
  3. **Inverse Distance - All**: $w_{jk}^3 = \frac{1}{d_{jk}}$

Identification

- Recall that network structure is stable over the long term.
- Geographic networks are plausibly exogenous — little mobility means producers did not sort into networks based on cooperative membership.
- Drought shocks provide identifying variation: conditional on network structure, drought is an exogenous shifter of adoption incentives.
- **Temporal frictions**: A large drop in the peer effect from FE to FD implies the effect is driven by long-run adaptation rather than recent adoption.
- **Spatial frictions**: Stronger indirect than direct effects imply that information travels beyond the village in adoption decisions.

Coffee Cooperative - Linear-in-Means

Network effect drops from ∼50% (FE) to ∼10% (FD) — look at columns 1 vs. 3.

	Joins Coffee Cooperative (1=Yes)			
	FE Short	FE Long	FD Short	FD Long
	(1)	(2)	(3)	(4)
Network Strength (Village)	0.541***	0.523***	0.104***	0.004
	(0.038)	(0.029)	(0.028)	(0.014)
Periods of Severe Drought	0.047***	0.024***	0.027***	0.005
	(0.008)	(0.006)	(0.007)	(0.004)
Periods of Extreme Drought	−0.050**	−0.018	0.003	−0.019**
	(0.024)	(0.014)	(0.011)	(0.008)
Severe Drought x Network Strength	−0.041***	−0.037***	−0.037***	−0.017***
	(0.007)	(0.006)	(0.007)	(0.005)
Extreme Drought x Network Strength	0.048***	−0.030**	−0.008	0.010*
	(0.018)	(0.013)	(0.010)	(0.006)
Year Fixed Effects	Y	Y	Y	Y
Producers	498	498	498	498
Years	12	23	12	23
Observations	5,976	11,454	5,478	10,956
Adjusted R^2	0.092	0.121	0.104	0.067

Honey Cooperative - Linear-in-Means

Same network effect drop, but drought interactions are insignificant throughout.

	Joins Honey Cooperative (1=Yes)			
	FE Short	FE Long	FD Short	FD Long
	(1)	(2)	(3)	(4)
Network Strength (Village)	0.517***	0.441***	0.126	0.072
	(0.124)	(0.104)	(0.123)	(0.071)
Periods of Severe Drought	−0.0003	−0.001	−0.0003	0.001
	(0.001)	(0.002)	(0.001)	(0.001)
Periods of Extreme Drought	0.002	−0.002	0.001	0.004
	(0.005)	(0.004)	(0.003)	(0.002)
Severe Drought x Network Strength	−0.006	−0.031***	0.005	0.001
	(0.007)	(0.010)	(0.005)	(0.005)
Extreme Drought x Network Strength	0.001	0.030**	0.001	−0.002
	(0.011)	(0.014)	(0.002)	(0.002)
Year Fixed Effects	Y	Y	Y	Y
Producers	498	498	498	498
Years	12	23	12	23
Observations	5,976	11,454	5,478	10,956
Adjusted R^2	0.049	0.027	0.018	0.008

LiM Results

- For coffee: severe drought $\rightarrow$ adoption $\uparrow$, but network effect offsets this; extreme drought $\rightarrow$ adoption $\downarrow$.
- For coffee: the FE to FD drop ($\sim$50% to $\sim$10%) suggests long-run adaptation, not recent peer influence.
- For honey: over the long term, extreme drought in high-network villages increases adoption; severe drought decreases it.
- For honey: the FE to FD drop is similar to coffee ($\sim$50% to $\sim$13%), confirming the network effect reflects long-run adaptation — but drought interactions are absent, unlike coffee.

Coffee Cooperative - SLX

Indirect network effects exceed direct effects — and indirect drought effects exceed direct.

	Joins Coffee Cooperative (1=Yes)					
	(1)	(2)	(3)	(4)	(5)	(6)
Direct Effect - Network	0.306***	0.348***	0.402***	0.350***	0.354***	0.393***
	(0.023)	(0.023)	(0.022)	(0.014)	(0.013)	(0.013)
Direct Effect - Severe Drought	0.006	0.022**	0.005	−0.007	0.003	−0.014*
	(0.009)	(0.009)	(0.009)	(0.007)	(0.008)	(0.007)
Direct Effect - Extreme Drought	−0.019	0.008	−0.032	−0.023	−0.009	−0.045***
	(0.021)	(0.024)	(0.020)	(0.019)	(0.019)	(0.017)
Indirect Effect - Network	0.586***	0.454***	0.670***	0.451***	0.417***	0.760***
	(0.033)	(0.031)	(0.058)	(0.022)	(0.018)	(0.039)
Indirect Effect - Severe Drought	0.022**	0.001	0.067***	0.030***	0.013	0.069***
	(0.010)	(0.010)	(0.018)	(0.009)	(0.009)	(0.015)
Indirect Effect - Extreme Drought	0.049*	0.003	0.196***	0.013	−0.010	0.090**
	(0.025)	(0.026)	(0.052)	(0.021)	(0.021)	(0.040)
Weighting Formula	Binary	Inv Dist	Inv Dist	Binary	Inv Dist	Inv Dist
Other Villages	Region Only	Region Only	All	Region Only	Region Only	All
Years	12	12	12	23	23	23
Log-Likelihood	912	845	778	-74	-31	-122
Observations	5,976	5,976	5,976	11,454	11,454	11,454

Honey Cooperative - SLX

Direct network effects only — no significant indirect effects or drought interactions.

	Joins Honey Cooperative (1=Yes)					
	(1)	(2)	(3)	(4)	(5)	(6)
Direct Effect - Network	0.512***	0.514***	0.512***	0.415***	0.414***	0.411***
	(0.059)	(0.059)	(0.058)	(0.034)	(0.035)	(0.035)
Direct Effect - Severe Drought	−0.002	−0.003	−0.006	−0.003	0.003	0.006
	(0.002)	(0.004)	(0.006)	(0.003)	(0.004)	(0.005)
Direct Effect - Extreme Drought	−0.002	−0.009	−0.021	−0.009	0.008	0.009
	(0.006)	(0.012)	(0.015)	(0.006)	(0.009)	(0.010)
Indirect Effect - Network	0.090	−0.038*	−0.206***	0.079*	0.006	0.238***
	(0.056)	(0.022)	(0.049)	(0.041)	(0.030)	(0.080)
Indirect Effect - Severe Drought	0.004	0.004	0.021	0.001	−0.008	−0.019
	(0.003)	(0.006)	(0.018)	(0.003)	(0.005)	(0.013)
Indirect Effect - Extreme Drought	0.008	0.016	0.085	0.013*	−0.013	−0.024
	(0.007)	(0.015)	(0.053)	(0.007)	(0.012)	(0.034)
Weighting Formula	Binary	Inv Dist	Inv Dist	Binary	Inv Dist	Inv Dist
Other Villages	Region Only	Region Only	All	Region Only	Region Only	All
Years	12	12	12	23	23	23
Log-Likelihood	6929	6933	6952	8458	8459	8476
Observations	5,976	5,976	5,976	11,454	11,454	11,454

Spatial Lag Results

- For coffee: direct network effect 30–40%; indirect network effect ∼40–75%.
- For coffee: indirect drought effects exceed direct drought effects — information about climate risk travels across villages.
- For honey: direct network effect 40–51%; indirect effects depend on how honey adoption is spatially concentrated.
- For honey: very little drought effect, consistent with honey being a newer technology with less codified climate-resilience information.

One Interpretation: Separating Homophily from Contagion

Challenge: Network correlations in adoption could reflect homophily (similar producers cluster) rather than genuine peer effects. We are inspired by Golub and Jackson (2012).

Our strategy: Use two technologies on the same fixed network as mutual placebos.

Under pure homophily

- Fixed producer characteristics ϕ^z_{1i} drive clustering
- Network effects should be proportional across technologies
- Drought interactions should not differ

Under contagion

- β^z_1 reflects technology-specific information value
- Drought interactions reflect information about *climate resilience*
- Coffee and honey effects can diverge

The Meaning of Asymmetry

What we find:

- Strong network $\times$ drought interactions for coffee
- Weak network $\times$ drought interactions for honey
- Both estimated on the same fixed network

Interpretation:

- Homophily predicts symmetric effects across technologies
- The asymmetry identifies a contagion channel
- Networks transmit information about coffee's climate resilience, but not honey's (a newer, less codified technology)

Next steps

Immediate fixes:

- Drop year fixed effects from the main specification.
- Treat drought as continuous rather than discrete (severe/extreme).
- Revisit the spatial lag element because of lack of cross-sectional variation.

Longer-run extensions:

- Frame econometrics around Bramoullé et al. (2020) — use intransitivity (peers-of-peers as instruments) to address the reflection problem.
- Exploit complementarity between coffee and honey (Cohen-Cole et al., 2018).

Thank you!

Appendix

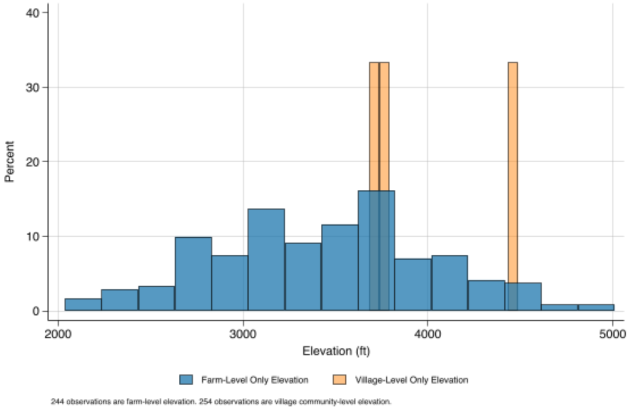
This Paper (original slide 4)

- We leverage a unique 23 year panel of entry decisions by indigenous producers.
- Producers enter a coffee cooperative, a honey cooperative, or both.
- Adoption is an absorbing state (for now).
- Network structure exhibits the "small worlds" property (Jackson, 2010).
- We argue network structure is stable for cultural reasons.
- We use drought shocks to identify peer effects.
- Conditional on experiencing a drought, we estimate the effect of last year's village adoption rate on this year's probability of adoption.

This Paper (2) (original slide 5)

- The setting lends itself to looking at two frictions:
    - **Temporal decay** means that it takes several years for producers who enter to experience the benefits of both cooperatives and spread information about these benefits to the neighbors.
    - **Spatial decay** means that the further this information travels, the less it influences entry decisions.
- We consider temporal decay by using work from Millimet and Bellemare (2025) that distinguishes between estimating first differences and individual fixed effects.
- We use spatial lag estimators (SLX) to estimate the effect of adoption in neighboring villages on adoption in this village (Halleck Vega & Elhorst, 2015).
- Finally, we interpret the results in a homophily vs. contagion framework.

Elevation Distribution



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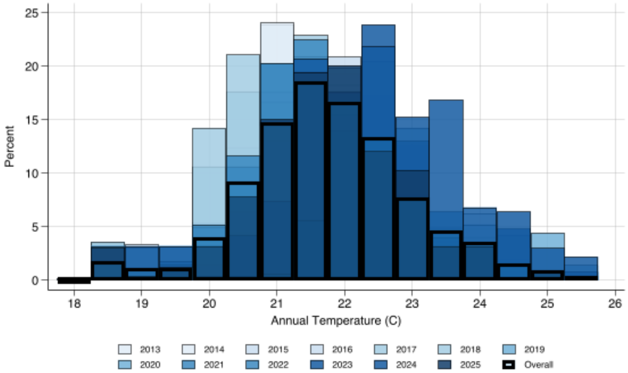
Annual Temperature Distribution



This histogram displays the distribution of average daily temperature for the years 2013 through 2025 for all 498 members in the study. 244 members are identified based on farm location, while the remaining 254 are identified based on village location. Temperature measurements provided by MODIS MOD11A1 V6.1. Daily values are calculated as the average of daytime and nighttime measurements. Resolution: 1km. https://doi.org/10.5067/MODIS/MOD11A1.061

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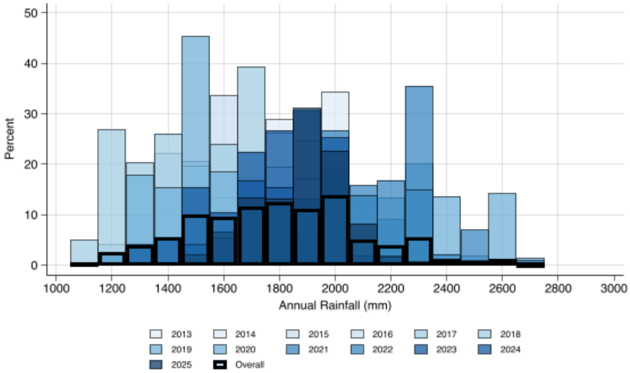
Annual Rainfall Distribution



This histogram displays the distribution of annual rainfall for the years 2013 through 2025 for all 498 members in the study. 244 members are identified based on farm location, while the remaining 254 are identified based on village location. Rainfall measurements provided by the Climate Hazards Center InfraRed Precipitation with Station data (CHIRPS). Resolution: 5.5km. https://doi.org/10.1038/sdata.2015.66

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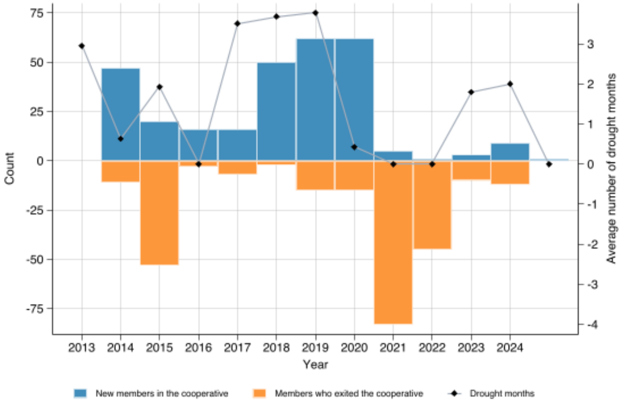
Coffee Cooperative Entry/Exit and Drought



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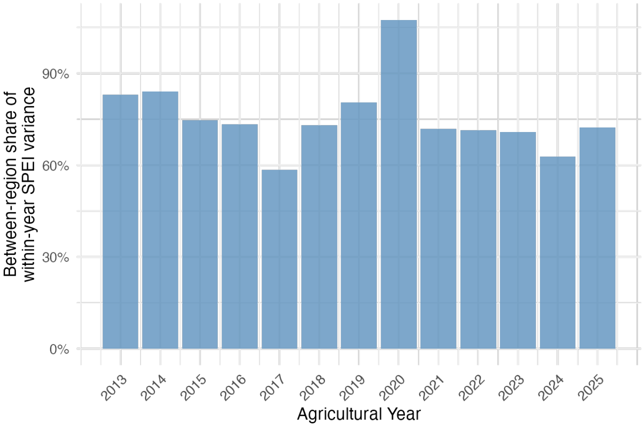
Within-Year ICC of SPEI by Region



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Adoption by Village

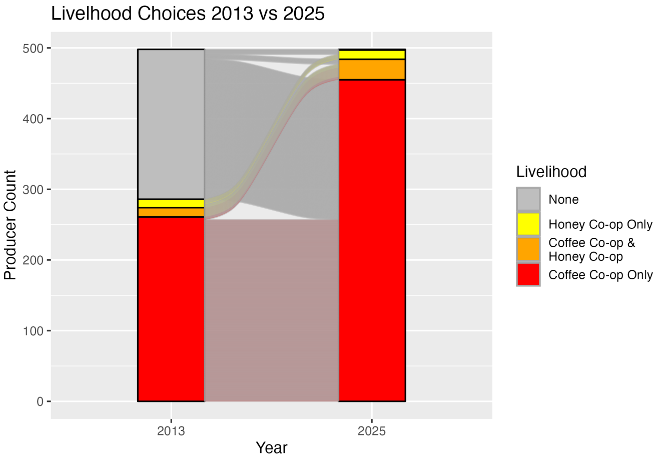
			Coffee			Honey		
	Region	Villages	2002	2013	2025	2005	2013	2025
	1	5	0	4	5	0	0	0
	2	15	0	7	15	1	2	4
	3	9	0	9	9	0	1	1
	4	9	1	7	8	0	5	5
	5	4	0	3	4	1	1	1
	6	22	0	9	21	1	3	5
	7	9	0	7	8	0	2	3
	8	20	0	8	19	0	2	5
	9	19	0	1	19	0	0	0
	10	12	0	8	12	0	0	0
Total	—	124	1	63	120	3	16	24

This table shows the number of villages in each region with members of the coffee and honey cooperatives at three time periods: the first year, a middle year, and the latest year in the dataset.

Adoption by Individual

			Coffee			Honey		
	Region	Individuals	2002	2013	2025	2005	2013	2025
	1	39	0	29	39	0	0	0
	2	49	0	18	46	1	2	5
	3	52	0	49	52	0	1	2
	4	72	4	53	67	0	8	10
	5	28	0	26	28	1	3	3
	6	51	0	18	50	1	3	7
	7	43	0	34	42	0	6	11
	8	58	0	21	54	0	2	5
	9	71	0	1	71	0	0	0
	10	35	0	25	35	0	0	0
Total	—	498	4	274	484	3	25	43

This table shows the number of individuals in each region with members of the coffee and honey cooperatives at three time periods: the first year, a middle year, and the latest year in the dataset.


Livelhood Choices 2013 vs 2025
500
400
300
200
100
0
Producer Count
2013
2025
Year
Livelihood
None
Honey Co-op Only
Coffee Co-op &
Honey Co-op
Coffee Co-op Only

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