Information decay and cooperative entry under risk

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Abstract

Producer organizations can help smallholder producers adapt to climate shocks by insuring production and teaching them climate-resilient production techniques. However, information about the benefits of membership takes time to reach potential adopters and often decays before it reaches an entire population. We examine entry into two different cooperatives by indigenous coffee producers: a coffee cooperative and honey cooperative. Our analysis leverages a network graph of entry decisions that spans 22 years and includes the locations of the producers, who live in 124 villages grouped in ten regions. To characterize the temporal lags, we estimate two specifications of a linear-in-means model: one with with producer fixed effects and another with first differences. To characterize the spatial lags, we estimate three specifications of a spatial lag model with different weighting matrices. In both models, we interact the peer adoption rate with the number of periods of seasonal drought. The linear-in-means estimation results reveal a longer entry period for coffee than for honey. The spatial lag estimation results reveal more information decay for honey than coffee. In space, seasonal drought in other villages and regions increases the probability of entry into the coffee cooperative but not the honey cooperative. In both, we find that periods of seasonal drought counteract network effects for coffee and honey. Our results provide insight for policy makers to strengthen producer organizations in contexts that experience climate shocks.

JEL Codes: Q13, Q56, R11, O33

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1 Introduction

Adoption rates of potentially welfare-improving production technologies remain stubbornly low in many contexts (Suri & Udry, 2022). Social networks play an important role in technology adoption by alleviating information frictions that inhibit adoption (Munshi, 2014). However, information transmission in social networks breaks down over space and time, and poorly connected individuals or firms suffer as a result. A better understanding of information decay would provide insight into how to reinforce these social networks. Strengthening them could, in turn, increase adoption and both individual and overall welfare.

This paper studies the effect of temporal and spatial lag on entry into two different cooperatives by indigenous producers who experience periods of seasonal drought. One cooperative is a coffee cooperative that offers technical training and price insurance to existing smallholder coffee producers. The other cooperative is a honey cooperative that offers these coffee producers an additional source of income during the coffee off-season. By temporal decay, we mean that it takes several years for producers who enter to experience the benefits of both cooperatives and spread information about these benefits to their neighbors. By spatial decay, we mean that the farther this information travels, the less it influences entry decisions. Both cooperatives operate in a remote area of rural southern Mexico with limited road connectivity that is isolated from outside influence and thus free of many of the usual confounders of the study of cooperative entry. We have an unusually rich data set: panel data that span 22 years with the complete set of entry decisions into both cooperatives and the coordinates of producers' coffee plots.

Our setting is ideal for studying the effect of temporal and spatial lag on entry into both cooperatives. By varying the method (first differences vs fixed effects) and the sample (11 year vs 22 year panel), we can capture the effect of temporal lag on entry. Moreover, the spatial organization of the producers exhibits a network structure: producers are organized in villages, which are then organized in regions. We consider three different levels of spatial spillovers: the direct effect of the adoption rate in a producer's village, the indirect effect of the adoption rate in neighboring villages within the same region, and the overall effect of the adoption rate of villages in other regions. Thus, we can also capture the effect of spatial lag on cooperative entry.

In addition to studying the direct and indirect effects of temporal and spatial lag, we also would like to study how climate shocks affect producer behavior. These Mexican producers suffer from the effects of seasonal drought, one kind of climate shock (Dobler-Morales & Bocco, 2021). We use the coordinates of producers' coffee plots and villages to augment the entry network above with periods of drought from the Standardized Precipitation-Evapotranspiration Index (Vicente-Serrano et al., 2010). In particular, we are interested in whether, in the face of seasonal drought, producers with stronger networks enter cooperatives with higher probability than producers with weaker networks. This heterogeneity would account for the direct effect of the network in mitigating the frictions that impede cooperative entry. We are also interested in how periods of seasonal drought in neighboring villages affect cooperative entry. These indirect effects could indicate how information on the effectiveness of membership in the coffee cooperative or honey production against seasonal drought affects the entry decision.

We estimate two types of models on the network graph of entry decisions. The first model allows us to study information lag over time over the 22-year period. We estimate a linear-in-means model that regresses the adoption rate within a producer's village in the previous year on his own decision to adopt (Bramoullé et al., 2009). We augment the baseline specification with the number of periods of severe and extreme drought in the previous year and interact these drought measures with the adoption rate of the village. Moreover, in line with recent work by Millimet and Bellemare (2023), we compare results from a specification with producer fixed effects and one with first differences to examine the effect of temporal lags: the differential effect of adoption rates in prior years and adoption decisions in the past year. The fixed effect specifications include the village adoption rate for all previous years. The first difference specifications only include the village adoption rate from the previous year.

The second model allows us to examine the effect of spatial lags: the differential effect of the adoption rate in the producer's own village, adoption rate in neighboring villages in the same region, and the adoption rate in villages in other regions. We estimate a spatial lag model in the style of Halleck Vega and Elhorst (2015) that uses a weighting matrix to incorporate the indirect effect of the shares of cooperative members and drought measures from neighboring villages alongside the direct effect of the adoption rate and drought measures from a producer's own village. By varying the weighting matrix, we compare three different models of information decay: one that weights neighboring villages within the same region equally, another that weights them by inverse distance, and a third that includes all villages across all regions, also weighting them by inverse distance.

Our results are as follows. Using the linear-in-means models, we find network effects in entry into both the coffee and the honey cooperative. In the model with producer fixed effects, the point estimate of the difference between living in a village with no adopters (network strength of 0) and a village with all adopters (network strength of 1) is around 50% for coffee and 40% for honey. The effect size is the same in both the short panel and the long panel. That means that a 10% increase in the village adoption rate of either cooperative in one year affects the probability that a producer in the same village will adopt the cooperative by 5% or 4% in the following year. In the model with first differences, the effect size decreases. In the short panel, it is 10% for the coffee cooperative and 12% for the honey cooperative. In the long panel, it is null for the coffee cooperative and 7% for the honey cooperative.

In general, periods of severe drought increase and periods of extreme drought decrease the probability of joining the coffee cooperative. Village network strength moves these effects in the opposite direction. For a period of severe drought, the base effect is 2% to 4% with a network effect of 3% to 4% in the opposite direction. For a period of extreme drought, the base effect is -2% to -6% with a network effect of 2% to 4% in the opposite direction. In the case of honey, the presence of periods of drought themselves does not affect the entry decision, but the interaction between the periods and network strength does, but only in one of the models: the one with producer fixed effects over the long panel.

Using the spatial lag model, for the coffee cooperative we find a direct effect that ranges from 30% to 35% in the short panel and 36% to 40% in the long panel. As in the linear-in-means results, the spatial-lag results show that periods of extreme drought decrease the likelihood of joining the cooperative. With a binary contiguity matrix at the regional level, we find an indirect network effect of 60% in the short panel which drops to 43% in the long panel. With an inverse distance matrix at the regional level, the indirect effect decreases to 45% and 43%. When we include villages in all regions, the indirect effects increase to 67% and 76%. We also find an indirect effect in the short term of periods of severe and extreme drought within the region and globally.

With the honey cooperative, we find direct network effects in the short panel of 49% and in the long panel of 39%. We find no direct effects of periods of either type of drought. In the short panel, we find indirect effects of periods of severe drought (3.6%) and extreme drought (8.1%) across the survey region. As in the linear-in-means model, we find very little effect of periods of drought on the entry decision for the honey cooperative, either in the short panel or the long panel. Thus, producers who experience drought do not look for alternative income in the form of honey production.

Our results contribute to a literature that uses network theory to analyze the effect of social networks on producer decisions. In particular, our work is closely related to the literature on technology adoption. Foster and Rosenzweig (1995) first document the role of peer learning in the adoption of high-yielding seed varieties in India. Conley and Udry (2010) use surveys to define information neighborhoods for pineapple producers and distinguish between nearby and farther-away peer effects as producers learn the correct amount of fertilizer. Next, Banerjee et al. (2013) expand their model so that even non-adopters can provide information as they examine the diffusion of microfinance in Indian communities. Recently, Beaman et al. (2021) explicitly model the network structure even more by considering not only the presence but the quantity of links among producers. They find that a threshold model explains the adoption of pit planting better than a simple contagion model.[1] We improve on their work by considering different temporal scales: last year with first differences versus a complete history with fixed effects.

We also contribute to a literature that studies the ability of social networks to protect against climate shocks. In the past decade, the availability of high-quality remote sensing data has opened up new research possibilities (Dell et al., 2014). The initial work of Townsend, Robert (1994) shows that village networks provide insurance for unexpected consumption expenses, since villagers borrow money from each other. More recent work by Kinnan et al. (2024) shows how health shocks

[1]"Pit planting" is an improved way to plant maize in Africa.

propagate through village networks. In our case, we are interested in how social networks provide information about the benefits of a potential technology and the working capital to adopt it. We also have a uniquely rich network. Our work contributes to a new literature that studies ex ante and ex post adaptation to climate change (Carleton et al., 2024).

Finally, we combine two different econometric techniques in a novel way to examine temporal and spatial decay in peer effects. The study of peer effects extends beyond cooperative entry to many classes of decisions (Bramoullé et al., 2020). Our study is one of the first to use panel data and the first that we know of to use two different panel lengths. [2] Moreover, we are the first to use first differences in addition to fixed effects (Millimet & Bellemare, 2023) to control for individual heterogeneity. Similarly, the study of spatial lag comes from the political science literature, for example the impact of the policy of neighboring countries on the policy of a particular country (Yesilyurt & Elhorst, 2017). To our knowledge, we are the first to compare estimation results from a linear-in-means model and from a spatial lag model to study temporal and spatial frictions.

Our paper proceeds as follows. Section 2 describes the context and the two cooperatives. Section 3 describes our entry network and drought data. Section 4 gives the empirical specifications for the linear-in-means and spatial lag models. Section 5 explains the results of both models. Section 6 concludes.

2 Background and Context

In this section, we first describe the context of our study and the two issues facing producers. Next, we describe the two cooperatives and how they address these issues. Finally, we describe conceptually how the entry decisions of other producers in the same village and in different villages would affect a given producer's decision to enter either cooperative.

[2] Bramoullé et al. (2020) only gives three other examples.

2.1 The Problem: Seasonal Drought and Coffee Leaf Rust

Our context is the state of Chiapas, Mexico, which is the largest coffee producing state in Mexico. Most coffee producers are smallholder producers with less than 5 hectares of land, like our population. These particular coffee plots are located on the sides of hills at altitude under a shade canopy and as part of a larger ecosystem (Soto-Pinto et al., 2000). Cooperatives have been highly operative throughout the region since the 1990s, when the Mexican government ended its subsidy programs (Martinez-Torres, 2006). They have functioned as extension programs, teaching farmers a variety of ways to respond to climate change (Soto-Pinto et al., 2012).

Smallholder agricultural producers often depend on income from one cash crop in order to finance the purchase of all items that they cannot produce themselves. Thus, they are particularly vulnerable to adverse production shocks that affect this cash crop. In our context, smallholders produce coffee, but the issues that we describe below could apply to any other cash crop, such as cacao.

We consider two vulnerabilities in particular: seasonal drought and coffee leaf rust. Seasonal drought is one of the channels through which climate change affects agricultural productivity (Ortiz-Bobea et al., 2021). To measure seasonal drought, we use the the Standardised Precipitation-Evapotranspiration Index (SPEI) compiled by Vicente-Serrano et al. (2010), which we describe in more detail in Section 3.1. Membership in a coffee cooperative in response to seasonal drought is an example of a producer's adaptive response to climate change (Carleton et al., 2024).

In addition to drought, which affects a variety of cash crops, coffee in particular is affected by coffee leaf rust (CLR), a fungus that affects Arabica coffee plants worldwide (Rhiney et al., 2021). Beginning in 2012, Mexico and Central America experienced an outbreak of CLR that significantly reduced production. The incidence of CLR is related to climate change. The increased heat of climate change makes coffee plants more susceptible to CLR. In addition, common agricultural practices such as monoculture and deforestation also make coffee plants more susceptible to the disease.

2.2 Mitigating Technologies

Both the coffee cooperative and the honey cooperative provide strategies to counter the effect of seasonal drought and coffee leaf rust on agricultural productivity and thus producer welfare.

We examine the question of membership in a coffee cooperative or in a honey cooperative by borrowing from the framework of technology adoption, in particular the notion of learning-from-others (Foster & Rosenzweig, 2010). Our approach contrasts with previous work that examines the determinants of producer entry into contract farming (Bellemare & Bloem, 2018) and fair trade arrangements (Dragusanu et al., 2014). Many producer cooperatives offer some version of these services: a guaranteed purchase price to insure production, microcredit to smooth consumption, and technical assistance to learn improved production techniques. These services are funded by upstream contracts. To our knowledge, we are the first to consider membership in a cooperative under the framework of technology adoption.

Much of the literature on technology adoption considers the adoption of improved inputs such as High Yield Variety (HYV) seeds and fertilizer (Foster & Rosenzweig, 2010). Producers will adopt the technology if the expected benefit outweighs the cost. Early work borrowed the notion of learning-by-doing from the endogenous growth literature using the target input model (Romer, 1994). In this model, producers observe the effect of a particular amount of input (usually an amount of fertilizer) and the resulting output. Over time, they learn to calibrate the amount of input to the amount of output.

One drawback to a purely learning-by-doing approach is that it may take many attempts for a producer to determine the correct input by trial and error. Thus, Foster and Rosenzweig (1995) introduce the notion of learning by observing others. In effect, every time a producer observes a neighbor's experience with a particular technology, it allows him to approximate more closely the optimal amount of the technology. The effectiveness of learning from others depends on the assumption that the experience of a neighbor is more similar to the producer's own than not, as Munshi (2014) points out. However, understanding the role of social networks in technology adoption has emerged as a key to increasing technology adoption (Beaman et al., 2021).

In the following, we describe in more detail the two cooperatives, how they mitigate the effect of seasonal drought and coffee leaf rust, and the decision problem the producer faces in deciding whether to join them.

2.2.1 Coffee Cooperative

Smallholder coffee producers suffer both from price risk and quantity risk. The price risk comes from output price volatility. They must sell their production to intermediaries whose prices vary depending on the international price of coffee. We consider the quantity risk that producers suffer due to the effects of climate change and coffee leaf rust. Coffee grows best at altitude in a wet, tropical climate. Thus, seasonal drought negatively impacts production. Improved agronomic techniques from technical assistance workshops offered by coffee cooperatives could mitigate these negative effects. Coffee leaf rust affects coffee plants directly by permanently reducing production. To mitigate the effects of CLR, producers must replace coffee plants with disease-resistant varieties. Coffee cooperatives both develop these plants and subsidize their planting. In addition, the technical assistance workshops teach alternatives to monoculture and deforestation that make coffee landscapes overall less susceptible to risk.

When deciding whether to join a coffee cooperative, a producer considers the expected cost and the expected benefit of technical assistance workshops. Uncertainty is involved in both of these estimates. Producers' neighbors can help them reduce the uncertainty around the expected benefit of the technical assistance workshop by sharing their own experience. In a drought situation, they can provide first-hand experience of how effective the techniques are in mitigating the effects. Similarly, replacing coffee plants due to CLR requires access to improved coffee plants, as well as labor and material costs. Cooperative membership could grant access to these plants, help in planting them, and a more certain estimate of whether the plants actually work against CLR.

2.2.2 Honey Cooperative

For the producers in our area of study, membership in a honey cooperative functions as a different kind of technology than membership in a coffee cooperative. Membership in a coffee cooperative offers producers the opportunity to improve their coffee production, while membership in a honey cooperative offers them the opportunity to diversify their income and insure themselves against the quantity risk that climate change and CLR pose to their coffee production.

Anderzén et al. (2020) highlight the benefits of beekeeping as a livelihood diversification strategy for a similar population of coffee growers to our own. They find that beekeeping is associated with a reduction in the incidence of food insecurity because it provides a separate source of income that comes at a different time as income from the coffee harvest. In general, coffee producers in the region are diversifying as a result of climate change (Eakin et al., 2012).

Despite the benefits of beekeeping, coffee producers have been reluctant to adopt the practice (Anderzén et al., 2024). One factor is that the technology is unfamiliar. Another factor is the initial capital investment. It takes a certain number of bees and specialized equipment to start beekeeping. Finally, they are concerned about a market for honey. Our partner honey cooperative provides training and the loan of the initial equipment. In addition, it certifies the honey as organic and provides market access to sell it in other parts of Mexico. As the number of producers' peers who adopt honey production goes up, the uncertainty around the welfare effect of adopting honey collapses. For many producers, this change in their cost-benefit analysis leads to an increase in the likelihood of entry.

3 Data and Descriptive Statistics

In this section, we describe the data that we use to analyze membership in the coffee cooperative and the honey cooperative. Our analysis leverages spatial variation in the location of producers and temporal variation in the timing of cooperative entry. Moreover, the spatial variation allows us to cross reference producers' locations and remote sensing drought data so that we can analyze the effect of the drought on producers' decisions to join one or both cooperatives.

3.1 Spatial Extent

Figure 1 shows a network graph of entry into the coffee cooperative. Producers are divided into regions which are, in turn, subdivided into villages. Colors indicate the year of entry. Clusters of the same color visually identify groups of producers in the same village or region that entered in the same year. This clustering reveals that producers who enter the coffee cooperative together tend to live with other producers in the same village.

Figure 2 shows a network graph of entry into the honey cooperative. Once again, producers are grouped into regions that branch out into villages. In contrast to the organization of coffee producers, this clustering reveals that producers who enter the honey cooperative together tend to be the only producers in their village and in many cases the only producers in their region. Moreover, even at the end of the time period, not every region has a honey producer.

Our region of interest includes substantial variation in altitude and climate. Figure 3 shows the variation in altitude. Of the 498 producers in our data set, we have geolocated the coffee plot of 244 of them; for the other 254, we use the coordinates of a nearby village. The combined set of elevations is normally distributed with most elevations in the range of 500 to 1500 meters. This altitude variation gives us substantial variation in rainfall and temperature for the region of interest.

We extracted Standardized Precipitation Evapotranspiration Index (SPEI) values for every coffee plot or nearby village for the years 2002-2024 using Google Earth Engine. The SPEI is a gridded measure of drought that uses variation from the mean in both precipitation and temperature over the past three months to build a rolling monthly drought index. Vicente-Serrano et al. (2010) gives more information about the calculation of the SPEI and the associated improvements over the SPI (Standardized Precipitation Index) and the self-reported Palmer scale. The SPEI has two thresholds that define the magnitude of drought conditions: **severe drought** if the drought index is between -1.5 and -2 and **extreme drought** if the drought index is below -2.

Figure 4 shows the average monthly value of the SPEI index for the area of interest over the 22-year interval. Red lines indicate the thresholds for severe and extreme droughts. Figure 5 relates the average number of producers who join the coffee cooperative each year and the average months of drought each year. We see that the number of producers who join the coffee cooperative decreases substantially in years with one or more months of drought. The year 2018 is an exception to this trend. Figure 6 relates the average number of members who join the honey cooperative each year and the average months of drought each year. We see that entry into the honey cooperative is somewhat inversely related to the number of months of drought in a year.

3.2 Temporal Extent

Our analysis is based on a unique data set of 22 years of entry into the coffee cooperative and the honey cooperative. The length of this panel allows us to perform our analysis on a shorter and longer time horizon.

We break up the data into two 11-year periods based on the two sets of administrative data that we merged. From these initial periods to 2013, we have self-reported entry dates in both cooperatives. From 2013-24, we have administrative records from both cooperatives that indicate whether the producers marketed coffee through the coffee cooperative or honey through the honey cooperative. This break in the type of data provides a natural way to run our analysis over two different time horizons: a short-term time horizon and a medium-term time horizon. Thus, we will run the empirical analysis we describe in the next section on a short 11-year panel from 2013-24 and a long 22-year panel from 2002-24.

Table 1 summarizes the entry patterns at the village level. Table 2 summarizes the entry patterns at the member level. As in the network graphs in Figures 1 and 2 above, we see quite different entry patterns among the two cooperatives.

The coffee cooperative began in 2002 with four producers in one village. In 2013, 274 producers in 63 villages had joined, with a substantial portion of villages in all but one region. By 2024, 484 producers in 120 villages had joined, almost all of the sample.

The honey cooperative began in 2005 with three producers in two villages. In 2013, 25 producers in 16 villages had joined, one or two villages apiece in most of the regions. By 2024, 43 producers in 24 villages had joined, more villages in the same regions but no new regions.

These differential entry patterns motivate our use of direct and indirect effects and different specifications for the indirect effects in the models in the following section.

4 Empirical Framework

4.1 Linear-In-Means Model

4.1.1 Basic Model

We estimate a linear-in-means model to estimate the effect of the share of cooperative members in a producer's village on the entry decision of the producer. Bramoullé et al. (2009) gives an overview of these models, which are often used in the peer effects literature to determine the association between an outcome variable for an individual and the mean of the same outcome variable for an individual's reference group. In our case, the reference group is the individual's village, as is typical in rural settings (Munshi, 2014).

The outcome is a binary indicator y^z_{ijt} of whether producer i in village j adopted cooperative z in year t. Cooperative is indexed by $z \in c, h$ where c denotes the coffee cooperative and h the honey cooperative.

We define the **network strength** N^z_{ijt} of a producer i in village j at time t for cooperative z as the share of producers in village j that have adopted z, excluding producer i. Network strength ranges from 0 (no other members in the village) to 1 (all other producers in the village are members).

$$N^z_{ijt} = \frac{1}{n_j - 1} \sum_{k=1,k\neq i}^{n_j} y^z_{kjt} \tag{1}$$

We use the lagged value of a producer's network N_{ijt-1} to estimate the effect of village network on the producer's entry decision.

Next, we incorporate the yearly measure of periods of severe drought and extreme drought that we described in Section 3.1. The SPEI uses rolling periods of three months. The index value for a given month uses precipitation and temperature data from that month and the prior two months. We add the level effects of the number of periods of both types of drought in the previous year.

The spatial resolution of our drought data allows us to compute these measures at the producer level, either using the location of a producer's coffee plot or the nearby village.

We denote the number of periods of severe drought and extreme drought experienced by producer i in community j in year t as D^s_{ijt} and D^e_{ijt}, respectively, and group them in a 2x1 vector $\mathbf{D_{ijt}}$ for notational convenience. Similarly, we denote the individual effects of these periods of drought on entry as δ^{zs}_{ijt} and δ^{ze}_{ijt} and group them in the 2x1 vector $\delta_{\mathbf{ijt}}$.

In addition, we add interaction terms to capture the differential effect of the number of periods of each type of drought on entry depending on the network strength. We denote the interaction effects as γ^{zs}_{ijt} and γ^{ze}_{ijt} and group them in a 2x1 vector $\gamma^{\mathbf{z}}_{\mathbf{ijt}}$ in Equations (2) and (3).

Finally, we present two specifications of this model that control for producer time-invariant characteristics in different ways. Equation (2) uses the number of periods of both types of droughts, the overall village share of cooperative members, producer fixed effects, and whether the producer joined the cooperative in the current year. Equation (3) uses the change in the number of periods of both types of droughts, the share of village members who adopted the cooperative in the previous year, and whether the producer joined the cooperative the current year. Both specifications incorporate time fixed effects.

$$y^z_{ijt} = \alpha^z_1 + \beta^z_1 N^z_{ijt-1} + \delta^{\mathbf{z}}_{\mathbf{1}}\mathbf{D_{ijt-1}} + \gamma^{\mathbf{z}}_{\mathbf{1}}\mathbf{D_{ijt-1}} N^z_{ijt-1} + \phi^z_{1i} + \xi^z_{1t} + \epsilon^z_{1ijt} \tag{2}$$

$$\Delta y^z_{ijt} = \alpha^z_2 + \beta^z_2 \Delta N^z_{ijt-1} + \delta^{\mathbf{z}}_{\mathbf{2}}\mathbf{\Delta D_{ijt-1}} + \gamma^{\mathbf{z}}_{\mathbf{2}}\mathbf{\Delta D_{ijt-1}} N^z_{ijt-1} + \xi^z_{2t} + \Delta\epsilon^z_{2ijt} \tag{3}$$

4.1.2 Identification

We first discuss identification of β^z, the effect of an increase in the share of producers who join cooperative z in time period $t-1$ on the probability that a given producer will join the cooperative in time period t. This coefficient of interest is present in the first specification above, Equation (2).

One threat to identification is time-varying shocks that affect all producers, such as large-scale drought, heat, or market shocks. In both equations, we rely on year-fixed effects ξ^z_t to control for these shocks. Another threat to identification is time-invariant unobservable producer characteristics such as ability or education. In Equation (2), we rely on producer fixed effects ϕ^z_i

to control for these characteristics.

However, recent work by Millimet and Bellemare (2023) suggests that in long panel setups the identification assumption for fixed effects may not hold. Unobservable unit-level heterogeneity may not be constant across all of the time periods of the a given panel. Both of our panels, the short 11-period one and the longer 22-period one, are much longer than the typical three- or four-period panels used in applied research.[3] For this reason, we also estimate first-difference versions of these specifications in Equation (3). However, as we mention in the previous and the following sections, it would be a mistake to think of the first difference specification in Equation (3) as a different version of Equation (2). It really is a completely different model representing entry behavior on a short one-year time period instead of a multi-year year (11 or 22) time period.

We next discuss identification of δ^{zs} and δ^{ze}, the effect of a the number of periods of severe drought and extreme drought. Because we use year fixed effects above, these coefficients capture the average effect of variation in the intensity of drought in the cross section. We consider such short-term climate variation as an exogenous weather shock and use the panel specification recommended by Dell et al. (2014). Similarly to the concerns about the produce fixed effects above, however, these authors also note that the length of our two panels blurs the line between a short-term effect, which goes one way from weather to producer behavior, and a medium-term effect, which may involve an adaptive response on the part of the producer. Thus, we compare estimates of these coefficients on both panels to look for evidence of a temporal lag in adoption.

Finally, we discuss identification of $\gamma^{\mathbf{z}}$: γ^{zs} and γ^{ze}. These scalars capture the joint effect of one additional period of severe or extreme drought, respectively, and the strength of the producer's network on the probability of a producer's entry in a cooperative. If the sign of γ^z is the same (opposite) as the sign of β^z, then a stronger network increases (decreases) the effect of drought on entry or a drought increases (decreases) the effect of the network.

[3]For example, McKenzie (2012) describes a more common scenario where researchers move from three to four or five waves of a survey.

4.2 Spatial Lag Model

We also estimate an Spatially Lagged X (SLX) model to allow for the effect of spatial spillovers on the entry decisions of the members of a producer's village on the entry decision of the producer. Halleck Vega and Elhorst (2015) gives an overview of these models. The SLX model is one of a set of spatial econometric models that are used to model processes with spatial spillover effects. These models incorporated spatially lagged versions of the explanatory variables on the right-hand side along with their direct counterparts to capture the indirect effect of changes in x in other spatial regions on the independent variable y. In our setting, the SLX model will incorporate spatially lagged versions of the network strength of other villages, as well as the number of periods of extreme and severe drought that these villages experience.

$$y^z_{ijt} = \alpha^z_3 + \beta^z_3 N^z_{ijt-1} + \boldsymbol{\delta^z_3 D_{ijt-1}} + \mathbf{W N^z_{t-1}} \theta_3 + \mathbf{W D_{t-1}} \lambda_3 + \epsilon^z_{3ijt} \tag{4}$$

The key element of the SLX model is the weighting matrix $\mathbf{W}$, which specifies how the spatially lagged dependent variables enter the estimation. The choice of $\mathbf{W}$ depends on the underlying theory of how the spatial process works. In all cases, the diagonal elements of $\mathbf{W}$ are 0, so that the direct effect of N^z_{ijt-1} does not enter the equation a second time. In practice, researchers often estimate equations with several different specifications of weighting matrices and compare the estimated results with a Durbin-Wu-Hausman test.

We use three different weighting matrices. All three weighting matrices have zeroes down the diagonal so that the direct effect does not enter the estimating equation more than once. The scalars of the off-diagonal elements are calculated in one of three ways below.

1. **Binary Contiguity.** This weighting matrix assigns a weight of 1 to each of the villages in the same region as the village j. The matrix is row-normalized so that the weights in each row add up to 1.

$$w^1_{jk} = 1 \tag{5}$$

2. **Inverse Distance - Region.** This weighting matrix assigns a weight to each village k in the same region as village j according to the inverse of the distance d_{jk} between j and k. The matrix is scaled by the largest eigenvalue.

$$w^2_{jk} = \frac{1}{d_{jk}} \tag{6}$$

3. **Inverse Distance - All Villages.** This weighting matrix assigns a weight to each village k i the sample according to the inverse of the distance d_{jk} between j and k. The matrix is scaled by the largest eigenvalue.

$$w^3_{jk} = \frac{1}{d_{jk}} \tag{7}$$

4.3 Inference

Here we describe how we calculate the standard errors and perform hypothesis tests for both the linear-in-means model and the spatial-lag model. We begin with the linear-in-means model. Because we are using two-way fixed effects in Equations (2) and time fixed effects along with first differences in Equation (3), one practice would be to cluster by producer and year in both equations.

Abadie et al. (2023) argues that this practice results in standard errors that are too conservative and proposes two considerations when considering the level of clustering: **a design component** and **a treatment assignment mechanism**. In our case, we are not estimating our equations on a sample but instead analyzing a diffusion process over a whole population. Moreover, every year contains a producer, and every producer eventually contains an entry year, so every cluster is treated. For this reason, we do not cluster our standard errors by village and year. Instead, we use heteroskedasticity-robust standard errors.

Next, we turn to the spatial lag model. Here, the appropriate use of standard errors is an active area of research, so we follow the guidelines of a recent working paper by Xu and Wooldridge (2022). They use the two-part framework above that consists of a design component and a treatment assignment mechanism. Instead of clustering standard errors by the spatial unit (in our case the village), they suggest using spatial heteroskedasticity and autocorrelation consistent standard errors.

5 Results and Discussion

In this section, we present results from the estimation of the linear-in-means model and the spatial lag model from the previous section. We compare and contrast the estimation results of both models on the short panel and the long panel.[4] In addition to the direct effects of the village adoption rate in the presence of the two types of drought shocks, we are also interested in the interaction between the network adoption rate and the drought shocks. For the linear-in-means models, we compare estimation results from the producer fixed effects specification in Equation (2) and estimation results from the first-difference specification in Equation (3). For the spatial lag model in Equation (4), we compare estimation results from three different specifications of the weighting matrix.

5.1 Linear-In-Means Results

Here we present results from estimating Equation (2) and Equation (3) on the short and the long panel for entry into the coffee cooperation and entry into the honey cooperative.

Since Equation (2) uses producer fixed effects and Equation (3) uses first differences, we can compare the long-term impact of drought and the overall village adoption rate of both cooperatives with the short-term impact of drought and the village adoption rate of both cooperatives in the previous year.

Moreover, since we estimate both specifications on a short panel with 11 years of entry decisions and a long panel with 22 years of entry decisions, we can compare the estimation results for two time horizons. In particular, we argue that the results from the short panel capture a diffusion process in progress, and the results from the long panel capture the same diffusion process from start to finish.

[4] Recall that short panel contains 11 years of entry decisions and the long panel contains 22 years of entry decisions.

5.1.1 Entry into Coffee Cooperative

Table 3 presents the results for the entry into the coffee cooperative. First, we focus on columns 1 and 2, which use producer fixed effects. A 10% increase in the previous time period of the overall membership rate of the village increases by 5% the probability that a given producer will join the coffee cooperative in the present time period.

Column 1 gives the effect of periods of severe drought and extreme drought on entry in the short panel. Here, each additional period of severe drought adds 4% to the probability that a producer will join the coffee cooperative. The additional network effect could eliminate this effect. On the other hand, each additional period of extreme drought decreases by 6% the probability that a producer will join. The additional network effect could be up to 4% in the opposite direction. One possibility is that the network corrects a producer's initial belief that the coffee cooperative will not help in situations of extreme drought.

Column 2 presents the same results estimated over the long panel. The point estimate of the network effect is very similar to the network effect in the short panel, as is the effect of extreme drought and the interaction between the network and extreme drought. The main difference between the estimation results on the short panel and the estimation results on the long panel is in the coefficient of the interaction effect between the network strength and the presence of one or more periods of extreme drought. In the long panel, the sign of this effect is positive, instead of negative in the short panel. One possibility is that the network reinforces a producer's initial belief that the coffee cooperative will not help in situations of extreme drought.

Next, we turn to columns 3 and 4, which estimate first difference versions of our model on the short panel. Due to the first differencing, the dependent variable Δy_{ijt}^c takes the value 1 only in the year when the producer joins the coffee cooperative. On the right-hand side, the first-differencing collapses the independent variables in the same way. The village network covariate ΔN_{ijt-1}^c is just the share of producers in the producer's reference group (village) who joined the cooperative in the previous year, not the total share of producers in the reference group who joined the cooperative up until the current year. Similarly, the drought covariate ΔD_{ijt-1} is an increase (or decrease) in the number of periods of extreme or severe drought from the previous year.

Thus, the point estimates in the estimation results for the first difference specifications capture responses to shocks and not trends. In column 3, the point estimates of Equation (3), are nonzero and statistically significant. If 10% of a producer's village joins the coffee cooperative in a given year, then there is a 1% chance that a producer will also join the cooperative. A period of severe drought in a given year increases the probability of joining by 2.5%. The network effect can mitigate this probability of joining by as much as 4%. In the short panel, we do not see an immediate response to extreme droughts. In column 4, which uses the long panel, we do not see a network effect at all. Only the effects of periods of drought remain. An additional period of extreme drought decreases the probability that a producer joins by 1.5%. The village network could potentially reverse that effect.

We summarize the estimation results from the linear-in-means models as follows. The strength of the village network affects a producer's decision to join the cooperative in both the short panel and the long panel. The effect comes from not only the immediate decisions of other producers in the same village to join the cooperative in the previous year, but also the cumulative decisions of other producers in the same village to join the cooperative up until the present year. Extreme drought discourages entry into the coffee cooperative and the village network reduces this effect. In the short panel, severe drought encourages entry into the coffee cooperative, and the village network also reduces this effect. One possible explanation is that the village network updates the producers' beliefs about whether cooperative membership is beneficial against severe drought and extreme drought.

5.1.2 Entry into Honey Cooperative

Next we turn to the estimation results of the linear-in-means model on entry into the honey cooperative. Once again, we estimate two specifications on both the short panel and the long panel. The specifications differ in that they use two different methods to control for producer-level unobservables: producer fixed effects and first differences. Table 4 presents the results.

First, we turn to column 1, which estimates Equation (2) on the short panel. Recall that this specification uses producer fixed effects. A 10% increase in the strength of the village network causes a 5% increase in the probability that a producer will join the honey cooperative. We find no effect of periods of severe drought or periods of extreme drought, either on their own or interacted with network strength.

Column 2 presents the results of estimating the same equation on the long panel. The network effect decreases slightly. A 10% increase in the strength of the village network causes a 4% increase in the probability that a producer will join the honey cooperative. Once again, periods of drought on their own do not affect entry, but in the presence of the network, a period of extreme drought increases the probability of entry by 5.1% and a period of severe drought decreases it by 3.9%. Perhaps in the first 11 years of the cooperative the network was less active in periods of severe drought and more active in periods of extreme drought.

Now we turn to estimation results from Equation (3) in columns 3 and 4. As we noted in the previous section, these specifications use first differences and thus capture the immediate effect of the village adoption rate of the the honey cooperative in the prior year on the probability of a producer joining the honey cooperative in a given year. In both columns, the effect of the village network is similar. A 10% increase in the village adoption rate of the honey cooperative is associated with a 1.2% increase in the short term or a 0.7% increase in the long term that a producer in the same village will join the honey cooperative. Neither point estimate is statistically significant. Wee see no effect of periods of drought, either on their own or interacted with network strength.

5.2 Spatial Lag Results

5.2.1 Entry into Coffee Cooperative

Table 5 presents the results of the estimation of Equation (4) on the short panel and the long panel with each of the three weighting matrices described in Section 4: a binary contiguity matrix of other villages in the same region, an inverse distance matrix of other villages in the same region, and an inverse distance matrix of all other villages across all regions.

In all six columns, we see a direct effect of network strength on a producer's decision to join the coffee cooperative. The effect size ranges from 30% to 40%. Like the network effect in the linear-in-means model, we interpret this coefficient to mean that a 10% increase in the membership rate in a producer's village is associated with an increase of 3% to 4% in the probability that the producer will join the coffee cooperative. The direct effect of an additional period of severe drought is only associated with entry in column 2, which shows the estimation results for the short panel with the regional inverse distance weighting matrix. In contrast, the direct effect of an additional period of extreme drought is associated in all columns but column 2 with a 2% and a 4% decrease in the probability that a producer will join the coffee cooperative. In most columns, this result is statistically significant at the 10% level. This coefficient has the same sign and magnitude as the corresponding coefficient in the linear-in-means results in Table 3.

We next move to the indirect network effects. The effect sizes across the specifications are not directly comparable because the weighting matrices are normalized in different ways. The binary contiguity weighting matrix in columns 1 and 4 is row normalized, while the inverse distance matrices in columns 2, 3, 5, and 6 are normalized by the largest eigenvalue in each matrix. However, we see a substantial indirect effect of the network in the six columns, larger than the direct effect. Thus, we confirm the presence of spatial spillovers.

Finally, we examine the indirect effects of drought. Columns 1 and 4 show that an additional period of severe drought or extreme drought in another village in the same region increases the probability that a producer will join the coffee cooperative by 2% - 5%. The effect sizes increase in columns 3 and 6, which use weighting matrices that take into account all villages in the study area.

Finally, we use the log-likelihood score at the bottom of the table to compare the specifications of the three weighting matrices for the two panels. For the short panel, the specification in column 3 with all villages fits the data better. For the long panel, the specification in column 5 with only villages in the same region fits the data better. This difference may indicate that as the coffee cooperative spread, initially only peer effects in the same region mattered but then peer effects in the whole area of study became more important. This model of diffusion reflects the descriptive trends that we saw in Table 2.

5.2.2 Entry into Honey Cooperative

Table 6 presents the results of the estimation of Equation (4) on the short panel and the long panel with each of the three weighting matrices described in Section 4.

As in the estimation results for the entry into the coffee cooperative in the previous section, we see a strong network effect of nearly 50% in the short panel and 40% in the long panel. We see little direct effect of periods of severe or extreme drought.

The magnitude and sign of the indirect effect of the network varies depending on the specification of the weighting matrix and the length of the panel. We first consider the short panel. Column 1 shows a positive network effect with the binary contiguity matrix. For columns 2 and 3, incorporating the inverse distances at the regional and all village level causes the effect size to change sign. This paradoxical result reflects the fact that the honey producers in a given region are typically concentrated in one village and that across the area of interest the honey producers are concentrated in a few regions. Thus, the entry decision of a given producer is inversely related to the entry decision of a producer not in the same village or region.

Next, we move to the long panel. For column 4, the indirect effect of the network is positive and significant, as in column 1 in the short panel. Using the regional inverse distance weighting matrix in column 5 eliminates the indirect effect. Using the inverse distance weighting matrix with all villages in column 6 brings it back even more strongly. Thus, in the long term, the honey cooperative is spreading throughout the region of interest.

At the village level, in the short term, both periods of severe drought and periods of extreme drought are associated with the entry into the honey cooperative. These associations are not present in the long term.

Finally, we examine the log-likelihood values at the bottom of the table. For both the short panel and the long panel, neither the regional or all-village inverse distance weighting matrices improves the model fit over the binary contiguity one.

5.3 Limitations

Both classes of our models suffer from limitations. Since our network graph is undirected, causal identification of the linear-in-means results is threatened by time-invariant shocks that affect producers in the same village or region. For example, improvement of roads or the destruction of a key bridge could affect a producer's entry decision through the channel of market access. As Bramoullé et al. (2009) describe, one way to control for these shocks is to instrument neighbors with neighbors-of-neighbors. However, this approach works only with directed graphs.

Along these lines, we note another important assumption for causal identification: that the network structure is stable and exogenous. The length of the time periods in question raises questions about that assumption, though a unique feature of this setting is that the indigenous tend to stay in the same place that their families have inhabited for generations.

In addition, our use of producer fixed effects and first differences represents two extremes: assuming stable individual heterogeneity across 11 (or 22) periods or only using variation from the previous period. In the real world, a substantial portion of producer fixed effects probably hold stable for a "Goldilocks mean" of five periods or so.[5] This limitation affects our spatial lag model as well, since we estimate it with producer fixed effects but not with first differences.

Finally, we choose to measure drought as two discretized periods of **severe drought** and **extreme drought** instead of a continuous variable of rainfall and temperature as in other studies in the climate shock literature described by Dell et al. (2014). We use the two SPEI categories because the SPEI index combines the magnitudes of deviation from the mean of temperature and rainfall and not just level effects. At the same time, the opposite signs of the coefficients in the severe and extreme drought raise the question of whether this discretization is artificial. The producers in our population experience the weather in a continuous way.

[5] The reference to the short story "Goldilocks and the Three Bears" by Robert Southey here refers to a quantity that is neither too short nor too long but just right.

6 Conclusion

In this paper, we have analyzed the effect of temporal and spatial lag on entry into two cooperatives that help smallholder producers in the face of one type of climate shock, seasonal drought. We are not the first to examine the determinants of contract farming, cooperative entry, or technology adoption. However, we bring a new approach. We apply two econometric methods—the linear-in-means model from the peer effects literature and the spatial-lag model from the regional science literature —in a novel way with a uniquely rich data set to analyze the way these technologies have diffused through an extremely isolated population over time and space.

Crucially, we do not make the unrealistic assumption of the absence of spillovers but explicitly take them into account and turn them into an object of study. We find differences in the adoption patterns of the coffee cooperative and the honey cooperative. They differences give insight into how information about the coffee cooperative and honey cooperative is transmitted across time and space in the presence of climate shocks.

Our results give insight into similar contexts in the developing world. It takes several years to learn about a new technology, whether it is learning by doing or learning from others. Moreover, it takes time for information about a new technology to be transmitted across space. Policy makers continue to lament the low uptake of many welfare-improving technologies. They and their implementing partners would do well to consider these temporal and spatial lags as they promote them.

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Exhibits

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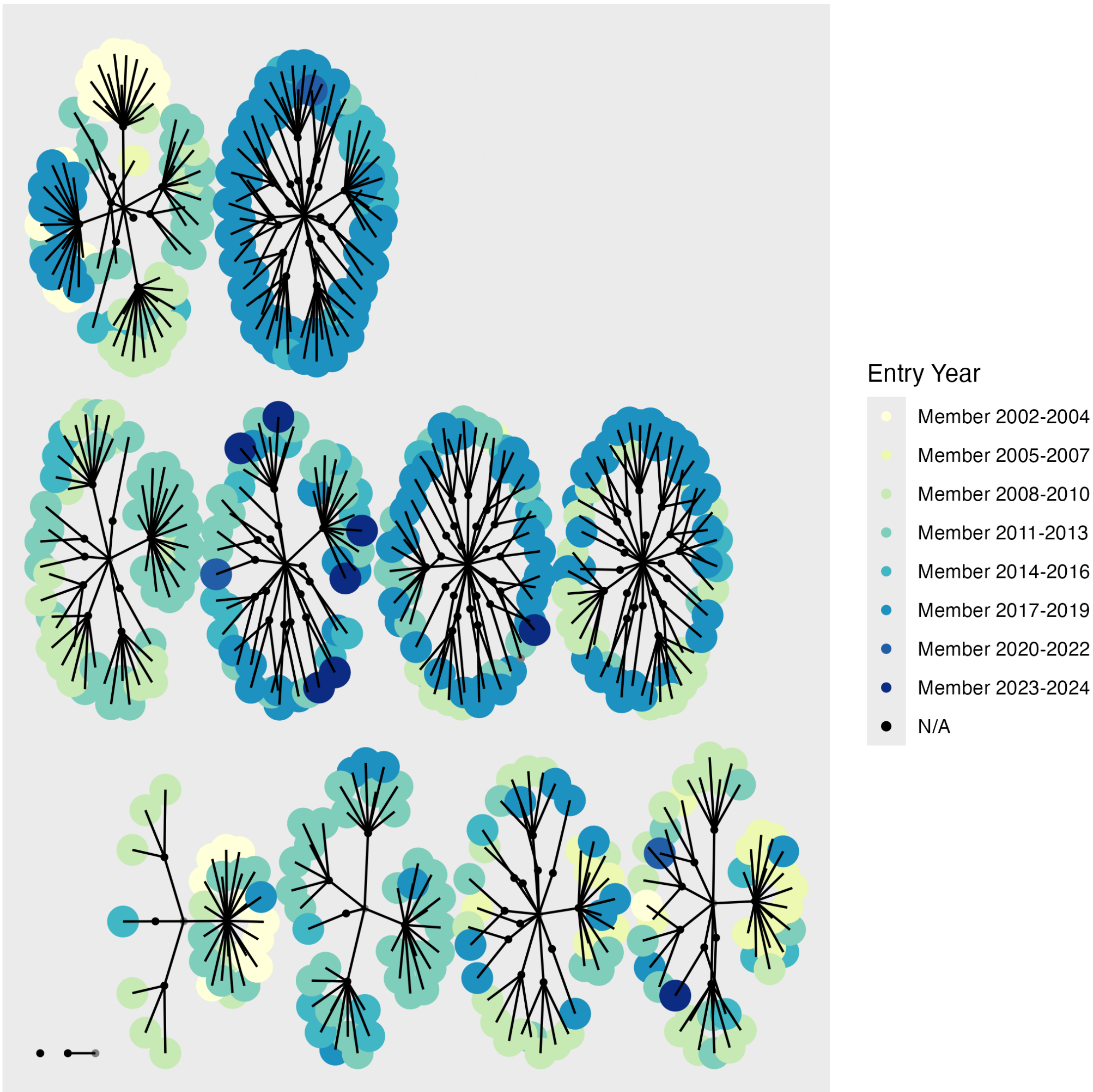
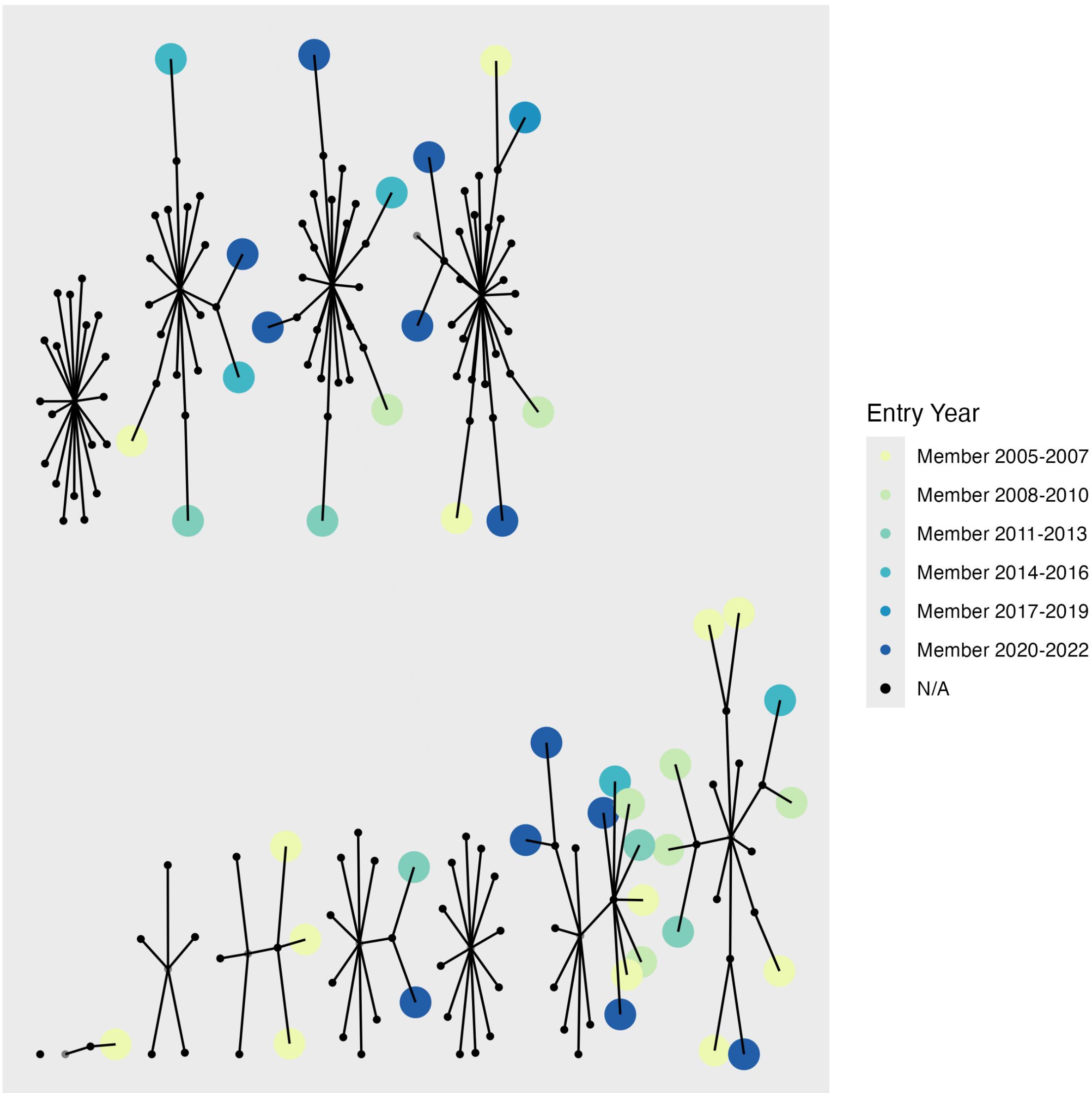
Figure 1: Entry Network of Coffee Cooperative



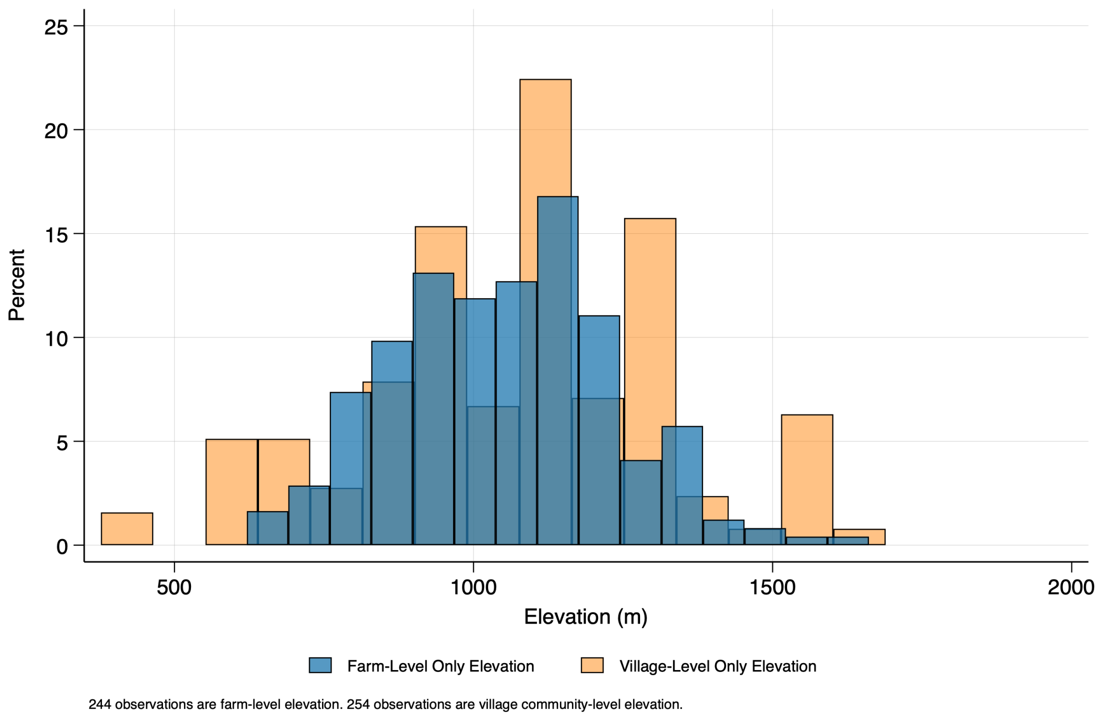
This figure displays the network of coffee cooperative members. Nodes indicate coffee producers. Colors indicate the year of entry. Nodes are grouped by village and then villages are grouped into regions. Black nodes are placeholders to position producers.

Figure 2: Entry Network of Honey Cooperative



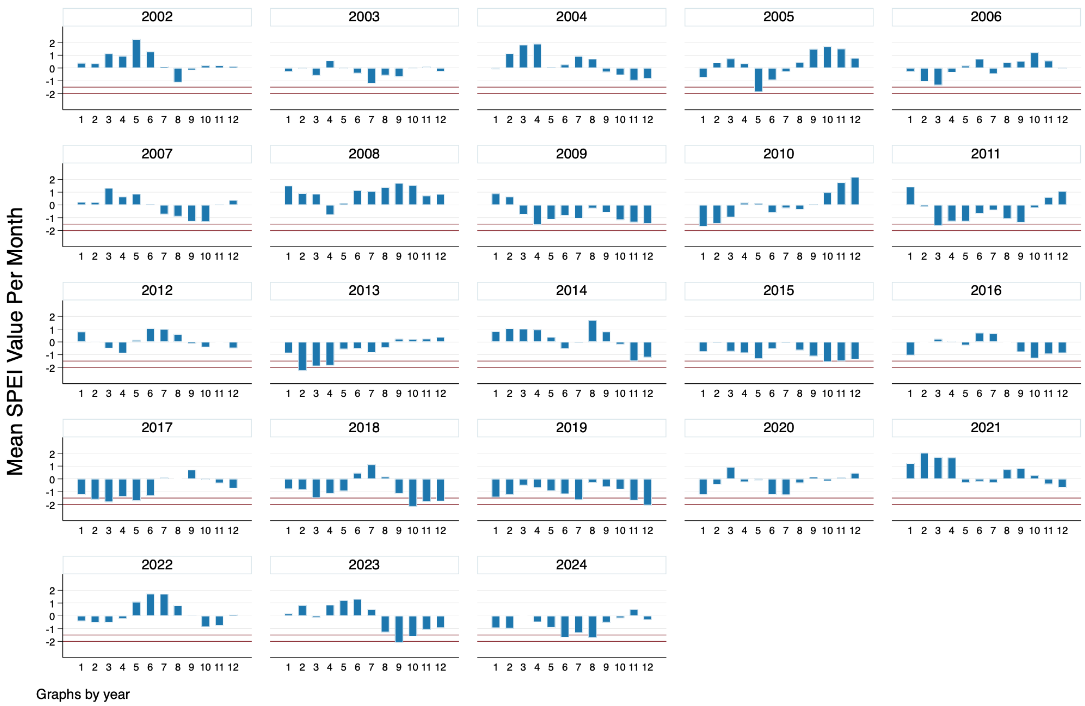
This figure displays the network of honey cooperative members. Nodes indicate honey producers. Colors indicate the year of entry. Nodes are grouped by village and then villages are grouped into regions. Black nodes are placeholders to position producers.

Figure 3: Elevation of Producers



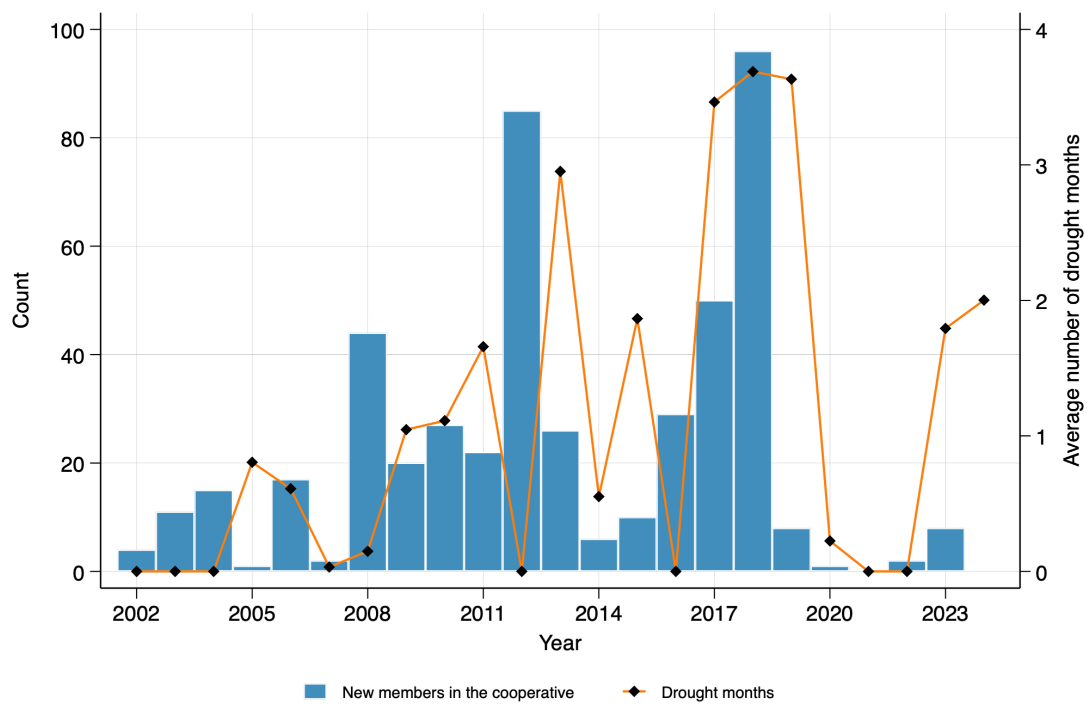
This figure displays the distribution of the elevation of the universe of producers. For the subsample of producers whose coffee plots have been geolocated, the blue bars indicate the plot elevation. For the remaining producers, the orange bars indicate the village elevation.

Figure 4: Monthly Variation in SPEI by Year



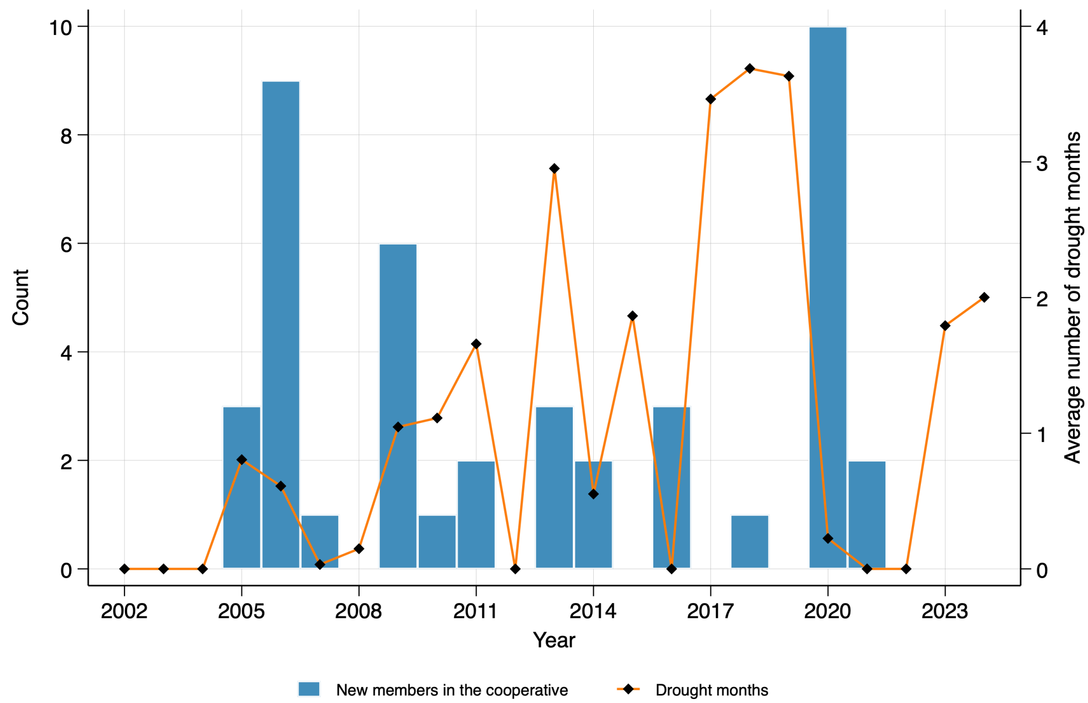
This figure displays the mean value of the SPEI (Standardised Precipitation-Evapotranspiration Index) by month from 2002-2024 for the survey region. Vicente-Serrano et al. (2010) gives more information about the data. Red lines show the thresholds for severe drought (below -1.5) and extreme drought (below -2).

Figure 5: Coffee Cooperative Entry and Drought by Year



This figure displays the number of producers who entered the Batsil Maya coffee cooperative each year and the number of three-month periods of severe or extreme drought based on the SPEI.

Figure 6: Honey Cooperative Entry and Drought by Year



This figure displays the number of producers who entered the Chabtic honey cooperative each year and the number of three-month periods of severe or extreme drought based on the SPEI.

Table 1: Village-Level Entry

	Region	Villages	Coffee 2002	Coffee 2013	Coffee 2024	Honey 2005	Honey 2013	Honey 2024
	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.

Table 2: Individual-Level Entry

			Coffee			Honey		
	Region	Individuals	2002	2013	2024	2005	2013	2024
	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.

Table 3: Linear-In-Means Estimates for Entry into Coffee Cooperative

	Joins Coffee Cooperative (1=Yes)			
	FE Short	FE Long	FD Short	FD Long
	(1)	(2)	(3)	(4)
Network Strength (Village)	0.533***	0.524***	0.104***	0.003
	(0.038)	(0.028)	(0.029)	(0.014)
Periods of Severe Drought	0.039***	0.019***	0.025***	0.004
	(0.008)	(0.006)	(0.007)	(0.005)
Periods of Extreme Drought	−0.063***	−0.019	−0.002	−0.015*
	(0.023)	(0.014)	(0.012)	(0.008)
Severe Drought x Network Strength	−0.040***	−0.031***	−0.038***	−0.017***
	(0.007)	(0.006)	(0.007)	(0.005)
Extreme Drought x Network Strength	0.048***	−0.036***	−0.001	0.012*
	(0.018)	(0.014)	(0.011)	(0.006)
Year Fixed Effects	Y	Y	Y	Y
Producers	498	498	498	498
Years	11	22	11	22
Observations	5,478	10,956	4,980	10,458
Adjusted R^2	0.078	0.124	0.100	0.065

The dependent variable is a dummy that indicates whether a producer joined the cooperative in a given year.
Columns 1 and 2 use producer fixed effects to control for unobserved heterogeneity.
Columns 3 and 4 use first differences to control for unobserved heterogeneity.
Columns 1 and 3 use a short 11 year panel. Columns 2 and 4 use a long 22 year panel.
Network Strength is the share of producers in the same village that joined the cooperative by the previous year.
Periods of Severe Drought (-2 ¡ SPEI ¡= 1.5) and Periods of Extreme Drought (SPEI ¡= -2) are calculated by matching a producer's coffee plot or village and SPEI drought data from the previous year.
Standard errors are heteroskedasticity-robust.

Table 4: Linear-In-Means Estimates for Entry into Honey Cooperative

	Joins Honey Cooperative (1=Yes)			
	FE Short	FE Long	FD Short	FD Long
	(1)	(2)	(3)	(4)
Network Strength (Village)	0.496***	0.411***	0.124	0.068
	(0.127)	(0.101)	(0.123)	(0.068)
Periods of Severe Drought	−0.0004	−0.002	−0.001	0.0005
	(0.002)	(0.002)	(0.001)	(0.001)
Periods of Extreme Drought	0.003	0.002	0.002	0.004*
	(0.006)	(0.004)	(0.004)	(0.003)
Severe Drought x Network Strength	−0.008	−0.039***	0.007	0.002
	(0.010)	(0.014)	(0.006)	(0.005)
Extreme Drought x Network Strength	0.008	0.051***	−0.001	−0.004
	(0.015)	(0.018)	(0.005)	(0.005)
Year Fixed Effects	Y	Y	Y	Y
Producers	498	498	498	498
Years	11	22	11	22
Observations	5,478	10,956	4,980	10,458
Adjusted R^2	0.019	0.016	0.017	0.008

The dependent variable is a dummy that indicates whether a producer joined the cooperative in a given year.
Columns 1 and 2 use producer fixed effects to control for unobserved heterogeneity.
Columns 3 and 4 use first differences to control for unobserved heterogeneity.
Columns 1 and 3 use a short 11 year panel. Columns 2 and 4 use a long 22 year panel.
Network Strength is the share of producers in the same village that joined the cooperative by the previous year.
Periods of Severe Drought (-2 ¡ SPEI ¡= 1.5) and Periods of Extreme Drought (SPEI ¡= -2) are calculated
by matching a producer's coffee plot or village and SPEI drought data from the previous year.
Standard errors are heteroskedasticity-robust.

Table 5: Spatial Lag Estimates for Entry into Coffee Cooperative

	Joins Coffee Cooperative (1=Yes)					
	(1)	(2)	(3)	(4)	(5)	(6)
Direct Effect - Network	0.303***	0.347***	0.399***	0.363***	0.359***	0.397***
	(0.024)	(0.023)	(0.022)	(0.014)	(0.014)	(0.013)
Direct Effect - Severe Drought	0.002	0.019**	0.001	−0.005	0.006	−0.010
	(0.008)	(0.009)	(0.008)	(0.007)	(0.008)	(0.007)
Direct Effect - Extreme Drought	−0.027	−0.004	−0.037*	−0.029*	−0.021	−0.032*
	(0.020)	(0.022)	(0.021)	(0.017)	(0.018)	(0.017)
Indirect Effect - Network	0.594***	0.454***	0.673***	0.433***	0.425***	0.757***
	(0.034)	(0.033)	(0.060)	(0.022)	(0.019)	(0.039)
Indirect Effect - Severe Drought	0.023**	−0.002	0.064***	0.024***	0.006	0.056***
	(0.010)	(0.010)	(0.018)	(0.009)	(0.008)	(0.015)
Indirect Effect - Extreme Drought	0.054**	0.001	0.166***	0.016	−0.002	0.038
	(0.025)	(0.027)	(0.049)	(0.020)	(0.020)	(0.038)
Weighting Formula	Binary	Inv Dist	Inv Dist	Binary	Inv Dist	Inv Dist
Other Villages	Region Only	Region Only	All	Region Only	Region Only	All
Producer and Year Fixed Effects	Y	Y	Y	Y	Y	Y
Producers	498	498	498	498	498	498
Years	11	11	11	22	22	22
Log-Likelihood	733	661	602	-154	-88	-180
Observations	5,478	5,478	5,478	10,956	10,956	10,956
Adjusted R^2	0.656	0.647	0.639	0.746	0.749	0.745

The dependent variable is a dummy that indicates whether a producer joined the cooperative in a given year.
Columns 1, 2, and 3 use a short 11 year panel. Columns 4, 5, and 6 use a long 22 year panel.
Network Strength is the share of producers in the same village that joined the cooperative by the previous year.
Periods of Severe Drought (-2 ¡ SPEI ¡= 1.5) and Periods of Extreme Drought (SPEI ¡= -2) are calculated
by matching a producer's coffee plot or village and SPEI drought data from the previous year.
Standard errors are heteroskedasticity-robust.

Table 6: Spatial Lag Estimates for Entry into Honey Cooperative

	Joins Honey Cooperative (1=Yes)					
	(1)	(2)	(3)	(4)	(5)	(6)
Direct Effect - Network	0.494***	0.498***	0.492***	0.390***	0.389***	0.386***
	(0.062)	(0.062)	(0.062)	(0.037)	(0.037)	(0.037)
Direct Effect - Severe Drought	−0.002	−0.008*	−0.011*	−0.003	0.0002	0.002
	(0.003)	(0.004)	(0.006)	(0.003)	(0.004)	(0.004)
Direct Effect - Extreme Drought	−0.0003	−0.007	−0.020	−0.005	0.011	0.006
	(0.006)	(0.012)	(0.015)	(0.005)	(0.009)	(0.010)
Indirect Effect - Network	0.149**	−0.062*	−0.265***	0.089**	0.002	0.234***
	(0.065)	(0.032)	(0.062)	(0.044)	(0.038)	(0.089)
Indirect Effect - Severe Drought	0.003	0.012**	0.036**	0.002	−0.004	−0.010
	(0.003)	(0.006)	(0.016)	(0.003)	(0.005)	(0.011)
Indirect Effect - Extreme Drought	0.009	0.017	0.081*	0.014**	−0.013	−0.007
	(0.007)	(0.017)	(0.049)	(0.007)	(0.012)	(0.032)
Weighting Formula	Binary	Inv Dist	Inv Dist	Binary	Inv Dist	Inv Dist
Other Villages	Region Only	Region Only	All	Region Only	Region Only	All
Producer and Year Fixed Effects	Y	Y	Y	Y	Y	Y
Producers	498	498	498	498	498	498
Years	11	11	11	22	22	22
Log-Likelihood	6106	6116	6137	8004	8003	8015
Observations	5,478	5,478	5,478	10,956	10,956	10,956
Adjusted R^2	0.895	0.895	0.896	0.695	0.694	0.695

The dependent variable is a dummy that indicates whether a producer joined the cooperative in a given year.
Columns 1, 2, and 3 use a short 11 year panel. Columns 4, 5, and 6 use a long 22 year panel.
Network Strength is the share of producers in the same village that joined the cooperative by the previous year.
Periods of Severe Drought (-2 ¡ SPEI ¡= 1.5) and Periods of Extreme Drought (SPEI ¡= -2) are calculated by matching a producer's coffee plot or village and SPEI drought data from the previous year.
Standard errors are heteroskedasticity-robust.