"You Quit?" Influence of Neighbor Experience and Exit on Small Farmer Market Participation

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Abstract

This research analyzes the relationship between a farmers’ participation in Nicaraguan supermarket supply chains and the market entries and exit of neighboring farmers. Drawing on insights from the technology adoption literature on learning and experimentation, we incorporate measures of neighbors’ experience into a model of a farmer’s decision to join or quit these markets. We also test for strategic delay by small farmers and estimate the price that some farmers may pay for experimentation.

Our results suggest both that that neighbors’ exits negatively influence a farmer’s own decision to join the supply chain and that some farmers engage in strategic delay. Early adopters bear costs of their neighbors’ “free riding” in the form of higher product rejection rates and lower annual transactions with supermarkets. Evidence of strategic delay on the part of farmers suggests a social process rather than a firm-level roll out of new contracts within a given village.

Keywords: contract farming, supermarkets, market adoption, Latin America, Walmart, Nicaragua, strategic delay

1 Introduction

Theoretical and empirical research into mechanisms of household technology adoption has increasingly focused on analyzing the role of social learning and mimicry. Considerable evidence now supports the hypothesis that social processes influence farmer experimentation with new agricultural methods and inputs. The existence of social adoption pathways for technology adoption has implications both for models of innovation diffusion and for policies to promote the uptake of welfare-improving technologies in the developing world. How might similar social dynamics apply to small farmers’ market participation?

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As a determinant of household poverty outcomes, market participation plays a major role; it can and should be analyzed as a methodological and theoretical extension of research on technology adoption. Like a new technology, adopting modern markets is something of a gamble for small farmers, requiring that they assume new production and marketing risks in exchange for uncertain remunerative benefit (Narayanan, 2012; Michelson, Reardon, and Perez, 2012). How and why do small farmers decide to join a supermarket supply chain? How and why do they decide to drop out? How do they incorporate what they observe of their neighbors' experiences into their own decision-making?

Moreover, the dynamics of market participation may have special consequences in circumstances in which there are externalities to farmers' entrance and exit. For example, in the case of supermarkets as contractual buyers, anecdotal evidence suggests that the likelihood of contractual hold-up by the supermarket rises as the number of village suppliers increases (Wiegel, 2012). Conversely, the entrance of new farmers as supply chain participants in a village might increase farmers' bargaining power or help them achieve scale economies in production or transport.

Even so, the social dynamics governing the adoption of a marketing contract are likely to differ in important ways from factors influencing the adoption of a new high yielding variety of maize or cotton. First, the externalities on existing suppliers of a new entrant into a modern value chain may be both more significant and more immediate than the effects of a farmer's adoption of a high yielding crop variety in a context of well-integrated output markets. A second dimension distinguishing participation in high value markets is the relatively high observed levels of farmer exit from modern marketing channels (Ruben, Boselie, and Lu, 2007; Jano and Mainville, 2006; Barrett et al., 2011). While some technology adoption research has considered the phenomenon of disadoption (Moser and Barrett, 2006; Neill and Lee, 2001; Reardon and Farina, 2000), estimates of and models for these processes have thus far been only minimal. In the context of modern markets, we need to understand better the influence that a farmer's exit can have upon neighbors in the same market system.

Building on insights from the technology adoption literature linking adoption to social processes, this paper tests for the existence of social dynamics in farmers' decisions to participate in new agricultural output markets. The site of the research is Nicaragua, where smallholders participating in modern supply markets have verbal agreements with large supermarkets to grow products meeting chain-specific quality standards. We use a unique data set that includes the year of entry into and exit from the supply chain covering every farmer known to have had a stable supply relationship with a supermarket in Nicaragua between January 2000 and December 2008. As in Foster and Rosenzweig (1995), we define a farmer's information set geographically; farmers living within the same village who enter the supply chain are the set of neighbors from which a farmer can learn. We argue that a farmers' participation in a supply chain would be readily noticed by other farmers living in his or her village. Note that our analysis does not assess the influence of farmers who decide to stay out of the supply chain entirely; nor do we have information about the social connectivity of farmers within a specific village.

We use a simple lifecycle model to explain supermarket supply chain participation and exit patterns in Nicaraguan supermarket supply villages. We hypothesize that farmers acquire information about the profitability of a new marketing channel relative to the traditional market from their own experience in the modern market, but also from their neighbors' accumulating experience in the supply chain and from their neighbors' decisions to exit the modern market. Our research therefore incorporates the farmer's own experience, neighbor experience, and neighbor exit from supermarket supply chains into a empirical model, to test whether farmers' observation of these variables influence the decision to participate in subsequent periods, and also to estimate whether some farmers pay a price for experimentation with the new market opportunity. Because the neighbor experience variables are critical to the analysis and because there are several plausible ways a farmer might accumulate information about his neighbors' experience, we construct four different measures of neighbor supply chain experience and run separate estimations for each of the four measures. Our method of including neighbor exit and tenure as possible determinants of farmer market participation has potential application to a variety of cases involving technology adoption and market participation.

Results from a model estimating the likelihood of participation in supermarket supply chains among Nicaraguan farmers suggest the following: First, neighbors' exits from the supermarket supply act as significant negative influences on a farmer's own decision to participate in the new market; Second, observation of neighbors' accumulating experience in the supply chain is a significant positive determinant of a farmer's participation; Finally, we find evidence that farmers free-ride on their neighbors' experience, reducing their own experimentation to benefit from the information they glean from their neighbors' entry and exit. The consequence of this free-riding: if farmers fail to incorporate their neighbors' learning externality into their participation decision, we may observe under-participation in the supply chain (and under provision of information about the supply chain) relative to a social optimum.

Our evidence suggests that early entrants into the supply chain (who often enter alone) experience less favorable contractual terms than those who join later in terms of the likelihood of supermarket payment default, product rejections, and number of annual transactions. This finding explains farmers' observed decision to strategically delay entry. Specifically, we find that the likelihood of supermarket payment default is inversely related to the number of suppliers in a village. We also find an inverse U relationship between the likelihood of a farmer reporting a signed contract with the supermarket buyer and the number of village farmers also selling to the supermarket. For tomato growers (the largest product represented in our sample), we find that the share of production rejected by the buyer decreases as more farmers join the supply chain in the village and we identify an inverse U relationship between the number of village suppliers and the number of annual deliveries made by the tomato farmer to the supermarket.

As with any analysis concerned with establishing evidence of a social process, we must deal with the potential problem of correlated outcomes. In other words, given that we observe correlations within villages in farmers' decisions to enter and exit the supermarket supply chain, we must distinguish between the existence of a socially mediated process and locally correlated production or price shocks that might drive entry and exit. Our strategy is to test for the interdependence of farmers' entry and exit decisions using farmer-level fixed effects models with errors clustered at the village level and to use a considerable amount of rich data on farmers' prices and production to rule out the possibility that within-village shocks drive the dynamics we observe.

We provide descriptive evidence related both to heterogeneous patterns of entry and exit within-villages as well as descriptives on prices and production which suggest that what we observe is not driven by within-village shocks. Moreover, evidence of strategic delay on the part of farmers suggests that we observe a social process rather than a firm-level roll out of new contracts within a given village. Our data include detailed information on credit, prices and production quantities, allowing us to control for a number of factors that might drive our results.

Note that it is not possible to distinguish learning from other factors that could underly the dynamic entry and exit from supply chains that we observe in the data; thus we must remain agnostic regarding whether what we observe reflects learning, mimicry, or even social pressures within villages (Maertens 2012). For this reason, our assessment that farmers learn from one anothers' outcomes must remain speculative. Nonetheless, we find a strong association between a farmer's entry into and exit from the supply chain and the entry and exit of neighbors. To our knowledge, our research is the first to identify such social dynamics in the analysis of farmers' contracting decisions.

The policy implications of our findings notably differ from work establishing social dynamics in technology adoption. Because high yielding crop varieties such as new hybrids allow all farmers to benefit without concern for market externalities, the policy question has generally been how to most efficiently promote universal adoption[1]. Yet the same is not necessarily true for market participation; the case of modern markets is more ambiguous. How do farmers incorporate their neighbors' market outcomes into their own decisions? What are the optimal village-level adoption dynamics? Can a farmer's exit or entry from a modern market have a net positive externality in the village? Our results raise questions about the optimal sequence and level of farmer market participation and exit as yet largely unasked and unanswered in the literature.

2 Contribution to the Literature

Research into the role of social learning and diffusion in technology adoption in the developing world is rooted in analysis of the adoption of high yielding varieties (HYV) and associated productivity-increasing technologies. Accumulating

[1] Leaving in the background questions of widening inequality attributable to the adoption of high yielding varieties.

evidence suggests that social influences indeed play a critical role in the uptake and spread of new technologies, whether through direct learning from neighbors or mediated through social pressures. Work by Narayan and Pritchett (1999) in Tanzania established a strong positive relationship between households' social capital and use of modern agricultural inputs such as agrochemicals, fertilizer, and improved seeds. Subsequently, Isham (2002) found that social affiliations in Tanzania influence farmers' adoption of fertilizer and Munshi (2004) identified that wheat growers' HYV adoption during the Indian Green Revolution incorporated the experience of neighbors. Foster and Rosenzweig developed an influential target-input model of HYV adoption (1995) and their results further established the influence of learning from others and free-riding on neighbors' adoption in HYV rice and wheat in India. The research into social networks and technology adoption has grown further nuanced. Maertens (2009) distinguishes between social mechanisms, untangling the effects of social pressures versus social learning in the adoption of Bt cotton in villages in central India.

Significantly less attention has been paid to social processes influencing participation in emerging modern output markets. In some research the role of a market is implicit, inextricable from the technology being adopted. For example, Conley and Udry's (2010) study of adoption of pineapple for export in Ghana is simultaneously a study of market participation and technology adoption. The authors find strong evidence that farmers learn about optimal input allocation from their successful neighbors; but the marketing decision itself is left largely in the analytical background.

A second gap in the literature concerns the need to incorporate disadoption of technologies and markets into estimates and models of adoption and learning. Moser and Barrett's (2006) study of the dynamics of smallholder adoption of a system of rice intensification (SRI) in Madagascar identifies a strong influence of learning from neighbors. The authors identify high rates of farmer exit from the technology: a village-level mean disadoption rate of 40 percent over seven years of exposure to SRI. They find that learning effects act as a strong influence on both a farmer's initial adoption decision and his later decision to continue or abandon the technology. Neill and Lee (2001) study the adoption and disadoption dynamics of an initially successful system of maize-bean crop rotation in Honduras but there is no social component to their estimation.

Market exit is a potentially important source of information about market adoption and several case studies suggest that disadoption or exit from modern value chains and markets is widespread. We see a significant amount of churning around participation in Nicaraguan supermarket supply chains, and researchers have documented farmer exit from modern output markets in other parts of the world including South Asia (Ruben, Boselie, and Lu, 2007), Brazil and Argentina (Reardon and Farina, 2000), and Guatemala (Jano and Mainville, 2006).

Failure to account for exit from either a technology or an output market implies an assumption that these choices are irreversible. However, the large number of exits from market participation in Nicaragua and elsewhere, as part of a dynamic process of adaptation – in other words, when new options were being evaluated by small farmer populations – suggests that the problem might not be entirely a function of differences in how, and how successfully, that new technology is deployed. In particular, the superior technology assumption in target input models built on Foster and Rosenzweig (1995) – that a new technology is an absorptive state – may not be appropriate. Moreover, possible pecuniary externalities of new entrants into a market on existing suppliers are not permitted by standard household technology adoption models, which are purely partial equilibrium without externalities other than learning.

Finally, because the outcomes of farmers who adopt a technology relatively early may provide valuable information to neighbors about expected benefits, there may be an incentive for famers to delay their own experimentation in order to observe others' experience. While evidence of strategic delay among farmers has been identified in a handful of empirical studies (Bandiera and Rasul, 2005), no research has tested as yet for strategic delay among farmers considering participation in a new market. While Bandiera and Rasul identify in a cross section of Mozambican farmers an inverse U-shaped relationship between the number of a farmer's family and friends adopting sunflower as a cash crop and their own adoption decision, we test for evidence strategic delay directly by testing for a relationship between neighbors' observed welfare outcomes – their accumulating productive assets – and a farmer's decision to join the supply chain in the next period.

3 Context

Two primary supermarket retail corporations operate in Nicaragua: the domestic chain La Colonia, and Walmart International, which purchased a controlling share in Dutch AHOLD's Central American holdings in 2006. By 2009, Walmart had opened 46 retail stores in Nicaragua and the domestic chain had opened ten stores. Michelson *et al.* (2012) describe the sector and the growth in Nicaraguan supermarket retail since 2000. The majority of farmers with supply relationships with a supermarket during this period were Walmart/AHOLD suppliers. Farmers sold a range of horticulture crops to supermarkets including: tomatoes, green peppers, lettuce, cabbage, cucumbers, herbs, and squash.

We study farmer entry and exit as a function of neighbor entry and experience, taking as given the initial entry of the first farmer in a village into the supply chain. The reason for this has to do with Walmart's buying strategy between 2000 and 2008. Walmart management during this period competed six buying agents against one another, using competition between regions to guarantee that weekly supply quantities are met at the lowest prices possible (Michelson, Reardon, and Perez, 2012). With agents under considerable pressure to meet strict regional quotas, sourcing during the period of this study (2000-2008) was chaotic. Buying agents habitually over-committed purchase order quantities with farmers or made up shortfalls at the last minute by establishing new contracts. Within this system, a farmer in a supply village would be largely free to determine his own entry into the marketing chain, once the buyer was purchasing in his or her village. Our model and estimation therefore take the locations of the supply chains and farmers as given.

Qualitative work in farmer supply villages and with former supermarket buying agents suggest that farmers primarily entered the supply chain in the following manner: a farmer living close to the central road or with a preexisting relationship with the buyer or a supermarket-affiliated NGO (see Michelson 2013) would begin to sell some production to a supermarket buyer. Often the buyer reported approaching the farmer after having seen from the road that the farmer was cultivating a crop that the buyer was interested in purchasing such as tomatoes, cucumbers, or peppers. Proximity to roads proved crucial for participation; as Walmart extended the geographic reach of its retail outlets into secondary cities, the company expanded procurement into more remote regions of the country, keeping transport costs down by using trucks supplying stores to backhaul agricultural production to the distribution centers located in central Nicaragua.[2] After an initial series of transactions, the supermarket agent would discuss with the farmer the crops that the supermarket was interested in purchasing in the next year, and the farmer and buyer would make a verbal agreement regarding the quantities he or she could expect the buyer to purchase and range the of prices the supermarket would pay. The farmer would provide specified quantities of a crop or crops according to an agreed-upon delivery schedule, cleaned and sorted to meet the supermarket's quality specifications and packed in plastic bins for easy transport. Supermarket buying agents agreed on a price range for the crop over a production season and agreed to pick up the crop at the farmgate or in the village. This option implicitly served to incentivize farmers under contract to increase their own production. These agents reported that once they had secured a relationship with an initial farmer in a village, other village farmers were free also to sell produce to the supermarket and to establish their own informal agreements with the buyer. These farmer entry and exit decisions (including the decision of the initial farmer to exit or stay in) are the focus of our analysis.

Note that nearly all farmers in the sample live within one kilometer of the highway. It is not the case therefore, that the decision of a village farmer living close to the highway to drop out of the supply chain would cut off his or her neighbors from accessing the supply chain.

Regarding benefits to participation in the supply chain, the advantage of suppling the supermarket versus a local market in Nicaragua during this time manifest in the following ways: (1) the stability of the price the supermarket offered, and (2) the supermarket assuming responsibility for transport costs and logistics from the farm gate to the distribution centers. Previous research es-

[2]Interviews with supermarket produce buying agents operating in Nicaragua between 2000 and 2008 indicated that primary criteria for a farmer to supply fresh produce centered around access: the buyer needed to be able to reach the farmer (initially by face-to-face communication and later by cellular phone) to arrange orders and the trucks picking up the produce for weekly or semi-weekly deliveries needed to easily reach the farm. In fact, we find that the majority of farmers supplying supermarkets in Nicaragua during this period lived within three kilometers of the central road network that runs in a Y-shape around lake Managua between Granada and Chinandega in the West and Granada and Ocotal in the East.

tablished (Michelson, Reardon, and Perez, 2012) that mean per unit farmgate revenues in the Walmart supermarket chain were not significantly higher than in the traditional market but that the Walmart supply agreement represented a significant reduction in price *risk* relative to the traditional market. The majority of the horticulture produced in Nicaragua is rain fed and the volatile price in the traditional market reflects the highly variable seasonal supplies. With Walmart guaranteeing a minimum price, farmers invested more in horticulture and increased their production (similar to the outcomes observed Karlan *et al.* (2013) when farmers were provided with production insurance), in some cases shifting from seasonal rained production to year-round horticulture cultivation relying on irrigation. The mechanism by which farmers benefit is neither improved price nor increased productivity but an increase in the total units sold. Michelson (2013) established that the supply relationship increased participant household farm-related productive assets in a manner consistent with increased farmer investment in horticulture cultivation. It is important to note that the supermarket buyers did not provide the farmer with farm credit or inputs during this period.

While the relationship mitigates some marketing risk for farmers, joining the supermarket supply chain is associated with a new set of production and marketing costs and risks. Evidence suggests that production and post-harvest processing and sorting increase production costs and introduce new production and marketing risks (Wiegel, 2012). Farmers bear the cost of payment delays from the supermarket; farmers reported that while traditional market buyers always paid in cash up front for production, supermarkets pay farmers by cash or by check with a delay ranging between a few days and a few weeks. Our data suggests that the likelihood of loss due to supermarket payment default is significantly higher than the traditional market; the reported annual incidence of supermarket payment default is 1.3 percent, nearly double the traditional market incidence rate at the farmgate and 14 times the payment default rate reported in regional wholesale markets. Wiegel (2012) documents that the supermarket imposes chain-specific and market-specific requirements on farmers including crop varieties and argues that it is difficult for farmers to switch costlessly between the supermarket and wholesale market. Moreover, because supermarkets only purchase the high quality share of a farmer's production (estimates are on the order of 70-80 percent, see Michelson (2013)), the farmer must assume the costs of transporting and marketing in the traditional market the share of his or her production not meeting supermarket quality standards.

We argue that observation of neighbor outcomes influences farmer supply chain entry and exit within villages. However, the value of the supply agreement likely varied over time, relative to the traditional market. The value therefore was likely observed by neighboring farmers with noise. In other words, there is a true stream of costs and benefits associated with supply chain participation relative to the traditional market but those costs and benefits fluctuate over time based on supply and demand dynamics in the traditional market. The presence of such noise would explain why some farmers initially enter the supply chain and then decide to exit.

In the next section we introduce a simple theoretical framework based on a lifecycle model to make clear how farmers' outcomes in the supermarket supply chain affect others' decisions to enter or exit.

4 Lifecycle model

We use a simple model of lifetime utility maximization to analyze the farmer's market participation decision. Building on the insights of the social networks and technology adoption literature, we expect that farmer i at time t learns about the profitability of a new marketing channel relative to the traditional market not only from his or her own experience in the supply chain so far, S_{it}, and exit from the supply chain, Z_{it}, but also from their neighbors' accumulating experience in the supply chain, S_{-it}, and from neighbors' exit, Z_{-it}. We define a farmer's neighbors $_i$ as all other residents of the same village who supply supermarkets at some point between time $t = 0$ and $t = T$. We assume that these informational sources enter separately into the farmer's decision problem and that the farmer making a decision at the start of time t uses the realized experience, exit, and asset variables from the previous period, $t - 1$.

Beliefs about the profits from the modern marketing channel, π_t^m, are increasing in own and neighbors' experience S_{it} and S_{-it} and decreasing in own and neighbors' exit Z_{it} and Z_{-it}. Neighbors' experience and the farmer's own experience reflect learning about optimal input levels and investment in the contract relationship conditional on participation, as in Foster and Rosenzweig (1995), while neighbors' exits Z_{-it} reflect the probability that the profitability of the modern market is less than the profitability of the conventional spot market, $\pi^m < \pi^c$, which would have induced others to exit. A_{it} and I_{it} represent farmer assets and irrigation stocks, respectively.

Our model and estimation take supply chain placement as a given. That is, we do not model the determinants of the situating of supply chains and sequential selection of farmers. In each period, the farmer chooses whether to participate in the supply chain or not, $b_{it} \in [0, 1]$, to maximize his utility $u(.)$:

$$u(b_{it}E[\pi_t^m(S_{it}, S_{-it}, Z_{it}, Z_{-it}, A_{it}, I_{it})] + (1 - b_{it})\pi^c) \tag{1}$$

with $\frac{\partial E\pi^m}{\partial S_{it}} > 0$, $\frac{\partial E\pi^m}{\partial S_{-it}} > 0$, and $\frac{\partial E\pi^m}{\partial Z_{-it}} < 0$. The farmer's period t uncertainty about the profitability of the modern marketing channel relative to the traditional channel is a result of uncertainty over, for example, the optimal investment level in a market with quality assessment, in post-harvest technology, negotiations, coordination, etc. In comparison, at time $t = 0$ the distribution of the traditional market is known as is the relationship of the central moments of the traditional market distribution to farmer investment. As modeled in Equation 1, π^c is deterministic.

The farmer's unconditional maximization problem can be written as the solution to the dynamic programming problem:

$$V_t(S_{it-1}, S_{-it-1}, Z_{it-1}, Z_{-it-1}, A_{it-1}, I_{it-1}) = \tag{2}$$
$$\max_{b_s} E_t \sum_{s=t}^{T} \theta^{s-t} (b_s \pi_s^m (S_{is-1}, S_{-is-1}, Z_{is-1}, Z_{-is-1}, A_{is-1}, I_{is-1}) + (1-b_s)\pi^c)$$

where S_{it-1} represents the farmer's own cumulative experience at the time of the decision, S_{-it-1} the farmer's neighbors' cumulative experience, Z_{it-1} the farmer's own exit, Z_{-it-1} neighbors' cumulative exits, A_{it-1} the farmer's assets, I_{it-1} the farmer's irrigation, and $\theta \in [0,1]$ the discount factor. Equation 3 can be rewritten using Bellman's equation:

$$V_t(S_{it-1}, S_{-it-1}, Z_{it-1}, Z_{-it-1}, A_{it-1}, I_{it-1}) = \tag{3}$$

$$max_{b_{it}} (1-b_{it})\pi^c + b_{it} E_t \pi_t^m (S_{it-1}, S_{-it-1}, Z_{it-1}, Z_{-it-1}, A_{it-1}, I_{it-1})$$
$$+\theta E_t V_{t+1}(S_{it}, S_{-it}, Z_{it}, Z_{-it}, A_{it}, I_{it})$$

The farmer's choice of b_{it} in period t both directly affects his utility in period t through changes in period t profit and also affects the optimal choice of b_{it+1} in the next period through changes in expected future profitability due to an increased stock of own experience, S_{it}.

We can solve for the farmer's optimal solution to the value function at $t = 0$. The first order condition is:

$$0 \leq -\pi^c + E_t \pi_t^m + \theta E_t (\frac{\partial V_{t+1}}{\partial b_{it}}) \tag{4}$$

which at time t=0 can be written:

$$\pi^c - E_t \pi_t^m \leq \theta (V_1(1) - V_1(0)) \tag{5}$$

Equation 4 tells us that in period $t = 0$ the farmer will adopt as long as the discounted value of the information he gains from participation is at least as large as the expected difference in profits between the modern and traditional market.

A coordination problem results if farmer's own participation in time t, b_{it} (assuming that b_{it} is continuous) is increasing in his own assets A_{it} or irrigation I_{it}. If this is the case for all farmers ($\frac{\partial b_i}{\partial A_i} > 0 \ \forall i$) then an individual's lifetime utility will be increasing in neighbors' participation and asset and irrigation stocks. If these cross-partials hold, there will be incentive for farmers to delay participation and free-ride on the accumulating experimentation of neighbors, i.e. to engage in strategic delay.

5 Empirical model

We are interested in the likelihood of participation, which depends on farmer observed and unobserved characteristics as well as village characteristics. Our simple model suggests that the likelihood of a farmer's participation is a function of his supply chain experience and exit and assets and irrigation as well as his or her neighbors' experience and exit, assets and irrigation.

$$b_{it} = F(S_{it-1}, S_{-it-1}, Z_{it-1}, Z_{-it-1}, A_{it-1}, A_{-it-1}, I_{it-1}, I_{-it-1}) \tag{6}$$

If unobserved farmer characteristics are uncorrelated with the set of observed explanatory variables, they are in the error term. If, however, the unobserved and the independent variables have some correlation, the omitted variables will bias the parameter estimates. For example, with regard to market participation, there may be some correlation between, on one hand, a willingness to take on additional risk, and on the other, unobserved social connections involving assets and access to irrigation. We run both an Ordinary Least Squares (OLS) and a conditional logit model.

The OLS model is written:

$$b_{it} = \gamma_1 S_{it-1} + \gamma_2 S_{-it-1} + \gamma_3 Z_{-it-1} + \beta_1 A_{it-1} + \beta_2 A_{-it-1} + \beta_3 I_{it-1} + \beta_4 I_{-it-1} + \alpha_i + \epsilon_{it} \tag{7}$$

Both the OLS and the conditional logit include farmer-level fixed effects (α_i) but the OLS model allows us to better handle the standard errors, given that we have data grouped at the village level[3]The relative magnitudes and significance of the results are largely consistent across the two models and we report both sets. Based on the predictions from the lifecycle model in Section we test the following hypotheses:

1. Farmers' participation in the supply chain is positively influenced by own experience:
   $H_0 : \gamma_1 = 0$ vs. $H_A : \gamma_1 > 0$
2. Farmers' participation in the supply chain is positively influenced by neighbors' cumulative participation:
   $H_0 : \gamma_2 = 0$ vs. $H_A : \gamma_2 > 0$
3. Farmers' participation in the supply chain is negatively influenced by neighbors' cumulative exits from the supply chain:
   $H_0 : \gamma_3 = 0$ vs. $H_A : \gamma_3 < 0$
4. Farmers' participation in the supply chain is negatively influenced by neighbors' mean asset holdings (evidence of strategic delay):
   $H_0 : \beta_2 = 0$ vs. $H_A : \beta_2 < 0$

[3]The estimation of the parameter vector will be biased and inconsistent with heteroskedastic errors in the nonlinear model.

5. Farmers' participation in the supply chain is positively influenced by his irrigation:
   $H_0 : \beta_3 = 0$ vs. $H_A : \beta_3 < 0$

6. Farmers' participation in the supply chain is negatively influenced by neighbors' mean irrigation (evidence of strategic delay):
   $H_0 : \beta_4 = 0$ vs. $H_A : \beta_4 < 0$

7. On the margin, observing a neighbors' exit from the supply chain is a stronger influence on farmer participation than observing additional neighbors' participation:
   $H_0 : |\gamma_3| = |\gamma_2|$ vs. $H_A : |\gamma_3| > |\gamma_2|$

6 Data and measures of neighbor experience

Data were gathered in Nicaragua between September 2007 and July 2008 in collaboration with the Nitlapan Institute at the Universidad Centro Americana. Researchers identified 425 supermarket suppliers who comprised the population of Nicaraguan farmers who regularly supplied horticulture to the two primary supermarket companies over some period between 2001 and 2008. Complete household and village-level data was collected for 396 supplier households. Because our estimations require that the farmer had within-village neighbors who also supplied the supermarket, we use the subset of farmers who lived in villages where more than one farmer supplied – 320 farmers in 77 communities. As a part of a comprehensive household survey, suppliers were asked to recall their history of participation in the supermarket supply chain, including the years that they entered and, if they had exited by 2008, the year that they exited. Note that if we leave the farmers without neighbors in the estimations with zero values for the neighbor experience variables, our results remain consistent.

Villages are defined administratively. Farmers are grouped by the name of the village in which they resided at the time of the survey and these groupings were confirmed by latitude and longitude coordinates taken at households at the time of the interview. The supplier population in each village is defined as all suppliers who sold to the supermarket between 2001 and 2008.

The first two rows of Table 1 presents the annual share of total village participants supplying the supermarket and the annual share of village participants that had exited, by year. The mean participant share increases until 2006, plateaus in 2007, and decreases in 2008. The mean share of exits (as a share of total village suppliers) is by construction cumulative and therefore increases steadily over the eight year period. By 2008, the mean exit share is nearly half of all suppliers who ever joined the supply chain between 2001 and 2008. The estimations for the determinants of the decision to participate in time t use the $t-1$ variables for neighbors' and own experience and exits, assets, and irrigation.

6.1 Participation and exit variables

The experience variables are critical to the analysis. An important question then: how would a farmer accumulate information about the market experiences of his neighbors. Would he treat each annual observed farmer's participation decision as providing equal information to his own decision making process? Would earlier entrants (and exits) carry more informational weight than later entrants? Instead, might he consider his neighbors' *average* experience tenure and exits in the village over time?

In this section we present four sets of experience variables and examine the relationships among them. We construct four sets of neighbor experience measures as a robustness check for the empirical analysis - we want to be sure that the results are not dependent on the choice of the measure of neighbor experience.

6.1.1 Farmers' own experience and exit

First, as a measure of own experience, b_{it} is equal to one in the year the farmer enters the supply chain and all subsequent years until exit and zero otherwise. Note that we also include a farmer's supplier status at $t-1$ in the estimations. At time $t' < T$, a farmer's experience is the sum of all years that he or she has been in the supply chain divided by the number of years that have elapsed since the start of supermarket sourcing in our data (2000):

$$S_{it} = \frac{1}{t'} \sum_{t=1}^{t'} (b_{it} | b_{it} = 1) \tag{8}$$

Second, as a measure of farmer's own exit, z_{it} is equal to one in the year of exit and all subsequent years and zero before and during participation. The z_i's are summed over t and divided by t' to yield Z_{it}:

$$Z_{it} = \frac{1}{t'} \sum_{t=1}^{t'} (z_{it} | z_{it} = 1) \tag{9}$$

6.1.2 Neighbors' experience and exit

We construct four measures of neighbor supermarket supply chain experience and exit: (1) measures of neighbors' average annual experience and exit (2) measures in which farmers give more informational weight to early entrants and less to the experience of neighbors who enter the supply chain as time goes on (3) annual cumulative participation and exit shares (4) average annual experience weighted by neighbor similarity using a euclidian distance measure. As discussed, neighbors are defined as the residents of the farmer's village who, at some point between 2000 and 2008, sold horticulture to a supermarket buyer.

Measure 1 - Neighbors' average annual experience

As a measure of neighbors' experience, we use the sum of all neighbors' years of experience in the supply chain divided by the number of neighbor-observation years at time t. In effect, this is a measure of the annual average experience of a farmer's neighbors. Therefore, if a farmer has one neighbor who participates in the year 2002 but then quits, the experience measures would be equal to zero in the 2001, .5 in 2002, .33 in 2003 and declining thereafter. The value of the measure will range between zero and one. In general, for village j with a size n_j supplier population:

$$S_{-it} = \frac{\sum_{k \neq i}^{n} \sum_{t=1}^{T} (b_{kt} | b_{kt} = 1)}{(n_j - 1) * t'} \tag{10}$$

Neighbors' annual average years of exit in village j are constructed just as experience. As with the measure of individual exit, neighbors' exit z_{-it} is equal to one in the year of exit and all subsequent years:

$$Z_{-it} = \frac{\sum_{k \neq i}^{n} \sum_{t=1}^{T} (z_{kt} | z_{kt} = 1)}{(n_j - 1) * t'} \tag{11}$$

Measure 2 - Neighbors' average annual experience - early entrant weights

This measure is constructed to give more informational weight to early entrants and less to the experience of neighbors who enter the supply chain in later years and, similarly, to the additional years of experience of neighbors who stay in the channel. So the entrance of a neighbor into the supply chain in 2001 would convey more information than one who entered in 2008. These measures are not bounded at one. For example, for neighbors' experience:

$$S_{-it} = \frac{\sum_{t=1}^{T} \sum_{k \neq i}^{n} (b_{kt} | b_{kt} = 1)/t'}{(n_j - 1)} \tag{12}$$

Similarly, for neighbors' exits:

$$Z_{-it} = \frac{\sum_{t=1}^{T} \sum_{k \neq i}^{n} (z_{kt} | z_{kt} = 1)/t'}{(n_j - 1)} \tag{13}$$

Measure 3 - Cumulative participation and exit shares

These experience variables measure annual neighbors' cumulative participation and exit shares in a farmer's village. In these measures each neighbors' entry and exit from the supply chain is counted once, rather than weighted by the length of his or her relationship with the supermarket or the time since exit. So a farmer that enters the supply chain and stays for a single year counts gives an equivalent signal as one who enters and remains in the channel for multiple years.

$$S_{-it} = \sum_{t=1}^{T} \sum_{k \neq i}^{n} \frac{(b_{kt}|b_{kt} = 1)}{(n_j - 1) * t'} \tag{14}$$

$$Z_{-it} = \sum_{t=1}^{T} \sum_{k \neq i}^{n} \frac{(z_{kt}|z_{kt} = 1)}{(n_j - 1) * t'} \tag{15}$$

These sums are normalized by the total number of suppliers in the village. They can be interpreted as measures of the share of the participant farmers in the village who had joined the supply chain by time t. By 2008, the experience measure will approach a value of one and the exit measure will approach the within-village share of total exiting farmers (as a share of total participants).

Measure 4 - Neighbors' average annual experience weighted by neighbor similarity

The final set of experience and weights neighbors' average annual experience (Measure 1) with weights $frac1d_k$ that measure how similar each neighbor is to the observing farmer. The experiences of other farmers are weighted using weights constructed using the inverse Euclidian distance based on farmer observables, so that the behaviors of those most like the farmer are given greater weight relative to those of neighbors who least resemble the farmer.

$$S_{-it} = \frac{\sum_{k \neq i}^{n} \sum_{t=1}^{T} \frac{1}{d_k} (b_{kt}|b_{kt} = 1)}{(n_j - 1) * t'} \tag{16}$$

$$Z_{-it} = \frac{\sum_{k \neq i}^{n} \sum_{t=1}^{T} \frac{1}{d_k} (z_{kt}|z_{kt} = 1)}{(n_j - 1) * t'} \tag{17}$$

6.1.3 Relationships among the neighbor experience and exit measures

Means and standard deviations of the four measures of neighbor experience are presented in Table 7. Figures 1 and 2 graph the mean values of measures of neighbors' experience and exit between 2001 and 2008.

The experience variables are constructed to permit neighbors' entry and exit from the supply chain to enter in a range of ways into the farmer's own entry or exit decision. For example, measures constructed from the cumulative share of farmers that have entered or exited the supply chain give relatively more informational weight to farmers with short spell length than those that factor in a farmer's tenure in the supply chain.

If both a neighbor's entry and length of supply relationship provide information to the farmer then the number of total neighbor farmer-years in the supply chain will be a better measure of the farmer's full information set. The measures that take into account the similarity of the neighbors' to the observing farmer introduce additional variation into the measure because each neighbor experience variable is weighted by a farmer-specific inverse distance. We run separate models for each of the four sets of experience variables. The correlations among the variables obviously decrease over time (as the number of participation years grows). Note that because a farmer must have neighbors in order to have values for the neighbor experience variables, the analysis drops any villages where only one farmer supplied the supermarket between 2001 and 2008, leaving 320 suppliers in 77 villages.

Figure 1: Experience variable means, 2001–2008

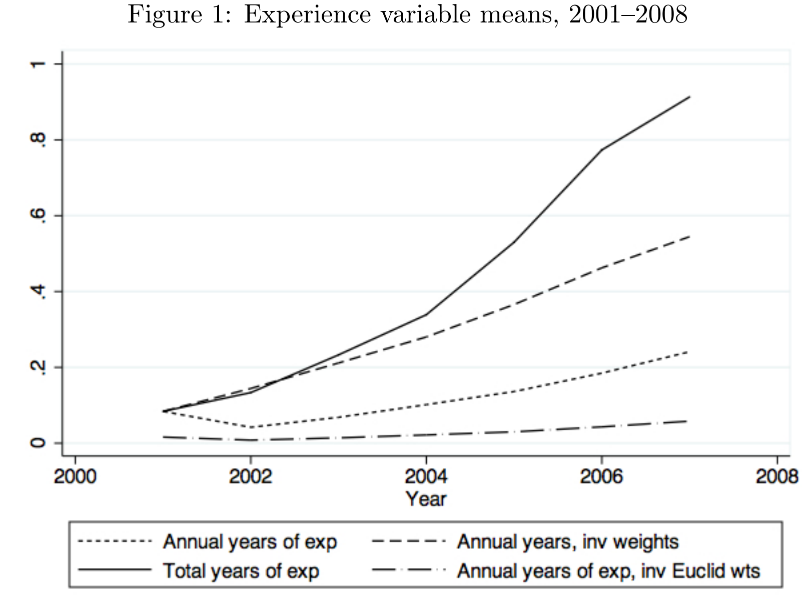
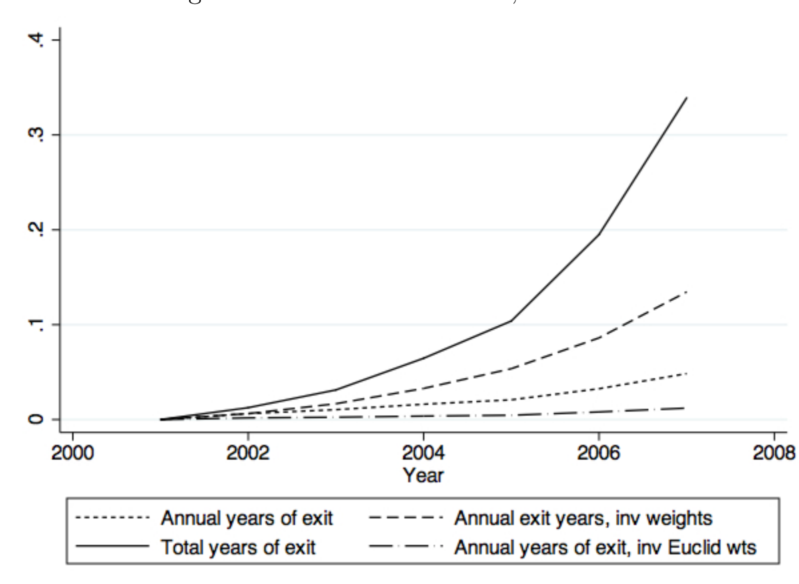


Table 1 presents descriptive statistics for the remaining variables used in the estimation: own experience and exit variables and annual mean productive asset holdings and irrigation. Productive assets are compiled into an index using factor analysis[4], (Sahn and Stifel, 2000); details regarding computation

[4]inputs into the index include household holdings of the following assets: cell phone, car,

Figure 2: Exit variable means, 2001–2008



of the productive asset index are available on request from the author. Mean values suggest a pattern of asset and irrigation accumulation among participants between 2001 and 2008. Note that because we report mean values, the mean of own experience, assets, and irrigation are nearly equivalent to neighbors' experience, assets, and irrigation.

7 Results

Results from all models suggest a strong significant influence of neighbors' exit on farmers' participation decision (see Tables 2 and 3). Model (1) uses the measures of neighbors' experience based on average farmer-years in the supply chain. In Model (2) we use the average experience and exit variables weighted with the inverse of the years elapsed since the supermarket started sourcing. Model (3) uses the cumulative entry and exit shares and Model (4) weights the annual experience measures by each neighbor's inverse difference from the observing farmer. All models include year dummies and farmer fixed effects. We also re-run each model as using an OLS specification with farmer fixed effects and standard errors clustered at the village level. These results are presented in Table 3.

bicycle, motorcycle, tractor, plows, carts, backpack sprayer, backpack fumigator, chainsaw, electric generator, light truck, truck, generator batteries, store room or shed, corral for livestock, small grain silo, or dam

Results are largely consistent and so we discuss the OLS specification results, which are easier to interpret and for which the errors are clustered at the village level. Neighbors' exit in time $t-1$ is a strong negative predictor of the farmer's participation in time t in all four models. Likewise mean neighbor assets in time $t-1$ are a strong negative predictor of a farmer's participation in time t, evidence of strategic delay. Because own exit from the supply chain is so strongly predictive of the farmer's time t decision (only a handful of farmers reenter the supply chain after exiting), we drop it from the model.

A farmer's own participation in time $t-1$ is negatively associated with his or her participation in the following period. This is a reflection of the high exit rates in the supply chain and may be evidence of the decreasing profitability of the supply relationship as more farmers in the village and/or region enter the supply channel. The significance and magnitude of the influence of a neighbors' experience years does not appear to depend on the construction of the neighbor experience and exit variables.

We find mixed evidence as to the relative magnitude of the influence of observing a neighbors' exit from the supply chain versus observing additional neighbors' participation. In Model (2) we reject the hypothesis that the absolute values are equivalent ($\chi^2(1)$=11.06) but in Models (1), (3) and (4) we cannot reject the hypothesis of equivalence.

Is the effect of viewing a neighbor exit the supply chain stronger for a farmer who is already selling to a supermarket or for a farmer contemplating entry? Our results indicate that a farmer takes more seriously a neighbors' exit if the farmer is already himself in the channel. Models with interactions included (Tables 4 and 5) allow us to compare the relative influence of neighbors' participation and exit depending on whether the deciding farmer is in or out of the supply chain. We find evidence that the negative effect of neighbor exit on the participation of farmers in the supply chain is largely on farmers who have already entered the supply chain rather than on those waiting to enter. A farmer in the supply channel is significantly less likely, relative to a farmer who is not in the channel, to participate in the supply chain in the next year if he witnesses an increase in the proportion of neighbors who have exited. The coefficients are large and highly significant.

The year dummy variables are positive and significant, increasing in magnitude over time, reflecting the aggregate growth in the number of total suppliers employed by the supermarket over the sample period.

In all models, the coefficient on neighbors' mean assets is large and significant, suggesting that farmers in supply villages may be strategically delaying their entry into the supply chain. Evidence that farmer's own participation in t is significantly negatively influenced by his neighbors' mean asset levels is further evidence that the effect we measure is a social process rather than a firm strategy of contract dissemination.

To identify strategic delay, however, we must distinguish farmers delaying entry from supermarkets' selecting farmers for contract offers based on observables, in particular on asset stocks. Supermarkets' selecting farmers for participation based on observables would generate spuriously correlated farmer behavior that could be misinterpreted as social processes. With respect to supermarket selection on observables, previous research by Michelson (2013) established supermarkets in Nicaragua did not select farmers based on productive assets or existing irrigation[5], suggesting that the firms were not targeting wealthier farmers first, delaying or withholding contracts to their poor neighbors. Instead, critical household characteristics predicting entry into supermarket supply chains were related to geography, proximity to the central road network, and access to water: altitude and year-round water for agriculture. These geographic characteristics are relatively homogeneous within villages in the sample. There is therefore no clear explanation of a significant negative relationship between farmer market participation and neighbor assets if the participation dynamics we document are exclusively firm-mediated.

7.1 Correlated outcomes

A central challenge in this and similar work is whether we can distinguish between farmers' correlated outcomes and the presence of a social process mediating supply chain entry and exit. In particular, we must deal with the potential problem of spatially or temporally correlated shocks. For example, farmers in a village might all exit the supermarket supply chain at the same time after incurring a local price or production shock. Moreover, we must distinguish between the supermarket offering farmers in a village a coordinated set of offers and the participation decision being mediated through social learning, mimicry or diffusion. The presence of such within-village shocks could drive empirical results that we attribute to farmer learning.

In this subsection we assess whether within-village shocks might be driving our results into two ways. First, do we see evidence of the existence of production or price shocks in supply villages? Second, is there evidence that changes in production or in price are related to farmer exit from the supply chain within supply villages? We have two types of data available to assess whether farmers are entering and exiting the supply chain in response to within-village shocks: detailed information about the prices and production of farmers while they sold to supermarkets and data on the patterns of farmer exit and entry within villages.

We test for the presence of correlated price and shocks in two ways. First, we difference the price and production data for each farmer to generate mean annual percent change in price and production. We then use an OLS model with farmer fixed effects and year dummies to assess whether a farmer's annual percent change in total production or change in mean annual price received from the supermarket is related to the average percent change among his or her supermarket supplying neighbors. We run two specifications for each dependent variable (production, price), including in a second specification a dummy variable equal to one if neighbors' mean annual change was equal to zero. Results from the four regressions are presented in Table 8. We find no relationship

[5]though supplier farmers were found to have a slightly higher starting asset stock than non-suppliers.

between a farmer's own annual price and production fluctuations and his neighbors' annual fluctuations. The magnitudes of the coefficients are small, ranging between -0.01 percent and -0.13 percent and they are imprecisely estimated, suggesting that one's neighbors' price and production outcomes have little explanatory power when it comes to a farmer's own annual outcomes.

We also compute the intraclass correlation coefficients within villages for farmers' annual production. Table 9 presents these coefficients by year for production quantity changes. The correlations are low, all less than 0.20 and in three of the six years, indistinguishable from zero.

We do not find evidence that annual changes in price and production are correlated in villages in ways that suggest the presence of significant within-village shocks. A second question, in their entry into and exit from supply chains do farmers behave in ways that would suggest that their behavior is driven by correlated within-village shocks?

If within-village shocks drive farmer entry into and exit from the supply chain, we would expect to see groups of village farmers moving in and out of the supply chain and, more macroscopically, a pattern of entire villages moving in and out of the supermarket supply chains. However, descriptives on farmer exit and entry and village exit do not support this hypothesis. Instead, we see that villages continued to be "supermarket supply villages" over time but with farmers *within* the village moving in and out of the supply chain from year to year. Farmers generally entered and exited supermarket supply chains alone or in pairs. For example, in 51 of the 77 supply villages a lone farmer entered the supply chain in the first year. And in 55 of the 77 supply villages, in the first year in which a farmer exited the supply chain he or she was the sole exit, not a group of farmers. In fact, we see considerable variation in the number of suppliers per supply village, ranging between one and 16. Table 10 presents statistics on supply village and supplier numbers over time. The point is that we do not observe the mass entry and exit of groups of farmers, by village, that would suggest that our results are driven by spatially correlated shocks.

While the set of villages that supply supermarkets remains largely stable (that is, once a village enters the supply chain, it is likely to stay in the supply chain), we see considerable churning in which farmers *within* a village operate as suppliers from year to year. The number of villages with supplying farmers increased from nine in 2001 to 60 in 2008.[6] And note that our data are not consistent with the story of mass, correlated exit from the supply chain within a given village; in 22 of the 77 supply villages, new farmers continued to enter the supply chain *after* an initial farmer exit.

While descriptives on farmer exit and entry dynamics do not support the hypothesis of temporal or spatially correlated shocks driving dynamics, we also test whether annual farmer changes in price and production are related to the number of farmers exiting annually from the supply chain. We run both a contemporaneous model (in which the number of exiting farmers and the annual

[6] Only seventeen villages drop out of the supply chain entirely between 2000 and 2008. The majority of these villages had only one or two suppliers at any given time between 2000 and 2008.

price and production change are for the same year) and a lagged model (in which the annual price and production changes are lagged one year), regressing the number of exiting farmers on price and production changes and a vector of annual dummy variables. The estimated relationships are extremely small and not statistically significant. In short, we find no evidence that the spatially or temporally correlated shocks that we can see are driving the entry and exit dynamics that we observe.

Finally, regarding the firm, we argue that there are few coordinated supply offers within villages in our data. The assumption that there are few coordinated contractual offers within villages by supermarkets is reasonable and appropriate in the case of Nicaragua during this period, where there has been minimal systematic management in establishing the network of farmer suppliers by supermarkets. We observe the full set of participants in the villages between the years 2000 and 2008. We argue that farmers were free to enter or exit the supply chain at any time, conditional on the annual expansion of the supermarket supply chain supplier network - and strong growth trends in both the number of supermarket retail outlets and the annual number of farmer suppliers suggest annual expansion over this period was steady and significant. Our estimations show that farmers entry and exit was influenced by neighbors' experiences and neighbors' assets. We argue therefore that our results describe social processes rather than a coordinated roll-out of contracting offers by the supermarket.

7.2 Costs of strategic delay

Given that we find evidence of strategic delay, we test for possible effects of delayed entry on contractual terms with the supermarket. Our question: does it matter if some farmers free-ride on the experiences of their neighbors? Do farmers that delay miss out on higher initial prices or better relationships with the supermarket buyer? Do contractual attributes improve as the number of farmers participating locally increases so that early adopters in fact bear costs associated with their experimentation?

We have rich data on farmers experiences with supermarkets in every year in which they sold: average price received (by product) and share of production rejected by the buyer, whether the farmer had a written contract with the buyer in a given year, how many times the buyer defaulted on payment in a given year, the number of annual transactions the farmer had with the supermarket. Our strategy: we test how these transactional attributes reported by the farmer are related to the number of sellers in the village in the same year. Table 11 presents descriptive statistics on the contractual attributes we observe. Because prices, number of deliveries, and quality standards (and therefore rejections) vary considerably by the horticulture product grown, we restrict our sample to the largest subgroup - tomato growers (n=97). Table 11 demonstrates variation across years in the reported incidence of contractual features such as contracts and mean price, rejections by the supermarket, and annual deliveries. We also see interesting intra-village variation in these measures, suggesting that within the same village within the same year farmers may report different experiences with the supply chain.

We test for a relationship between the attributes in Table 11 and the number of suppliers in the village by running a series of fixed effects models regressing the number of annual village suppliers in time t on contractual attributes in time t. We include a time trend and control for mean neighbors' productive assets and farmers' own productive asset stock.

Table 6 presents results from fixed effects models fun on the tomato grower sample of suppliers. We find evidence that contractual terms improve with the number of contracting farmers in a village, even controlling for farmer wealth, a time trend, and time-invariant farmer-level characteristics (such as working with an NGO). Evidence that contractual terms improve with the number of contracting farmers suggests that early entrants into the supply chain may in fact bear some cost for experimentation relative to village members who enter later on. These costs are incurred in the form of fewer annual transactions with the supermarket, higher project rejection rates and rates of contractual default, and a decreased likelihood of having a signed contract with the supermarket.

Specifically, we find that the likelihood of supermarket payment default is inversely related to the number of suppliers in a village. We also find an inverse U relationship between the likelihood of a farmer reporting a signed contract with the supermarket buyer and the number of village farmers also selling to the supermarket. For tomato growers (the largest product represented in our sample), we find that the share of production rejected by the buyer decreases as more farmers join the supply chain in the village and we identify an inverse U relationship between the number of village suppliers and the number of annual deliveries made by the farmer to the supermarket.

The explanatory power of the models in Table 6 are generally quite low, though with reasonable significance on the coefficients capturing the effect of the number of suppliers in the village. The evidence should be taken as suggestive and further research into the benefits and costs of delayed entry into supply chains is clearly warranted.

8 Discussion

Because the analysis is based only on the sample of farmers who joined the marketing channel between 2001 and 2008 but excludes those who do not change their participation status over this period (primarily those who never join as there are very few farmers who supply continuously between 2001 and 2008), the coefficients are relevant to a model of the likelihood of participation among farmers who have joined the supply chain. The sample excludes (and we do not observe) farmers who are dissuaded by their observations of neighbors' participation, outcomes, and exits, from ever joining. Because we do not observe farmers who saw the exits and experiences of neighbors in the village and *never* entered the supply chain, the total negative effect from learning neighbors' exit in the village may be larger than estimated here.

With respect to high rates of farmer exit from supermarket supply chains,

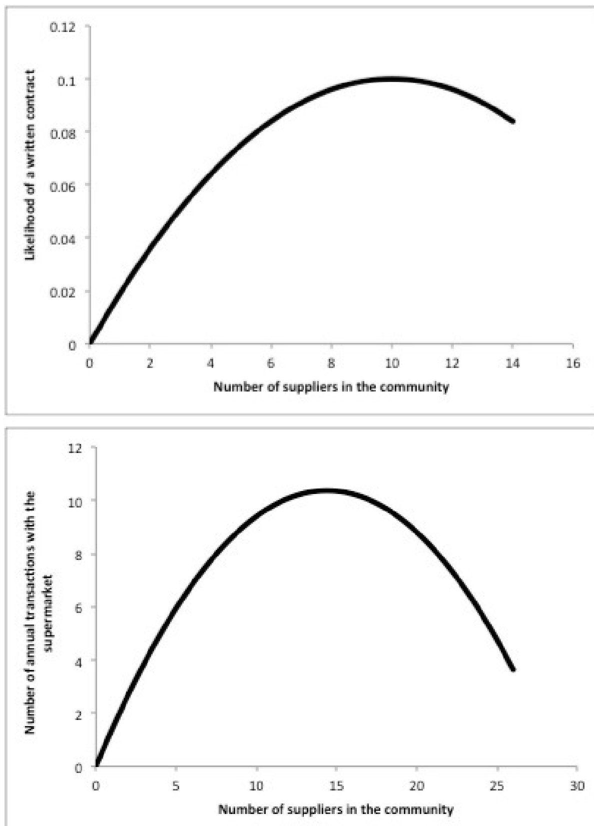


Figure 3: Graphs depict the estimated relationship between the number of tomato suppliers in the village and the likelihood of a written contract with the supermarket buyer (top panel) and the number of annual transactions with the supermarket (bottom panel).

if producers leave these supermarket-driven opportunities not because they are graduating to newer, preferred markets but because they cannot perform or keep up with changing quality or transaction requirements or because procurement from their region is phased out by the buyer, then a primary set of empirical questions surrounding disadoption will concern once-participant producer welfare effects. For example, is adoption of the marketing and production techniques reversible; how specialized to the particular procurement channel are the investments producers make in time, relationships and equipment; under what circumstances might exit from the supply chain act as a negative economic shock to the household?

Finally, our analysis cannot explain initial farmer entry into the supply chain and further study characterizing the participation of the first-adopter and the sequence of adoption would be valuable. A related issue for future study is whether farmers with limited village social connections might be excluded from information networks that would inform them about the profitability of a new marketing opportunity.

9 Conclusions

This research investigates the existence of social influences on farmers' participation in modern markets. We use a panel of 320 farmers over seven years to control for farmer fixed effects in a model of market entry and exit. Consistent with the recent literature on social processes in technology adoption, our results support the hypotheses that social processes mediate farmers market participation. Specifically, we find a relationship between a farmer's decision to enter and exit a supermarket supply chain and his or her neighbors' experience in and exit from a new marketing channel. The influence of neighbors' experiences is not limited to the farmer's initial entry decision but continues to inform a farmer once he or she has entered the supply channel. In other words, their subsequent decision whether to continue with the marketing channel once they have already entered is strongly related to the decisions of their neighbors to exit or continue. It may be that a farmer is persuaded by his or her neighbors' exit that the supermarket supply channel is not as remunerative as expected; or they may find in the subsequent period that there any scale economies in production or post-harvest processing that can no longer be realized with a smaller number of village suppliers. Though it might seem plausible that the exit of neighbors could actually increase the likelihood of participation, incentivizing a participant to boost his or her own production to take up the perceived slack, our our evidence provides no support for this hypothesis.

We find evidence of strategic delay on the part of farmers, evidence that farmers are waiting to enter until they observe the outcomes of their neighbors. We also find evidence that early entrants incur costs associated with their neighbors' delay; that contractual terms improve with the number of farmers in a village, even controlling for farmer wealth, a time trend, and time-invariant farmer-level characteristics (such as working with an NGO). This suggests that early entrants into the supply chain may in fact bear some cost for experimentation relative to village members who enter later on. These costs are incurred in the form of fewer annual transactions with the supermarket, higher project rejection rates and rates of contractual default, and a decreased likelihood of having a signed contract with the supermarket.

While data limitations require that we remain agnostic regarding whether the social phenomenon we document constitutes actual social learning or merely mimicry, our results provide clear evidence that farmers' participation in modern markets is influenced through social processes. An implication both of the presence of strategic delay and of non-contracting farmers (who we do not observe) staying out of the modern channel based on the observed experiences of their neighbors is that, if there is a net cost to entry and exit, some farmers may pay a price for early experimentation. In the extreme, we may see non-participation in supply chains in villages where the opportunity might have good remunerative potential. The welfare effects of delayed entry are ambiguous. To estimate the overall effects of farmer learning within and across villages it is necessary to compare the costs' associated with farmers' delayed entry into the supply chain with the advantages of better understanding the costs, requirements, and potential benefits of participation through observation.

The relevance of market participation research to broader questions of development economics and policy hinges on better understanding the specific pathways and dynamics through which market relationships affect participant welfare. How do farmers choose among market opportunities, given that market selection implies a varying set of investments and transaction requirements, and what are the consequences of their choices for household welfare? Answering these questions is important to understanding how some agricultural producers are able to make the transition out of poverty in the context of new dynamic markets.

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Table 1: Descriptive statistics, 2001-2008, n=320.

	2001	2002	2003	2004	2005	2006	2007	2008
Participant share	0.07	0.12	0.20	0.28	0.45	0.61	0.60	0.55
Exit share	0.00	0.01	0.04	0.07	0.11	0.21	0.37	0.45
Own experience, S_{it-1}	.	0.04	0.02	0.04	0.07	0.11	0.16	0.22
	.	(0.19)	(0.10)	(0.13)	(0.16)	(0.18)	(0.20)	(0.20)
Own exit, Z_{it-1}	.	0.0	0.01	0.01	0.02	0.02	0.04	0.05
	.	(0.0)	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)
Own assets $(t-1)$ (index)	-0.53	-0.48	-0.40	-0.29	-0.14	0.09	0.30	0.53
	(1.49)	(1.55)	(1.61)	(1.71)	(1.81)	(1.97)	(2.04)	(2.12)
Neighbors' assets $(t-1)$ (mean)	-0.50	-0.46	-0.40	-0.30	-0.15	0.05	0.23	0.43
	(0.64)	(0.67)	(0.68)	(0.76)	(0.86)	(0.96)	(0.97)	(1.02)
Own irrigation $(t-1)$ (mzs)	0.24	0.26	0.27	0.35	0.41	0.48	0.54	0.63
	(0.79)	(0.83)	(0.83)	(0.98)	(1.07)	(1.10)	(1.13)	(1.17)
Neighbors' irrigation $(t-1)$ (mean mzs)	0.23	0.25	0.27	0.35	0.40	0.46	0.53	0.60
	(0.54)	(0.58)	(0.60)	(0.64)	(0.66)	(0.69)	(0.72)	(0.83)

Note: standard errors in parentheses.

Table 2: Annual means of experience measures. Standard deviations in parentheses.

Neighbor experience measures	2001	2002	2003	2004	2005	2006	2007	2008
Average annual exp	0.06	0.03	0.05	0.09	0.12	0.17	0.23	0.34
	(0.15)	(0.08)	(0.11)	(0.12)	(0.13)	(0.14)	(0.14)	(0.19)
Average annual exp with early entrant weights	0.06	0.11	0.17	0.23	0.32	0.41	0.49	0.56
	(0.15)	(0.23)	(0.28)	(0.32)	(0.34)	(0.35)	(0.37)	(0.38)
Cumulative entry shares	0.06	0.11	0.21	0.31	0.51	0.75	0.89	0.92
	(0.15)	(0.21)	(0.25)	(0.29)	(0.32)	(0.28)	(0.24)	(0.22)
Average total years inv difference wts	0.03	0.01	0.02	0.04	0.05	0.07	0.10	0.13
	(0.08)	(0.04)	(0.05)	(0.06)	(0.06)	(0.07)	(0.08)	(0.10)

Table 3: Results of conditional logit regression predicting participation choice using neighbor experience variables.

Dependent variable: Participation ($a_i = 1$) or not ($a_i = 0$) at time t	Model (1)		Model (2)		Model (3)		Model (4)	
	Coef.	(s.e.)	Coef.	(s.e.)	Coef.	(s.e.)	Coef.	(s.e.)
Participation at time $(t-1)$	-2.77***	(0.63)	-2.80***	(0.62)	-2.84***	(0.62)	-2.79***	(0.63)
S_{it-1}: Own experience (log)	-3.68***	(0.52)	-3.56***	(0.54)	-3.53***	(0.55)	-3.63***	(0.54)
A_{it-1}: Own assets	0.14	(0.17)	0.17	(0.17)	0.18	(0.16)	0.16	(0.16)
I_{it-1}: Own irrigation	0.03	(0.31)	0.02	(0.31)	0.05	(0.31)	0.10	(0.30)
A_{-it-1}: Mean neighbor assets	-1.43**	(0.67)	-1.38**	(0.64)	-1.28**	(0.58)	-1.34**	(0.59)
I_{-it-1}: Mean neighbor irrigation	0.05	(0.39)	0.05	(0.38)	0.11	(0.38)	0.13	(0.37)
Neighbor experience variables								
(1) Average exp years (log)	1.27**	(0.69)						
(1) Average exit years (log)	-1.43**	(0.66)						
(2) Average exp years, early entrant weights (log)			0.51	(0.36)				
(2) Average exit years, early entrant weights (log)			-1.15**	(0.50)				
(3) Cumulative entry shares (log)					0.28*	(0.17)		
(3) Cumulative exit shares (log)					-0.38**	(0.19)		
(4) Average exp years, inverse difference weights (log)							1.88*	(1.17)
(4) Average exit years, inverse difference weights (log)							-1.56	(1.09)
Year dummies	Y		Y		Y		Y	
n	1923		1923		1932		1923	
pseudo R^2	0.64		0.64		0.64		0.64	

Note: *, **, *** indicate statistical significance at the ten, five, and one percent levels, respectively.

Table 4: Results of OLS regression predicting participation choice with neighbor experience variables.

Dependent variable: Participation ($a_i = 1$) or not ($a_i = 0$) at time t	Model (1)		Model (2)		Model (3)		Model (4)	
	Coef.	(s.e.)	Coef.	(s.e.)	Coef.	(s.e.)	Coef.	(s.e.)
Participation at time $(t-1)$	- 0.003	(0.05)	-0.01	(0.05)	-0.02	(0.05)	-0.004	(0.05)
S_{it-1}: Own experience (log)	-0.30***	(0.02)	-0.30***	(0.02)	-0.29***	(0.02)	-0.30***	(0.02)
A_{it-1}: Own assets	0.01	(0.02)	0.01	(0.02)	0.01	(0.02)	0.01	(0.02)
I_{it-1}: Own irrigation	0.02	(0.02)	0.02	(0.02)	0.02	(0.02)	0.02	(0.02)
A_{-it-1}: Mean neighbor assets	-0.10*	(0.05)	-0.10**	(0.05)	-0.10*	(0.05)	-0.10*	(0.05)
I_{-it-1}: Mean neighbor irrigation	0.02	(0.04)	0.01	(0.04)	0.01	(0.04)	0.02	(0.04)
Neighbor experience variables								
(1) Average exp years (log)	0.08**	(0.04)						
(1) Average exit years (log)	-0.12*	(0.06)						
(2) Average exp years, early entrant weights (log)			0.10***	(0.04)				
(2) Average exit years, early entrant weights (log)			-0.09**	(0.05)				
(3) Cumulative entry shares (log)					0.06**	(0.03)		
(3) Cumulative exit shares (log)					-0.05**	(0.03)		
(4) Average exp years, inverse difference weights (log)							0.12**	(0.06)
(4) Average exit years, inverse difference weights (log)							-0.08	(0.12)
Year dummies	Y		Y		Y		Y	
n	1977		1977		1977		1977	

Note: *, **, *** indicate statistical significance at the ten, five, and one percent levels, respectively. Standard errors are clustered at the village level.

Table 5: Results of conditional logit regression predicting participation choice using neighbor experience variables.

Dependent variable: Participation ($a_i = 1$) or not ($a_i = 0$) at time t

	Model (1)		Model (2)		Model (3)		Model (4)	
	Coef.	(s.e.)	Coef.	(s.e.)	Coef.	(s.e.)	Coef.	(s.e.)
Participation at time $(t-1)$	-8.02***	(1.56)	-5.18***	(0.97)	-4.91***	(0.64)	-10.35***	(2.84)
S_{it-1}: Own experience (log)	-3.62***	(0.52)	-3.25***	(0.31)	-3.46***	(0.56)	-3.60***	(0.53)
A_{it-1}: Own assets	0.09	(0.17)	0.11	(0.18)	0.10	(0.17)	0.11	(0.16)
I_{it-1}: Own irrigation	0.01	(0.31)	0.03	(0.32)	0.05	(0.32)	0.08	(0.30)
A_{-it-1}: Mean neighbor assets	-1.52**	(0.73)	-1.46***	(0.37)	-1.38**	(0.62)	-1.43**	(0.63)
I_{-it-1}: Mean neighbor irrigation	-0.003	(0.39)	0.22	(0.49)	0.03	(0.39)	0.10	(0.37)
Neighbor experience variables								
(1) Average exp years (log)	1.03	(0.65)						
(1) Average exit years (log)	0.63	(0.89)						
(2) Average exp years, early entrant weights (log)			0.37	(0.37)				
(2) Average exit years, early entrant weights (log)			0.05	(0.64)				
(3) Cumulative entry shares (log)					0.24	(0.17)		
(3) Cumulative exit shares (log)					0.55*	(0.29)		
(4) Average exp years, inverse difference weights (log)							1.67	(1.15)
(4) Average exit years, inverse difference weights (log)							1.39	(1.68)
Neighbor experience interactions								
Neighbor Experience*Farmer $(t-1)$ participation	0.004	(0.27)	-0.06	(0.23)	-0.20	(0.24)	-0.13	(0.38)
Neighbor Exit*Farmer $(t-1)$ participation	-2.43***	(0.81)	-1.12**	(0.47)	-1.01***	(0.28)	-3.27**	(1.39)
Year dummies	Y		Y		Y		Y	
n	1923		1923		1923		1923	
pseudo R^2	0.64		0.65		0.65		0.64	

Note: *, **, *** indicate statistical significance at the ten, five, and one percent levels, respectively.

Table 6: Results of OLS regression predicting participation choice with neighbor experience variables.

Dependent variable: Participation ($a_i = 1$) or not ($a_i = 0$) at time t	Model (1)		Model (2)		Model (3)		Model (4)	
	Coef.	(s.e.)	Coef.	(s.e.)	Coef.	(s.e.)	Coef.	(s.e.)
Participation at time $(t-1)$	-1.23***	(0.32)	-0.77***	(0.25)	-0.53***	(0.12)	-1.35**	(0.60)
S_{it-1}: Own experience (log)	-0.29***	(0.02)	-0.28***	(0.02)	-0.27***	(0.03)	-0.29***	(0.02)
A_{it-1}: Own assets	0.002	(0.02)	0.002	(0.02)	0.0001	(0.02)	0.005	(0.02)
I_{it-1}: Own irrigation	0.02	(0.02)	0.02	(0.02)	0.02	(0.02)	0.02	(0.02)
A_{-it-1}: Mean neighbor assets	-0.10*	(0.05)	-0.11**	(0.05)	-0.10*	(0.05)	-0.10*	(0.05)
I_{-it-1}: Mean neighbor irrigation	0.01	(0.04)	0.01	(0.04)	0.01	(0.04)	0.02	(0.04)
Neighbor experience variables								
(1) Average exp years (log)	0.07*	(0.04)						
(1) Average exit years (log)	0.25**	(0.12)						
(2) Average exp years, early entrant weights (log)			0.08**	(0.03)				
(2) Average exit years, early entrant weights (log)			0.19*	(0.10)				
(3) Cumulative entry shares (log)					0.07***	(0.02)		
(3) Cumulative exit shares (log)					0.13***	(0.04)		
(4) Average exp years, inverse difference weights (log)							0.14**	(0.06)
(4) Average exit years, inverse difference weights (log)							0.29*	(0.16)
Neighbor experience interactions								
Neighbor Experience*Farmer $(t-1)$ participation	-0.04	(0.05)	-0.03	(0.04)	-0.08**	(0.04)	-0.07	(0.08)
Neighbor Exit*Farmer $(t-1)$ participation	-0.53***	(0.15)	-0.34***	(0.12)	-0.22***	(0.05)	-0.53*	(0.28)
Year dummies	Y		Y		Y		Y	
n	1977		1977		1977		1977	

Note: *, **, *** indicate statistical significance at the ten, five, and one percent levels, respectively. Standard errors are clustered at the village level.

Table 7: Relationship between farmers' own annual price and production changes and neighbors' mean annual price and production changes, OLS regression with farmer-level fixed effects and year dummies.

	(1) production pct change	(2) price pct change	(3) production pct change	(4) price pct change
Neighbors' annual change	-0.02	-0.13	-0.01	-0.10
	(0.16)	(0.16)	(0.16)	(0.16)
No annual change (1=Y)			15.47	-0.91
			(13.86)	(4.82)
Year dummies	Y	Y	Y	Y
n	419	425	419	425

Table 8: Within-village intraclass correlation coefficients, annual change in farmer production.

year	production intraclass correlation coef.
2003	0.00
2004	0.00
2005	0.17
2006	0.15
2007	0.00
2008	0.20

Table 9: Supply chain descriptives by year: number of supply villages, number of suppliers per village. In Model (1) the variables are from the same period and in Model (2) the annual percent change variables are lagged one period.

	(1)	(2)
Annual production change	0.00002	-0.00002
	(0.0001)	(0.0002)
Annual price change	-0.0001	0.0002
	(0.0007)	(0.0006)
Year dummies	Y	Y
n	433	361

Table 10: Contractual attributes, descriptive statistics

Share reporting	2001	2002	2003	2004	2005	2006	2007	2008
Written contract	0.38	0.14	0.24	0.21	0.30	0.31	0.33	0.38
Payment default	0.33	0.07	0.02	0.05	0.06	0.03	0.03	0.04
Tomato growers (n=97)								
Mean annual price (real cordobas/lb)	3.44	2.96	1.85	1.91	1.85	1.96	1.56	1.26
Mean share rejected, per transaction	0.22	0.18	0.18	0.17	0.14	0.11	0.12	0.10
Mean annual deliveries	42.00	37.44	32.16	31.66	31.18	27.41	26.96	35.53

Table 11: Results of models regressing number of village participants in the supply chain at time t with contract and transaction features at time t; random effects or fixed effects models

	Contract	Buyer Default	Tomato price	Share rejected	Deliveries per year
Mean neighbors' assets	0.05	-0.06	-0.31	0.73*	9.08**
	(0.04)	(0.05)	(0.35)	(0.38)	(3.74)
Own assets	-0.01	-0.003	0.04	-0.03	-0.49
	(0.01)	(0.01)	(0.08)	(0.09)	(0.72)
Number of village suppliers in time t	0.02**	-0.01**	0.02	-0.06***	1.44***
	(0.1)	(0.004)	(0.03)	(0.02)	(0.46)
village suppliers^2	-0.001**	.	.	.	-0.05**
	(0.0004)	.	.	.	(0.02)
time trend	Y	Y	Y	Y	Y
n	822	796	123	275	270
R^2	0.03	0.004	0.14	0.14	0.001