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Abstract: Using a unique data set covering four years and six semi-annual sales periods of an index-based livestock insurance (IBLI) product in southern Ethiopia, we examine the dynamics of pastoralists' demand for IBLI. We find that: (1) there is intertemporal dependence of an uptake decision, represented by correlations of unobserved household factors over time; (2) conditional on previous purchase decisions, factors related to continuing the purchase of IBLI to augment existing coverage and replace lapsing contracts differ significantly; (3) controlling for time-invariant household-fixed effects, neither a one-shot subsidy nor the uptake of others in one's social network influence subsequent demand, whereas less vegetation and reduced insurance premiums induce households to purchase IBLI. Overall, our study provides rigorous micro-evidence to better understand the dynamic uptake of IBLI and signifies the importance of an empirical analysis that takes into account the dynamic demand structure.

Keyword: index-based livestock insurance, dynamic demand, Ethiopia
JEL codes: D12, D14, D81, G22, O12

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1. Introduction

Index-based insurance products hold great promise for protecting the poor in developing countries who are vulnerable to weather risks, such as droughts and floods. Existing studies show that index insurance is welfare-enhancing, not only by compensating losses through payouts, which help smooth consumption and reduce distress sales of productive assets in the face of downside risks, but also by stimulating policyholders to change their production decisions toward more risky, but more profitable activities, generating higher production and income (Karlan et al., 2014; Nicola, 2015; Cai, 2016; Cole et al., 2017; Jensen et al., 2017; Bertram-Huemmer and Kraehnert, 2018; Janzen and Carter, 2019; Hill et al., 2019; Matsuda et al., 2019; Noritomo and Takahashi, 2019). It has also been shown that index insurance coverage improves buyers' subjective well-being even without payouts (Tafere et al., 2019).

Despite its demonstrated welfare gains, the uptake of index insurance has remained low across many of the contexts in which it has been introduced. Research has identified several important factors affecting uptake, including basis risk (i.e., the deviation between actual losses and losses predicted by the index) (Gine et al., 2008; Mobarak and Rosenzweig, 2012; Jensen et al., 2018), household risk and ambiguity preference (Gine et al., 2008; Hill et al., 2013; Belissa et al., 2019b; Bryan, 2019), upfront premium payments (price) and credit constraints (Cole et al., 2013; Gine et al., 2008; Ntukamazina et al., 2017; Casaburi and Willis, 2018; Belissa et al., 2019a), a lack of trust and understanding (Cole et al., 2013; Ntukamazina et al., 2017; Belissa et al., 2019a), and social network and existing alternative risk-management mechanisms (Mobarak and Rosenzweig, 2012; Dercon et al., 2014; Cai et al., 2015; Sibiko et al., 2018; Takahashi et al., 2019). Due to data constraints, most research in this field has focused on insurance demand at one point in time. Thus, limited attention has been paid to the dynamics of demand for index insurance. This has left several important issues—such as the prevalence of and factors related to continuous adoption and dis-adoption—largely unanswered.

This study contributes to the literature by revealing the dynamic decision-making process involved in insurance uptake. The product under study is index-based livestock insurance (IBLI) introduced in the Oromia region in southern Ethiopia in 2012. Most households in this region are pastoralists, primarily relying on extensive livestock grazing for their livelihood. Recurrent droughts have historically occurred every six to seven years, causing widespread livestock mortality and thus substantially threatening the pastoralists' lives. Furthermore, the existing customary informal insurance arrangements, such as lending livestock to those who are in need, have been eroding over time (Lybbert et al., 2004; Huysentruyt et al., 2009; Santos and Barrett, 2011). In this setting, IBLI is expected to offer a formal mechanism to protect pastoralists against otherwise uninsured drought risk.

Using unique panel data from over 450 households which cover four years and six semi-annual IBLI sales periods from August 2012 to February 2015, we first describe the IBLI adoption and dis-adoption rates among purchasing households. We then apply econometric analysis to explore various factors related to dynamic household decision-making. We primarily focus on a binary purchase decision, rather than the quantity to insure, to understand why specific households appear to be repeat purchasers (non-purchasers) and what factors lead to their decision-making patterns.

More concretely, we first closely assess each sales-period decision using a multivariate probit model. This model allows the unobserved error terms to be correlated over time, which helps us better understand the extent to which, and when, the uptake decisions are intertemporally correlated due to factors not accounted for by observable characteristics. We then examine the dynamic adoption behavior, conditional on previous IBLI purchases. We use a Heckman probit model for this analysis, where the second stage is implemented separately for half a year later and a year later. This allowed us to obtain insight into whether factors related to augmenting insurance coverage (half a year later) and replacing the lapsing contract (a year later) differ for our insurance product whose policies last for one year. Finally, we apply a household-fixed effect estimator to control for time-invariant observed and unobserved characteristics and examine the role of time-varying exogenous factors, including contemporary and lagged weather shocks, the insurance uptake of other people in the social network, and the subsidized price offered to a random subset of the sample at each sales period.

Our study primarily contributes to the literature on the demand for index insurance, particularly in relation to its dynamic aspects. A handful of studies on the dynamics of insurance demand have revealed that one's own experiences with insurance payouts as well as those of one's network members positively affect the subsequent uptake (Cole et al., 2014; Hill et al., 2016; Karlan et al., 2014; Stein, 2018). Meanwhile, a one-time subsidy to reduce insurance premiums does not dampen the subsequent uptake, suggesting that there are no price-anchoring effects related to the subsidy (Takahashi et al., 2016; Matsuda and Kurosaki, 2019). Using panel data which cover six sales periods over four years, we reconfirm the absence of price-anchoring effects. Moreover, departing from previous studies which have focused extensively on the impacts of one's own and others' payouts, we investigate other channels through which past uptake decisions affect subsequent purchase decisions. After controlling for observed household characteristics, our study reveals that households that have bought insurance once tend to buy it repeatedly, regardless of payouts. It also reveals that their decisions are not substantially affected by the decisions of others in their social network.

Our study also speaks to the literature on the demand for IBLI among pastoralists in southern Ethiopia, which has been based on shorter observations than ours. Using data from the two rounds of sales windows, Takahashi et al. (2016) find that the demand for IBLI is insensitive to better knowledge of the product, represented by correct answers to a quiz about the product. Bageant and Barrett (2017) show that there is no discrimination of demand based on the gender of household head. Tim et al. (2018) show that receiving payouts, either by policyholders or their network members, does not affect subsequent uptake. We do not revisit several issues, such as the role of knowledge and receiving payouts, to avoid the complexity related to endogeneity concerns and simply repeat the same previous exercises. Instead, using longer-term data with multiple specifications, we extend those previous studies for a firmer understanding of the drivers of, and barriers to, the demand for IBLI.

The rest of this paper is organized as follows: Section 2 describes the study setting and descriptive statistics; Section 3 explains our estimation strategies; Section 4 discusses the results; and Section 5 presents the conclusions with policy implications.

2. Study Setting

2.1. Study area

This study was conducted in the Borana plateau in the Oromia regional state of southern Ethiopia. The study area comprised arid and semi-arid ecological zones, characterized by a bimodal rainfall pattern with four seasons: two rainy seasons from

March to June (*Gaana*) and October to November (*Hagaya*), and two dry seasons from July to September (*Adolessa*) and December to February (*Boonahagaya*). Most of its population practices a pastoral livelihood, typically owning cattle, camel, goats, and/or sheep. These transhumant households often maintain semi-permanent settlements and mobile herds which search for pasture and water in the face of seasonal forage scarcity. These pastoralists are overwhelmingly poor and extremely vulnerable to weather shocks, particularly droughts, which have occurred regularly since the 1970s (i.e., 1973/74, 1983/84, 1991/92, 1999/00, 2005/06, and 2011/12). In this region, widespread market failures combined with drought-related livestock mortality cause many pastoralists to slip into a poverty trap. This forces them to suffer poverty for prolonged periods (Lybbert et al., 2004; Santos and Barrett, 2011; Takahashi et al., 2019).

2.2. IBLI product

To help pastoralists manage drought risk and protect livestock assets, IBLI was introduced by the Oromia Insurance Company in partnership with the International Livestock Research Institute and Cornell University in 2012. Its design followed a successful pilot project in the Marsabit district of northern Kenya, which was rolled out in 2010 (Chantarat et al., 2013, Jensen et al., 2017). Although IBLI contracts have been updated several times since its launch, this study focuses on the one that was active at the time of data collection.

IBLI uses an index of relative forage scarcity based on remotely sensed and freely available data collected by satellite (Chantarat et al., 2013, Takahashi et al., 2016). There are two IBLI sales windows each year, occurring in January-February and August-September, directly before each rainy season. Insurance premium rates vary across geographic regions based on estimates of drought-related mortality risk. The premium paid is the premium rate multiplied by the total insured herd values (TIHV), which reflect the value of each animal species.[1] Contracts cover one full year. There are two potential payout periods, in October and March, immediately after each dry season. Payouts are triggered if the index falls below the 15th percentile of the empirical distribution of the index since 1981. The amount of payouts depends on the realized normalized difference vegetation index (NDVI) and TIHV. If a household purchases IBLI in two consecutive sales periods, the household can have overlapping policies and could receive payouts on both (Ikegami and Sheahan, 2015).

2.3. Research design

The household survey covered 17 *reeras* (hereafter the study site, equivalent to a sub-district containing 100–300 households) in eight *woredas* (local administrative unit that encompasses *reeras*) in Borana: Dilo, Teltele, Yabello, Dire, Arero, Dhas, Miyo, and Moyale. The study sites were selected depending on the balance between logistical challenges and geographic distribution in the sites, so as to capture variation in agro-ecology, access, and livelihood. In each study site, census data of households were first collected and then households were split into wealth terciles based on the number of livestock held. At each site, 15% of households were selected for this study, one third from each of the livestock-holding terciles.

The first round of the household survey was conducted for 515 households in March

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[1] Total insured herd value (in ETB) = (number of camels insured × 15,000) + (number of cows insured × 5,000) + (number of goats and sheep insured × 700) from the first to the third sales periods. After the third sales period, the insurance company revised the values of animals, responding to opinions from local communities. The revised total insured herd value (in ETB) from the fourth to the sixth sales periods = (number of camels insured × 10,000) + (number of cows insured × 6,000) + (number of goats and sheep insured × 800).

2012, prior to the first sales period of IBLI in August 2012. Thereafter, follow-up surveys were conducted annually every March until 2015, totaling four annual surveys. To maintain a sample size of around 500 households, attritted households were replaced by other households from the same site that had similar tropical livestock unit (TLU)[2] holdings with the attritted households.

To stimulate IBLI uptake and increase people's awareness of it, discount coupons were distributed to a randomly selected sub-sample of study households, allowing them to purchase IBLI at a premium discount for the first 15 TLUs insured in the season. Discount rates ranged from 10% to 80% of the insurance premiums. The distribution of discount coupons was independently re-randomized for each sales period. Thus, coupon recipients and realized discount rates changed across the sample households over time. In each sales period, one-tenth of the sample households received a 10% discount; another tenth received a 20% discount, and so on up to a maximum discount rate of 80%. Each season, 20% of the sample households did not receive a discount coupon.[3] IBLI had been sold six times by the end of the survey panel in 2015.

In this study, we use data from 458 balanced panel households that remained in the sample for the entire panel survey period. Appendix Table 1 shows the baseline household characteristics of those attritted and non-attritted households, with a *t*-test for equality of means. Most household characteristics are not systematically different between the two groups, and an F-test across the entire set of characteristics reveals that they are not jointly, statistically, and significantly different from zero. Given the overall balance, we consider that the attrition in our sample is mostly random and the exclusion

[2] One tropical livestock unit is equivalent to 1 cow, 0.7 camel, or 10 goats or sheep.
[3] Ten households received a 100% discount for a specific purpose related to a parallel, but separate study.

of attritted households should not significantly bias our inferences.

2.4. Summary statistics

Table 1 presents summary statistics of the 458 balanced-panel households at the baseline. Panel A shows that, on average, households have 6.3 members and are headed by a male with less than one year of formal education. Most households are poor; the mean annual household income per capita is about 4,300 Ethiopian birr (ETB)[4], while the mean annual household expenditure per capita is 3,800 ETB. Using the international poverty line standard of an expenditure of 1.90 US dollars per day (2011 purchasing power parity), more than 56% of households are classified as extremely poor. Households depend heavily on livestock-rearing for their livelihood, including milk and meat production, which accounts for an average of 71.5% of total household income. Livestock also comprises these households' main non-human asset, with average holdings of 14.7 TLU, dominated by cattle (11.7 TLU, representing 80% of total TLU) and supplemented by goats and sheep (1.5 TLU), as well as camels (1.5 TLU).

To examine the role of risk preferences in insurance demand, we implemented an ordered lottery selection following Binswanger (1980). Each respondent was offered a chance to choose one of the six lotteries with payouts in birr of (50, 50), (45, 95), (40, 120), (30, 150), (10, 190), and (0, 200). This was implemented using coin flips and real cash payouts. A respondent is considered highly risk-averse if he/she chose either of the first two options, moderately risk-averse if he/she chose either of the middle two options, and less risk-averse if he/she chose one of the last two. About 12%, 46%, and 42% of the respondents belonged to the first, second, and third categories, respectively

[4] USD 1 is equivalent to 20.46 birr as of March 31, 2015, while USD 1 is equivalent to 4.92 birr in 2011 purchasing power parity.

(Panel B).

Panel C shows the number of households that purchased IBLI during the six sales periods. While livestock is by far the most vital asset, the demand for livestock insurance was not very high. More than 40% of the households never bought IBLI and only 1.5% bought it in all six windows.

Table 2 shows the most important reasons why the sample households did not purchase IBLI, summarized by each survey round (IBLI 1 to IBLI 6). The number of observations differs because this question applies only to those that did not hold effective insurance coverage at each survey round. The top reason reported for not purchasing is a lack of comprehension of the insurance product ("Did not understand insurance well enough to buy it"), even though this percentage declined over time. However, using the same data set as in this study, Takahashi et al. (2016) show that improved knowledge through the provision of a learning kit, such as a comic and tape, does not result in improved uptake. The second most important reason is lack of liquidity ("Don't have money to spend on insurance") followed by lack of opportunity to buy it ("Did not have an opportunity to buy it"). Although everyone in the sample was eligible to buy IBLI at each sales period, sample households live far apart from each other and it is possible that the insurance agents did not visit all the survey locations for every sales season.[5]

Table 3 shows the average premium discount rate, the cumulative standardized

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[5] Using baseline household characteristics as covariates, we run a multinomial probit model to examine factors correlated with the reasons for not purchasing index-based livestock insurance (IBLI). The baseline category of the outcome includes all other reasons aside from the lack of understanding, money, opportunities, and animals. The result, presented in Appendix Table 2, is mostly consistent with intuition. For example, households with less educated heads are more likely to consider lack of understanding as a major barrier, while those with less animals, as well as female heads, are more likely to consider lack of animals and money as the major barriers to purchase IBLI.

NDVI zero to six months before the sales period[6], and the dynamic patterns of IBLI uptake from the first to the sixth sales periods between 2012 and 2015.

Panel A of Table 3 shows the uptake rates for each sales period and the number of TLU insured. Generally, the uptake rate was moderate, ranging from 13% to 30%, and higher in the August-September periods (i.e., IBLI 1, 3, and 5) than the January-February sales periods (IBLI 2, 4, and 6). Given that the policy covered one year, it seems reasonable to observe a recurring pattern of higher uptake in the odd sales periods because those who purchased IBLI in the first sales window were eligible to receive payouts until the following year. The uptake rates declined across years, with the exception of a slight improvement from the IBLI 1 to the IBLI 3 sales periods. As shown in Table 2, an increasing number of people became skeptical about the effectiveness of IBLI over time (i.e., the number of people who raised “afraid,” “waiting on others’ results,” “do not think IBLI helps,” and “do not trust insurance companies” as major reasons for not purchasing IBLI increased over time), reducing the insurance uptake.

Following the terminology of Jensen et al. (2018), Panel B of Table 3 presents the frequency of: (1) the total number of “purchasing” households, (2) a new purchaser (“New”) who buys IBLI for the first time, (3) an augmenter (“Augment”) who purchases additional coverage that overlaps with existing coverage; (4) an insurance holder (“Holding”) who does not purchase IBLI but has existing coverage; (5) a replacing individual (“Replacement”) who buys IBLI when the previous policy lapses; (6) an individual who lapsed (“Lapsed”) whose past policy has lapsed and they do not purchase additional coverage; and (7) a reentering individual (“Reenter”) who buys

[6] The intertemporal changes in the cumulative standardized normalized difference vegetation index by study site are presented in Appendix Figure 1.

IBLI at the current period and buys it before the previous one lapses. By definition and insurance design, the sum of "Augment" and "Holding" is equivalent to the number of total purchasing households in the previous sales period, whereas the sum of "Replacement" and "Lapsed" is equivalent to the total number of households that held the policy in the previous sales period.

Several findings are noteworthy. First, a non-negligible number of households that purchased IBLI in a previous sales period augmented it in the current period. Indeed, the augmenting rate [(3)/[(3)+(4)]] was approximately 18% to 62% in the IBLI sales periods 2–6. This seems to reflect that households could not afford to insure the desired level of livestock at once due to cash and credit constraints, or that they expanded the insurance period given the same amount of money. Second, among those who held contracts, more than half replaced (renewed) their insurance coverage in the 3rd sales season. However, over time they did not do so, thus allowing their coverage to lapse. The rate of lapsed contracts [(6)/[(5)+(6)]] was approximately 46% to 79% during the IBLI sales periods 3–6. Similarly, 30% to 58% of those who had purchased IBLI one year ago neither augmented nor replaced their coverage before it lapsed.[7] These statistics reflect the short-term dis-adoption rates. Third, once policyholders let their contracts lapse, they usually did not re-enter the market. However, dis-adoption and non-reentering are somewhat expected, particularly if policyholders do not receive indemnity payments. Indeed, according to our field interviews in 2015, most households specified lack of payouts when they purchased IBLI as a major reason for not

[7] These numbers are obtained by [$(4)_{t+1}$ – $(5)_{t+2}$]/$(1)_t$. For example, 38% (=(104-56)/127) of households who purchased IBLI at period 1 did not augment IBLI at period 2, and did not replace IBLI at period 3.

re-entering the market.[8]

3. Estimation Strategy

To examine a variety of factors associated with the dynamic patterns of demand for IBLI in more detail, we conduct regression analysis. We first examine a set of probit models for each sales period, allowing the error terms to be correlated over time. We then examine the demand for IBLI conditional on previous purchase decisions. Finally, we examine the role of time-variant factors in IBLI uptake, using a household-fixed effect estimator.

3.1. *IBLI purchase at each sales period*

We first estimate factors associated with the uptake for each sales period. Let Y_i^{*t} be the latent dependent variable and $Y_i^t = 1$ if household *i* purchases IBLI in sales period, *t*. A set of equations can be written as follows:

$$Y_i^t = \begin{cases} 1 \ \ if\ Y_i^{*t} = \beta^t X_i + e_i^t > 0 \\ \quad 0\ otherwise \end{cases},\ \mathrm{t} = \{1, 2, 3, 4, 5{,}6\} \quad (1)$$

where β^t is the vector of equation-specific coefficients to be estimated; X_i is the vector of household characteristics at the baseline; and e_i^t is the corresponding error term. We can estimate this system of equations using a probit model separately if the error term, e_i^t, is independent across equations. However, if they are correlated, estimated parameters may be biased. Thus, we use a multivariate probit model that allows the error terms to be correlated over time. We assume that e_i^t follows a

[8] Payouts were observed once in November 2014 against the June to September 2014 drought. Those who purchased IBLI at the third and fourth sales periods were eligible to receive payouts. As noted in the introduction, see Tim et al. (2018) for details on the impact of payouts on subsequent purchases.

multivariate normal distribution with a mean of zero and the variance-covariance matrix $\sum$, where $\sum$ has values of 1 for the leading diagonal and correlations as $\rho_{jk} = \rho_{kj}$ $(j \neq k)$ for off-diagonal elements. A positive covariance estimate suggests that those who (did not) purchase IBLI at the previous period are more (less) likely to buy it again in a later period. We are particularly interested in whether a positive autocorrelation, if any, can only be observed every two sales periods (i.e., when the former contract lapses) or even every subsequent sales period (which may indicate inter-period persistency).

To avoid estimation bias arising from reverse causality, we use the baseline data as covariates, which were collected before IBLI was launched in the region and before any extension or discount treatments were implemented. The set of baseline household characteristics include: (1) demographics of the household and household head, such as household size and age, years of completed education, and gender of household head; (2) annual per capita household income and the proportion of household income from livestock; (3) household livestock holdings, measured in TLU; (4) the value of non-livestock assets; and (5) risk preference dummies elicited through field experiments (reference category is highly risk-averse). In addition to those baseline characteristics, we also include woreda dummy variables that function as controls for unobserved differences between study sites, as well as a premium discount rate randomly distributed at each sales period. We do not include weather- and pasture-related variables, such as NDVI, as the available data vary only at the study site level, which are captured by woreda dummies.[9]

[9] The premium discount rate is orthogonal to the error term because the distribution of discount coupons is random.

3.2. *The dynamics of IBLI uptake*

While the multivariate probit model can identify the (non-)existence of intertemporal correlations of uptake decisions, it does not allow us to fully understand factors related to the dynamic purchase patterns. Therefore, we examine the initial and subsequent purchase decisions simultaneously using a Heckman probit model (Van de Ven and Van Pragg 1981), allowing the purchase of IBLI for each sales period to be contingent upon previous decisions.

Let Y_{it-1} be a binary variable equal to one if household *i* buys IBLI at time *t-1*. Then, the set of our estimation models can be specified as follows:

$$Y_{it-1} = \begin{cases} 1 \; if \; Y^*_{it-1} = \alpha_{-1} Z_{it-1} + \beta_{-1} X_i + s_t + \; e_{it-1} > 0 \\ 0 \text{ otherwise} \end{cases} \quad (2a)$$

$$Y_{it} \; = \begin{cases} 1 \; if \; Y^*_{it} = \alpha_0 Z_{it} + \beta_0 \; X_i + s_t + u_{it} \; > 0 \\ 0 \text{ otherwise} \end{cases} \quad \text{iff} \;\; Y^*_{it-1} > 0 \quad (2b)$$

where Y^*_{it-1} and Y^*_{it} are the latent variables for the observed demand status at time *t-1* and *t*, respectively; X_i is the vector of household characteristics at the baseline, which is the same in the multivariate probit model; Z_{it-1} and Z_{it} are the discount premium rates for household *i* for the previous and current periods, respectively; s_t is the sales-period-fixed effects; α_t, β_t, and β^1_{t+1} are parameters to be estimated; and e_{it-1} and u_{it} are the error terms, jointly distributed as bivariate normal with means equal to zero. We implement the second-stage analysis separately for half a year later and a year later from the initial period given that factors related to augmenting insurance coverage (half a year later) and replacing the lapsing contract (a year later) may differ.

3.3. *IBLI purchase with household-fixed effect*

Finally, we estimate the linear probability model with the household-fixed effect.

Because all time-invariant characteristics, including observed baseline characteristics, are absorbed in household-fixed effects, this exercise focuses on the role of time-variant factors, including the current and lagged exogenous weather shocks, others' uptake in the social network, and premium discount coupons provided in each sales period. We also include one's own lagged uptake.

Our regression model can be written as:

$$Y_{it} = \gamma_0 + \gamma_1 Z_{it} + \gamma_2 Y_{i,t-1} + \gamma_3 \bar{Y}_{i,t}^{N} + \gamma_4 \bar{Y}_{i,t-1}^{N} + \gamma_5 NDVI_{i,t} + \gamma_6 NDVI_{i,t-1}$$

$$Jan_t + Round_t + \theta_i + u_{it} \quad (3)$$

where Y_{it} is one if household i buys IBLI at sales period *t*; Z_{it} is the sales-period-specific discount rate; $Y_{i,t-1}$ is a dummy variable for IBLI purchase at the previous sales period, which is expected to capture the learning-by-doing effect; $\bar{Y}_{i,t}^{N}$ and $\bar{Y}_{i,t-1}^{N}$ are average IBLI uptake rates of one's network members at the current and previous sales periods, respectively; $NDVI_{i,t}$ and $NDVI_{i,t-1}$ are the cumulative standardized NDVI over zero to six months before the current and previous sales periods (i.e., either March to September or October to February), respectively; Jan is a dummy variable equal to one if the sales period is January to February; Round is the survey round-fixed effect; and θ is the household-fixed effect.

To elicit ones' social network to construct the average IBLI purchase in their network (i.e., $\bar{Y}_{i,t}^{N}$ and $\bar{Y}_{i,t-1}^{N}$), we conducted a network survey in 2015 via a "random matching within sample method," following Conley and Udry (2010).[10] We assigned each respondent to eight households randomly drawn from the sample and asked whether the respondent knows the match. Five out of eight matches were selected from the same study site, while the remaining three were selected from relatively far away,

[10] For more details of the sampling method, see Takahashi et al. (2019).

outside the community but within a 40–50 km radius of the respondent's permanent residence. To reduce recall and reporting errors as much as possible, we provided respondents with the match's information, such as age, clan, and residential location. It was revealed that most respondents did not know three matches living outside the community (Takahashi et al., 2019). Thus, we focus on five matches within the community and construct $\bar{Y}_{i,t}^{N}$ and $\bar{Y}_{i,t-1}^{N}$ as:

$$\bar{Y}_{i,t}^{N} = \frac{\#IBLI\ uptake_{it}^{N}}{\#\ Network\ member_i} \text{ and } \bar{Y}_{i,t-1}^{N} = \frac{\#IBLI\ uptake_{it-1}^{N}}{\#\ Network\ member_i} \quad (4)$$

where the denominator of the right-hand side is the number of matches (out of five) who respondent i knows well (we call this the network member).[11] The numerator of the right-hand side is the number of network members who purchase IBLI at sales period t for $\bar{Y}_{i,t}^{N}$ and t-1 for $\bar{Y}_{i,t-1}^{N}$. Because we implement the network analysis only once, the denominator does not vary over time while the numerator does.

Admittedly, this exercise ignores the possibility that interventions can alter the underlying network structure (Comola and Prina 2017; Advani and Malde 2018). To mitigate the potential endogeneity bias, we use an instrumental variable (IV) approach where the current and previous-period average discount rates of network members are used as IV for $\bar{Y}_{i,t}^{N}$ and $\bar{Y}_{i,t-1}^{N}$, respectively. We also use the lagged discount rate as IV for $Y_{i,t-1}$. Since the use of multiple endogenous and IVs would lead to an overly complex estimation and sensitive results, we also check them in the reduced form without any IV, as well as those with potential endogenous variables separately included in the explanatory variables. The summary statistics of the average uptake in one's network for each sales period are presented in Appendix Table 3.

[11] No sample household has zero as the denominator.

4. Estimation Results

4.1. *IBLI purchase at each sales period*

Table 4 shows the estimation results of each period-specific uptake decision through the multivariate probit model. Standard errors are clustered at the study site level. As expected, households that receive higher discount rates are more likely to purchase IBLI in most periods. The result holds throughout with the exception of the second sales period. While we do not observe any other systematic patterns, there is a tendency for households with a better-educated head to purchase IBLI, presumably because they understand the product more. The gender of the household head affects the demand slightly, which is consistent with the findings of Bageant and Barrett (2017).

Per capita income tends to be positively correlated with purchase, indicating that financial liquidity matters. Herd size is also generally positively correlated with purchase, although mostly not statistically significant. Despite the fact that IBLI focuses on compensation for livestock losses, there is no evidence that the share of livestock in the total income is significantly correlated with IBLI uptake.

Contrary to conventional economic theory, less risk-averse households are more likely to buy IBLI, which is also the finding of Gine et al. (2008). This is especially obvious at the first period uptake, presumably because there is possible uncertainty about the insurance product and the provider when the insurance product is new to this area. Thus, those who can tolerate risk are more eager to buy IBLI. This is consistent with the fact that a lack of understanding of the product was the most common explanation cited by households for not purchasing insurance. Similarly, the household head’s years of education has a positive impact on insurance uptake at the first sales period.

Table 5 reports the results of the correlation of error terms. Most of them are positive and statistically significant, except between the 1st and 2nd periods (negative but insignificant). This implies the existence of an unobserved bifurcated tendency, where those who have experienced purchasing IBLI once tend to repeatedly purchase IBLI, and at the same time, there exists a certain group of people who never buy IBLI. It is important to find the positive relationships, even for consecutive sales periods, although overlapping could reduce the demand in successive sales periods.

Given the structure of the error terms, we also test the extent of bias caused by ignoring the autocorrelation in the error terms. Appendix Table 4 presents the results of separate regressions for each sales period by a binary probit model. We find that the signs of coefficients are mostly consistent with those of the multivariate probit model. However, there are some differences in the coefficient and statistical significance level, which signifies the importance of taking autocorrelation into account, even though the extent of bias is not large.

4.2. *The dynamics of IBLI uptake*

Next, we turn to the dynamic decision model in Table 6, estimated by a Heckman probit model. Column 1 presents the previous period uptake and Column 2 is the uptake in the current sales period, conditional on the previous purchase. These cover t-1 and t sales periods, which correspond to the overlapping sales periods. Since the first sales period does not have observations for t-1, the number of observations becomes 458×5=2,290. Columns 3 and 4 present results of similar exercises, but they cover sales periods t-2 and t, which corresponds to the time when the insurance coverage at t-2 has lapsed. Only the observations from the third to the sixth sales periods can be used in

Columns 3 and 4, which yields 458×4=1,832 observations in total. There are some households that augment insurance coverage at the t-1 sales period. However, given that our focus is on the decision concerning replacement as well as the factors determining replacement or the discontinuing of insurance uptake, we exclude those augmenting households in Columns 3 and 4, generating 1,696 observations. Standard errors are clustered at the study site level again.

The factors associated with the initial uptake in Columns 1 and 3 are mostly similar with the previous results via the multivariate probit model. That is, households with higher premium discount rates, better-educated heads, higher per capita income, and less risk aversion are more likely to purchase IBLI than others.

Subsequently, we look at factors related to continuous IBLI uptake in consecutive periods. The estimation results significantly differ between the initial and continuous uptake. Contrary to the initial uptake in Column 1, household characteristics, such as the head's education and per capita income do not significantly affect continuous IBLI purchase, while less risk-averse households are more likely to stop purchasing. Given that some households have already experienced the product, some uncertainties about the product and the companies providing it would have been addressed. Thus, it is intuitive that more risk-averse households tend to buy insurance, as the conventional economic theory predicts. Households with larger herd size are likely to continue purchasing, presumably because they are less likely to face binding credit constraints or because they value the loss of livestock more than those who are asset poor.

The factors associated with renewing the contract also differ from those associated with augmenting the contract. Generally, household characteristics tend to matter more, as presented in Column 4. For example, household size is negatively correlated, and the gender of the head is positively correlated with renewing the contract. The age of the head has an inverted-U-shaped relationship. The coefficient on the head's years of education is negative and significant for the decision to replace the contract or not. This is probably because those who understand the product better are likely to discontinue it if they are disappointed by the result. Household risk preference is no longer the crucial determinant, conditional on the initial purchase.

4.3. *IBLI purchase with household-fixed effect*

Finally, we estimate the household-fixed effects that effectively control for time-invariant observed and unobserved household characteristics to better understand the role of time-variant factors. The estimation result is presented in Table 7, where Panel A presents the ordinary least squares (OLS) results while Panel B presents the IV results. The dependent variable is the household's binary purchase decision for each sales period. Because of the autocorrelation in the error term which we found in the multivariate probit estimation, we cluster the standard error at the household levels.

The main findings are as follows. First, consistent with the previous results (Takahashi et al., 2016), the contemporary discount rate positively affects the uptake, while the lagged discount rate has no direct impact, showing no price-anchoring effects (Column 1). The latter result validates our identification strategy, where the lagged discount rate is used as an instrument for the lagged uptake, which satisfies the exclusion restriction. Second, the coefficient on the January/February sales period is negative and significant, supporting the recurring pattern of uptake within a year, as we confirmed in the descriptive statistics. Third, the current (zero to six months before the current purchase) and lagged NDVI (seven to twelve months before the current purchase) have negative impacts on the probability of IBLI purchase, with the former having a large impact. This result suggests that households exploit ecological signals when making purchase decisions by buying IBLI when they anticipate a bad season. This is perhaps because vegetation conditions do not change immediately and past NDVI can be a good predictor for future NDVI, or pastoralists become willing to buy IBLI once animals get weaker due to poor vegetation. Fourth, one's own lagged uptake has a negative impact on the subsequent uptake in the reduced form using OLS (Panel A, Column 2). However, its sign turns positive once we appropriately instrumentalize this endogenous choice, which is our preferred estimation (Panel B, Column 2). This confirms that those who purchase IBLI tend to repeatedly purchase it not only because of the unobserved persistency which we found in the previous sub-section, but also because of behavioral traits. The result suggests the existence of some positive learning effects, wherein those who purchase and understand the product are more likely to repeatedly buy it. However, the result does not stand up to a robustness check when we instrumentalize all potential endogenous variables, although the sign remains positive (Panel B, Column 5). Furthermore, while the contemporary and lagged uptake of acquaintances have positive impacts on one's own uptake in the reduced form (Panel A, Columns 3–5), its statistical significance disappears once we use the IV methods (Panel B, Columns 3–5). This appears reasonable because the previously mentioned study reveals that most pastoralists do not know the status of the actual uptake of others, even if they are in the same social network (Takahashi et al., 2019).

To check whether our results are robust if we include the two-lagged-period variables, we extend the analysis of Equation (3). For potential endogenous variables, such as one's own lagged uptake and the uptake of others in one's network, we again apply the IV method by using the corresponding one's own and network members' period-specific premium discount rates as IVs. The numbers presented in Appendix Table 5 show that the results are mostly similar to those having only one-lagged period. We confirm that the premium discounts in the prior two sales periods have no direct impact on the current uptake, suggesting no price-anchoring effects in this extended model as well. Moreover, we find that even the two-period lagged NDVI negatively affects the current uptake. Partly because of the reduction of the sample size due to the inclusion of two-period lagged variables, we fail to reject the significant impact of the one-period-lagged-own uptake on the current purchase through the IV method, even though the sign is positive.

Overall, we find little evidence that others' uptake affects one's own decision in the demand dynamics for IBLI. Meanwhile, we observe weak, suggestive evidence of learning by doing effects, represented by positive coefficients of one's own lagged uptake.

5. Conclusions and policy implications

Index insurance has attracted much attention in developing countries due to its ability to protect the poor from climate risks. Despite the associated potential large gains, one puzzling observation is that the uptake of index insurance remains low. Using four-year, six-sales-period data collected in southern Ethiopia, this study investigated the dynamic uptake patterns and the underlying mechanisms of the uptake of IBLI.

We first find that households with higher per capita income, more risk-tolerance and higher education of household heads are more likely to buy IBLI. These results may suggest that it is those relatively better-off that have better access to and possibly benefit more from IBLI. The results are largely consistent with the other settings in the literature with shorter-term data, suggesting external validity of our findings (e.g., Gine et al., 2008; Cole et al., 2013; Hill et al., 2013; Jensen et al., 2018; and Ntukamazina et al., 2017). Although we confirm that reduced insurance premiums effectively increase the insurance uptake without lowering future demand, how to better reach the poorer segment of the society who are more vulnerable to climate risks and need the insurance most is obviously an important agenda for future research.

We also find that controlling for the baseline household characteristics, there is autocorrelation in the error terms over time, indicating that a household that purchases IBLI once is more likely to purchase coverage again. This autocorrelation is not explained by a standard set of household characteristics. We confirm that the existence of autocorrelation results in a biased estimate if we analyze the decisions for each period's uptake separately, even though the extent of bias is not very substantial. Our findings further suggest that the factors associated with the initial and subsequent uptake significantly differ, and household characteristics tend to matter more when we consider households' dynamic decisions about whether to renew the lapsing contract. These results highlight the importance of an empirical analysis that takes into account the dynamic demand structure with the long-term data.

Finally, conditional on time-invariant household characteristics, we find that the uptake of others in one's network do not influence one's own demand, whereas we observe some suggestive evidence of positive learning-by-doing effects. While the results are weak, our study reveals other channels than payout effects through which past uptake decisions affect subsequent purchase decisions, which is also confirmed in the existence of autocorrelation discussed above. Overall, our study provides solid micro-evidence to better understand the dynamic uptake of index insurance in a longer term than usually considered in the literature.

References

Advani, A., and B. Malde. 2018. "Methods to identify linear network models: a review." *Swiss journal of economics and statistics*, 154 (1): 12.

Bageant, E. R., and C.B. Barrett. 2017. "Are there gender differences in demand for index-based livestock insurance?" *The Journal of Development Studies*, 53 (6): 932-952.

Belissa, T., E. Bulte, F. Cecchi, S. Gangopadhyay, and R. Lensink. 2019a. "Liquidity constraints, informal institutions, and the adoption of weather insurance: A randomized controlled Trial in Ethiopia." *Journal of Development Economics*, 140: 269-278.

Belissa, T., R. Lensink, and M. van Asseldonk. 2019b. "Risk and ambiguity aversion behavior in index-based insurance uptake decisions: Experimental evidence from Ethiopia." *Journal of Economic Behavior and Organization*, In Press.

Bertram-Huemmer, V., and K. Kraehnert. 2018. "Does index insurance help households recover from disaster? Evidence from IBLI Mongolia" *American Journal of Agricultural Economics*, 100 (1): 145–171.

Binswanger, H. P. 1980. "Attitudes toward risk: Experimental measurement in rural India." *American journal of agricultural economics*, 62 (3): 395-407.

Bryan, G. 2019. "Ambiguity aversion decreases demand for partial insurance: Evidence from African farmers. *Journal of the European Economic Association*, In Press.

Cai, J. 2016. "The Impact of Insurance Provision on Household Production and Financial Decisions" *American Economic Journal: Economic Policy*, 8(2): 44-88.

Cai, J., A. De Janvry, and E. Sadoulet. 2015. "Social networks and the decision to insure." *American Economic Journal: Applied Economics*, 7 (2): 81-108.

Casaburi, L., & J. Willis. 2018. "Time versus state in insurance: Experimental evidence from contract farming in Kenya." *American Economic Review*, 108 (12): 3778-3813.

Chantarat, S., A.G. Mude, C.B. Barrett, and M.R. Carter. 2013. "Designing index - based livestock insurance for managing asset risk in northern Kenya." *Journal of Risk and Insurance*, 80(1): 205-237.

Cole, S., X. Giné, J. Tobacman, P. Topalova, R.Townsend, and J. Vickery. 2013. "Barriers to household risk management: Evidence from India." *American Economic Journal: Applied Economics*, 5 (1): 104-35.

Cole, S., X. Giné, and J. Vickery. 2017. "How does risk management influence production decisions? Evidence from a field experiment" *The Review of Financial Studies*, 30 (6): 1935–1970.

Cole, S., D. Stein, and J. Tobacman. 2014. "Dynamics of demand for index insurance: Evidence from a long-run field experiment." *American Economic Review*, 104 (5): 284-90.

Comola, M., and S. Prina. 2017. "Treatment effect accounting for network changes: Evidence from a randomized intervention." http://www.silviaprina.com/pdfs/CP_networks_2014.pdf

Conley, T. G., and C.R. Udry. 2010. "Learning about a new technology: Pineapple in Ghana." *American Economic Review*, 100 (1): 35-69.

De Nicola, F. 2015. "The impact of weather insurance on consumption, investment, and welfare." *Quantitative Economics*, 6 (3): 637-661.

Dercon, S., R. V., Hill, D. Clarke, I. Outes-Leon, and A.S. Taffesse. 2014. "Offering rainfall insurance to informal insurance groups: Evidence from a field experiment in Ethiopia." *Journal of Development Economics*, 106: 132-143.

Giné, X., R. Townsend, and J. Vickery. 2008. "Patterns of rainfall insurance participation in rural India." *The World Bank Economic Review*, 22(3): 539-566.

Hill, R.V., J. Hoddinott, and N. Kumar. 2013. "Adoption of weather-index insurance: Learning from willingness to pay among a panel of households in rural Ethiopia." *Agricultural Economics*, 44: 385-398.

Hill, R.V., N. Kumar, N. Magnan, S. Makhija, F. Nicola, D.J. Spielman, and P.S. Ward. 2019. "Ex ante and ex post effects of hybrid index insurance in Bangladesh", *Journal of Development Economics*,136: 1-17.

Hill, R. V., M. Robles, and F. Ceballos. 2016. "Demand for a simple weather insurance product in India: theory and evidence." *American Journal of Agricultural Economics*, 98 (4): 1250-1270.

Huysentruyt, M., C.B. Barrett, and J.G. McPeak. 2009. "Understanding Declining Mobility and Inter -household Tra
Economica, 76 (302): 315-336.

Ikegami, M., and M. Sheahan. 2015. "Index Based Livestock Insurance IBLI Borena Household Survey Codebook." Nairobi, Kenya: International Livestock Research Institute.

Janzen, S. A., and M.R. Carter. 2019. "After the drought: The impact of microinsurance on consumption smoothing and asset protection." *American Journal of Agricultural Economics*, 101 (3): 651-671.

Jensen, N.D., C.B. Barrett, A.G. Mude. 2017. "Cash transfers and index insurance: a comparative impact analysis from northern Kenya" *Journal of Development Economics*, 129: 14–28.

Jensen, N.D., A.G. Mude and C.B. Barrett. 2018. "How basis risk and spatiotemporal adverse selection influence demand for index insurance: Evidence from northern Kenya", *Food Policy*, 74: 172-198.

Karlan, D., R. Osei, I. Osei-Akoto and C. Udry. 2014 "Agricultural decisions after relaxing credit and risk constraints" *The Quarterly Journal of Economics*, 129 (2): 597-652

Lybbert, T. J., C.B. Barrett, S. Desta, and D. Layne Coppock. 2004. "Stochastic wealth dynamics and risk management among a poor population." *The Economic Journal*, 114 (498): 750-777.

Matsuda, A., and T. Kurosaki. 2019. "Demand for temperature and rainfall index insurance in India." *Agricultural Economics*, 50 (3): 353-366.

Matsuda, A., K. Takahashi, and M. Ikegami. 2019. "Direct and indirect impact of index-based livestock insurance in Southern Ethiopia." *The Geneva Papers on Risk and Insurance-Issues and Practice,* 44:481-502.

Mobarak, A.M. and M. Rosenzweig. 2012. "Selling formal insurance to the informally insured." Yale Economics Department Working Paper No. 97.

Noritomo, Y, and K. Takahashi. 2019. "Can insurance payouts prevent a poverty trap? Evidence from randomized experiments in northern Kenya." Sophia Institute for Human Security Discussion Paper Series 1.

Ntukamazina, N., R. N. Onwonga, R. Sommer, J.C. Rubyogo, C. M. Mukankusi, J. Mburu, and R. Kariuki. 2017. "Index-based agricultural insurance products: challenges, opportunities and prospects for uptake in sub-Sahara Africa." *Journal of Agriculture and Rural Development in the Tropics and Subtropics,* 118 (2): 171–185

Santos, P., and C.B. Barrett. 2011. "Persistent poverty and informal credit." *Journal of Development Economics,* 96 (2): 337-347.

Sibiko, K. W., P.C. Veettil, and M. Qaim. 2018. "Small farmers' preferences for weather index insurance: insights from Kenya." *Agriculture & Food Security,* 7 (1): 53.

Stein, D. 2018. "Dynamics of demand for rainfall index insurance: evidence from a commercial product in India." *The World Bank Economic Review*, 32 (3): 692-708.

Tafere, K., C.B. Barrett, and E.Lentz. 2019. "Insuring well-being? Buyer's remorse and peace of mind effects from insurance." *American Journal of Agricultural Economics*, 101 (3):627-650.

Takahashi, K., C.B. Barrett, and M. Ikegami. 2019. "Does index insurance crowd in or crowd out informal risk sharing? Evidence from rural Ethiopia." *American Journal of Agricultural Economics*, 101 (3): 672-691.

Takahashi, K., M. Ikegami, M. Sheahan, and C.B. Barrett. 2016. "Experimental evidence on the drivers of index-based livestock insurance demand in Southern Ethiopia.” *World Development*, 78: 324-340.

Tim, A.G., C.R. Gustafson, M. Ikegami., and N.D. Jensen. 2018. “Indemnity payouts, learning from others and index insurance uptake.” Paper prepared for presentation at the 2018 Agricultural & Applied Economics Association Annual Meeting, Washington, D.C

Van de Ven, W. P. M. M., and B. M. S. Van Pragg. 1981. “The demand for deductibles in private health insurance: A probit model with sample selection.” *Journal of Econometrics* 17: 229–252.

Table 1: Baseline Summary Statistics

Panel A: Household Characteristics		Panel B: Risk Preference	
Household size	6.264	Highly risk averse (=1)	0.124
	(0.116)		(0.330)
Age of head	50.485	Moderate risk averse (=1)	0.456
	(0.852)		(0.023)
Sex of head (=1 if male)	0.793	Less risk averse (=1)	0.419
	(0.019)		(0.023)
Years of education of head	0.600		
	(0.103)	Panel C: # Purchase IBLI	
Annual household income per capita (000ETB)	4.324	0	0.419
	(0.223)	1	0.192
Ratio of livestock per total income	0.715	2	0.205
	(0.033)	3	0.107
Annual household expenditure per capita (000 ETB)	3.754	4	0.061
	(0.112)	5	0.013
Extreme poverty (=1)	0.572	6	0.002
	(0.023)		
Herd size (TLUs)	14.639		
	(1.048)		
Non-livestock asset value (000 ETB)	2.917		
	(0.232)	# Obs	458

Note: Standard deviations are in parenthesis

Table 2: Most Important Reason for Why Households Did Not Purchase IBLI

	2nd		3rd		4th	
	No.	%	No.	%	No.	%
Did not understand insurance well enough to buy it	96	29.0	73	23.0	59	16.9
Don't have money to spend on insurance	70	21.1	74	23.3	68	19.4
Did not have an opportunity to buy it	48	14.5	60	18.9	72	20.6
Don't have enough animals	39	11.8	64	20.1	61	17.4
Afraid of uncertainty in insurance	2	0.6	16	5.0	24	6.9
Waiting to see what happens to the people who bought the insurance	11	3.3	8	2.5	23	6.6
Don't think insurance will help me	7	2.1	9	2.8	19	5.4
Don't trust any insurance companies	3	0.9	4	1.3	10	2.9
Other	55	16.6	10	3.1	14	4
Total	331	100	318	100	350	100

Table 3: Dynamic Patterns of IBLI Uptake

Sales period	IBLI1	IBLI2	IBLI3	IBLI4	IBLI5	IBLI6
Panel A						
Average discount rate (%)	38.035	38.450	38.210	38.035	38.384	38.384
	(29.147)	(28.798)	(28.894)	(28.890)	(29.055)	(28.904)
Cumulative normalized NDVI	-16.809	10.435	1.980	2.179	5.033	2.955
	(4.606)	(1.911)	(4.924)	(2.619)	(8.286)	(2.780)
Uptake Rate	0.277	0.194	0.303	0.129	0.216	0.127
	(0.448)	(0.396)	(0.460)	(0.335)	(0.412)	(0.333)
TLU insured conditional on purchase	2.459	2.469	2.644	2.380	1.985	2.312
	(3.206)	(3.857)	(5.267)	(4.301)	(3.439)	(4.365)
Panel B						
(1) # Purchased HH	127	89	139	59	99	58
(2) # New	127	66	28	10	23	12
(3) # Augmenting	0	23	55	31	27	28
(4) # Holding	0	104	34	108	32	71
(5) # Replacement	0	0	56	7	28	8
(6) # Lapsed	0	0	48	27	80	24
(7) # Reentering	0	0	0	11	21	10

Table 4: Period-Specific Uptake Decision (Multivariate probit estimation)

	IBLI 1	IBLI2	IBLI 3	IBLI 4	IBLI 5	IBLI 6
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Contemporary discount rate	0.011***	0.001	0.004**	0.010***	0.004*	0.007**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Household size	0.001	0.019	−0.001	−0.023	−0.068***	0.012
	(0.022)	(0.033)	(0.028)	(0.035)	(0.019)	(0.043)
Age of head	−0.013	−0.020	−0.030	0.049*	0.016	0.038*
	(0.022)	(0.021)	(0.022)	(0.027)	(0.016)	(0.020)
Age of head squared	0.085	0.129	0.235	−0.367	−0.118	−0.388**
	(0.189)	(0.175)	(0.179)	(0.234)	(0.151)	(0.180)
Years of education head	0.064***	−0.024	−0.003	0.083**	0.049	0.003
	(0.024)	(0.029)	(0.017)	(0.035)	(0.059)	(0.048)
Sex of head (=1 if male)	−0.158	−0.217	−0.113	0.153	0.228	−0.199
	(0.186)	(0.160)	(0.173)	(0.199)	(0.278)	(0.205)
Annual household income per capita (000ETB)	0.006	0.012	0.027**	0.037*	−0.007	−0.020
	(0.015)	(0.015)	(0.014)	(0.019)	(0.017)	(0.019)
Ratio of livestock per total income	0.382*	0.070	0.181	−0.090	−0.036	0.200
	(0.227)	(0.098)	(0.240)	(0.298)	(0.084)	(0.235)
Herd size (TLUs)/000	2.137	5.062	3.885	−15.745***	1.264	2.371
	(4.453)	(4.084)	(6.048)	(4.888)	(3.874)	(4.017)
Non-lievstock asset value (000 ETB)	−0.003	0.001	0.007	0.006	0.010	−0.017
	(0.009)	(0.014)	(0.009)	(0.017)	(0.012)	(0.017)
Less risk averse (=1)	0.667***	0.228	−0.086	−0.125	0.326*	−0.174
	(0.188)	(0.190)	(0.167)	(0.237)	(0.191)	(0.217)
Moderate risk averse (=1)	0.425**	0.193	−0.348*	−0.180	0.301	0.108
	(0.200)	(0.158)	(0.192)	(0.253)	(0.207)	(0.236)
Constant	−1.551**	0.272	0.184	−3.211***	−5.851***	−2.903***
	(0.624)	(0.613)	(0.640)	(0.838)	(0.341)	(0.452)
Woreda fixed effects	YES	YES	YES	YES	YES	YES
Observations	458	458	458	458	458	458

Note: Clustered standard errors at the study site level are in parenthesis. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

Table 5: Correlation of Error Terms

	1	2	3	4	5	6
IBLI 1						
IBLI 2	-0.008					
	(0.101)					
IBLI 3	0.630***	0.617***				
	(0.119)	(0.097)				
IBLI 4	0.434***	0.321*	0.485***			
	(0.124)	(0.186)	(0.146)			
IBLI 5	0.423***	0.180*	0.250***	0.465***		
	(0.106)	(0.104)	(0.070)	(0.138)		
IBLI 6	0.240***	0.316**	0.271***	0.374***	0.437***	
	(0.081)	(0.129)	(0.076)	(0.138)	(0.108)	

Note: Clustered standard errors at the study site level are in parenthesis. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

Table 6: Dynamic Uptake Model (Heckman probit estimation)

	Augumenting		Replacing	
	Previous (t-1)	Current (t)	Previous (t-2)	Current (t)
VARIABLES	(1)	(2)	(3)	(4)
Discount rate at each period	0.006***	0.003*	0.006***	0.009***
	(0.001)	(0.002)	(0.001)	(0.003)
Household size	-0.017	0.007	0.004	-0.161***
	(0.017)	(0.015)	(0.017)	(0.056)
Age of head	-0.003	0.006	-0.008	0.076**
	(0.010)	(0.015)	(0.007)	(0.035)
Age of head squared	0.017	-0.025	0.043	-0.656*
	(0.072)	(0.116)	(0.057)	(0.337)
Years of education head	0.034***	0.018	0.008	-0.095***
	(0.013)	(0.016)	(0.015)	(0.029)
Sex of head (=1 if male)	-0.037	-0.132	-0.076	0.541**
	(0.120)	(0.102)	(0.078)	(0.220)
Annual household income per capita (000ETB)	0.010***	-0.008	0.019***	-0.027***
	(0.002)	(0.009)	(0.004)	(0.005)
Ratio of livestock per total income	0.075	-0.098	0.151	-0.570**
	(0.119)	(0.222)	(0.156)	(0.229)
Herd size (TLUs)/1000	1.314	3.552*	-1.464	7.082
	(3.080)	(1.827)	(3.446)	(5.423)
Non-livestock asset value (1000ETB)	0.003	-0.000	0.000	-0.003
	(0.004)	(0.007)	(0.006)	(0.013)
Less risk averse (=1)	0.211*	-0.329*	0.308**	0.030
	(0.116)	(0.194)	(0.137)	(0.118)
Moderate risk averse (=1)	0.094	-0.321	0.193**	0.109
	(0.119)	(0.207)	(0.079)	(0.112)
Constant	-0.916***	0.110	-0.950***	-1.767
	(0.330)	(0.702)	(0.260)	(1.833)
Woreda fixed effect	YES	YES	YES	YES
Sales period fixed effect	YES	YES	YES	YES
Observations	2,290	2,290	1,696	1,696

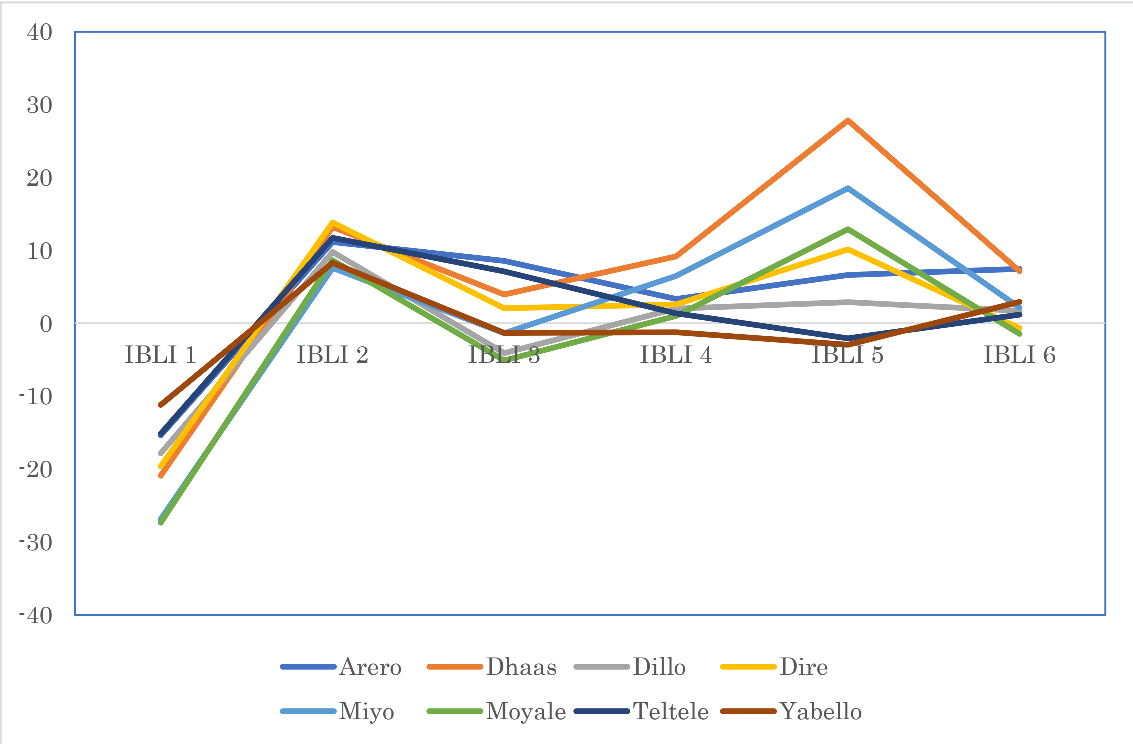
Note: Clustered standard errors at the study site level are in parenthesis. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

Table 7: Dynamic Uptake Model with Household Fixed Effect

Panel A: OLS	(1)	(2)	(3)	(4)	(5)
Discount rate (t)	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lagged discount rate (t-1)	0.001				
	(0.000)				
Lagged uptake (t-1)		-0.184***			-0.190***
		(0.028)			(0.028)
Average uptake of network members			0.120*		0.139**
			(0.061)		(0.064)
Lagged average uptake of network members				0.067	0.121**
				(0.046)	(0.049)
NDVI	-0.010***	-0.010***	-0.009***	-0.010***	-0.008***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Lagged NDVI	-0.004**	-0.005***	-0.004**	-0.004**	-0.004**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
January dummy	-0.153***	-0.137***	-0.135***	-0.158***	-0.126***
	(0.020)	(0.018)	(0.022)	(0.020)	(0.019)
Constant	0.317***	0.359***	0.295***	0.336***	0.298***
	(0.049)	(0.044)	(0.050)	(0.046)	(0.050)
Round fixed effects	YES	YES	YES	YES	YES
Observations	2290	2290	2290	2290	2290
Panel B: Instrumental Variable Method	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Discount rate (t)		0.001***	0.001***	0.001***	0.001**
		(0.000)	(0.000)	(0.000)	(0.000)
Lagged uptake (t-1)		0.363*			0.242
		(0.220)			(0.231)
Average uptake of network members			-0.829		-1.060
			(0.626)		(0.660)
Lagged average uptake of network members				-0.041	0.275
				(0.418)	(0.539)
NDVI		-0.010***	-0.018***	-0.010***	-0.021***
		(0.002)	(0.007)	(0.002)	(0.007)
Lagged NDVI		-0.002	-0.007***	-0.004	-0.005
		(0.002)	(0.003)	(0.003)	(0.004)
January dummy		-0.183***	-0.273***	-0.149***	-0.349***
		(0.029)	(0.094)	(0.039)	(0.122)
Round fixed effects		YES	YES	YES	YES
Observations		2290	2290	2290	2290

Note: Clustered standard errors at the household level are in parenthesis. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

Appendix Figure 1. Cumulative Standardized NDVI



Appendix Table 1: Baseline Characteristics of Attrited and Non-attrited Households

	Attreted	Non-attrited	Difference
	(1)	(2)	t-test
Household size	6.018	6.264	-0.247
	[0.305]	[0.116]	
Age of head	44.105	50.485	-6.379**
	[2.222]	[0.852]	
Sex of head(=1 if male)	0.702	0.793	-0.091
	[0.061]	[0.019]	
Years of education of head	0.351	0.600	-0.250
	[0.212]	[0.103]	
Per capita household income (000ETB)	4.999	4.324	0.675
	[0.662]	[0.223]	
Ratio of livestock per total income	0.762	0.715	0.047
	[0.038]	[0.033]	
Per capita household expenditure (000ETB)	3.842	3.754	0.089
	[0.355]	[0.112]	
Extreme poverty (=1)	0.526	0.572	-0.046
	[0.067]	[0.023]	
Non-lievstock asset value (000 ETB)	2.560	2.917	-0.357
	[0.479]	[0.232]	
Herd size (TLUs)	15.839	14.639	1.199
	[2.567]	[1.048]	
Less risk averse (=1)	0.456	0.419	0.037
	[0.067]	[0.023]	
Moderate risk averse (=1)	0.456	0.456	-0.000
	[0.067]	[0.023]	
woreda==Arero	0.175	0.192	-0.017
	[0.051]	[0.018]	
woreda==Dhas	0.018	0.052	-0.035
	[0.018]	[0.010]	
woreda==Dillo	0.228	0.166	0.062
	[0.056]	[0.017]	
woreda==Dire	0.105	0.096	0.009
	[0.041]	[0.014]	
woreda==Moyale	0.105	0.041	0.064**
	[0.041]	[0.009]	
woreda==Teltele	0.175	0.168	0.007
	[0.051]	[0.017]	
woreda==Yabello	0.123	0.214	-0.091
	[0.044]	[0.019]	
woreda==Miyo	0.070	0.070	0.000
	[0.034]	[0.012]	
Number of observations	57	458	
F-test of joint significance (F-stat)			1.171

Note: ***, **, and * indicate significance at the 1, 5, and 10 percent critical level. Standard deviations are in bracket.

Appendix Table 2: Reasons for Not Purchasing (Multinomial probit estimation)

(base=Others)	(1)	(2)	(3)	(4)
VARIABLES	Animal	Money	Understanding	Opportunity
Household size	0.044	0.007	0.023	-0.011
	(0.032)	(0.020)	(0.015)	(0.038)
Age of head	0.027	0.048	0.061*	0.049*
	(0.020)	(0.030)	(0.032)	(0.027)
age of head squared	-0.183	-0.429	-0.573**	-0.469*
	(0.147)	(0.282)	(0.288)	(0.240)
Years of education head	-0.017	-0.050	-0.076*	-0.060***
	(0.054)	(0.055)	(0.043)	(0.021)
Sex of head (=1 if male)	-0.464**	-0.664***	-0.209	-0.136
	(0.184)	(0.149)	(0.184)	(0.237)
Annual household income per capita (000ETB)	-0.050	0.013	-0.002	-0.011
	(0.037)	(0.033)	(0.018)	(0.015)
Ratio of livestock per total income	0.111	0.024	0.106***	0.145**
	(0.084)	(0.089)	(0.030)	(0.074)
Herd size (TLUs)/000	-73.320***	-22.014**	4.553*	4.714
	(15.862)	(8.792)	(2.356)	(4.918)
Non-livestock asset value (000ETB)	-0.020	-0.054***	-0.018	-0.027
	(0.022)	(0.017)	(0.023)	(0.023)
Less risk averse (=1)	0.333	0.331	0.038	-0.042
	(0.340)	(0.228)	(0.166)	(0.217)
Moderate risk averse (=1)	-0.025	0.165	-0.005	-0.183
	(0.263)	(0.171)	(0.126)	(0.184)
Constant	0.173	-0.185	-0.902	-1.890***
	(0.909)	(0.873)	(0.815)	(0.552)
Woreda fixed effects	Yes	Yes	Yes	Yes
Round fixed effects	Yes	Yes	Yes	Yes
Observations	1,009	1,009	1,009	1,009

Note: Baseline category is other reasons than lack of animal, money, understanding, and opportunity to buy. Clustered standard errors at the study site level are in parenthesis. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

Appendix Table 3: Summary statistics of average uptake in the network

Sales period	Uptake in Network
1	0.265
	(0.240)
2	0.187
	(0.219)
3	0.288
	(0.230)
4	0.122
	(0.167)
5	0.215
	(0.224)
6	0.129
	(0.178)

Note: Standard deviations are in parenthesis

Appendix Table 4: Separate Probit Regressions for Each Sales Period

	IBLI 1	IBLI2	IBLI 3	IBLI 4	IBLI 5	IBLI 6
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Contemporary discount rate	0.013***	0.001	0.003*	0.012***	0.005	0.007**
	(13.64)	(0.52)	(2.00)	(5.90)	(1.56)	(3.10)
Household size	-0.004	0.020	-0.007	-0.027	-0.073***	0.010
	(-0.14)	(0.71)	(-0.30)	(-0.93)	(-3.30)	(0.26)
Age of head	-0.016	-0.018	-0.025	0.044	0.015	0.038
	(-1.08)	(-0.85)	(-1.40)	(1.62)	(1.51)	(1.91)
Age of head squared	0.116	0.108	0.195	-0.318	-0.097	-0.376*
	(0.84)	(0.65)	(1.30)	(-1.53)	(-0.90)	(-2.34)
Years of education head	0.059	-0.020	-0.003	0.090***	0.054***	0.001
	(1.92)	(-1.26)	(-0.13)	(4.64)	(3.77)	(0.05)
Sex of head (=1 if male)	-0.129	-0.257	-0.067	0.127	0.227	-0.192
	(-1.01)	(-1.38)	(-0.35)	(1.05)	(1.10)	(-1.15)
Annual household income per capita (000ETB)	0.002	0.014	0.020	0.033	-0.011	-0.015
	(0.09)	(1.03)	(1.52)	(1.55)	(-0.87)	(-0.58)
Ratio of livestock per total income	0.364	0.063	0.118	-0.103	-0.022	0.114
	(1.27)	(0.61)	(0.66)	(-0.31)	(-0.30)	(0.42)
Herd size (TLUs)/000	2.326	5.165	3.675	-15.546**	1.736	3.128
	(0.51)	(1.09)	(0.55)	(-2.68)	(0.33)	(0.53)
Non-livestock asset value (000 ETB)	-0.003	-0.001	0.005	0.005	0.007	-0.018
	(-0.21)	(-0.05)	(0.74)	(0.23)	(0.55)	(-1.33)
Less risk averse (=1)	0.676**	0.182	-0.009	-0.035	0.395	-0.133
	(2.67)	(0.85)	(-0.04)	(-0.16)	(1.88)	(-0.89)
Moderate risk averse (=1)	0.480*	0.140	-0.261	-0.088	0.375	0.164
	(2.26)	(0.97)	(-1.94)	(-0.32)	(1.41)	(0.72)
Constant	-1.622**	0.243	0.150	-3.187***	-6.268***	-2.950***
	(-2.92)	(0.39)	(0.24)	(-3.40)	(-19.04)	(-4.56)
Woreda fixed effects	YES	YES	YES	YES	YES	YES
Observations	458	458	458	458	458	458

Note: Clustered standard errors at the study site level are in parenthesis. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

Appendix Table 5: Dynamic Uptake Model with Household Fixed Effect (Two-lagged)

Panel A: OLS	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Discount rate (t)	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lagged discount rate (t-1)	0.001							
	(0.000)							
Two lagged discount rate (t-2)		-0.000						
		(0.000)						
Lagged uptake (t-1)			-0.146***					-0.200***
			(0.034)					(0.039)
Two lagged uptake (t-2)				-0.110***				-0.168***
				(0.040)				(0.037)
Average uptake of network members (t)					0.084			0.116
					(0.072)			(0.073)
Lagged average uptake of network members (t-1)						0.118*		0.160**
						(0.062)		(0.068)
Two lagged average uptake of network members (t-2)							-0.009	0.077
							(0.060)	(0.060)
NDVI (t)	-0.008***	-0.008***	-0.008***	-0.007***	-0.007**	-0.007***	-0.008***	-0.006**
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Lagged NDVI (t-1)	-0.004*	-0.004*	-0.006**	-0.005*	-0.004*	-0.003	-0.004*	-0.004
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Two laggd NDVI (t-2)	-0.004***	-0.004***	-0.005***	-0.004***	-0.004**	-0.004**	-0.004***	-0.004**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
January dummy	-0.094***	-0.094***	-0.076***	-0.111***	-0.087***	-0.109***	-0.096***	-0.093***
	(0.025)	(0.026)	(0.024)	(0.027)	(0.027)	(0.026)	(0.027)	(0.027)
Constant	0.196***	0.224***	0.252***	0.254***	0.200***	0.205***	0.225***	0.232***
	(0.036)	(0.038)	(0.032)	(0.033)	(0.038)	(0.032)	(0.035)	(0.052)
Round fixd effects	YES	YES	YES	YES	YES	YES	YES	YES
Observations	1832	1832	1832	1832	1832	1832	1832	1832
Panel B: Instrumental variable method	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Discount rate (t)			0.002***	0.001***	0.001***	0.001***	0.001***	0.001***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lagged uptake (t-1)			0.555					0.320
			(0.401)					(0.385)
Two lagged uptake (t-2)				-0.011				0.081
				(0.234)				(0.245)
Average uptake of network members (t)					-0.805			-0.573
					(0.558)			(0.717)
Lagged average uptake of network members (t-1)						0.172		0.540
						(0.641)		(0.808)
Two lagged average uptake of network members (t-2)							0.718	0.649
							(0.593)	(0.747)
NDVI (t)			-0.007***	-0.008***	-0.014***	-0.007***	-0.011***	-0.014**
			(0.002)	(0.002)	(0.005)	(0.002)	(0.003)	(0.006)
Lagged NDVI (t-1)			0.002	-0.004**	-0.008**	-0.002	-0.003	0.005
			(0.005)	(0.002)	(0.003)	(0.007)	(0.002)	(0.012)
Two lagged NDVI (t-2)			-0.002	-0.004***	-0.007***	-0.003	-0.005***	-0.004
			(0.002)	(0.001)	(0.003)	(0.003)	(0.002)	(0.005)
January dummy			-0.163***	-0.096**	-0.168***	-0.115	0.009	-0.147
			(0.059)	(0.043)	(0.059)	(0.084)	(0.091)	(0.233)
Round fixd effects			YES	YES	YES	YES	YES	YES
Observations			1832	1832	1832	1832	1832	1832

Note: Clustered standard errors at the household level are in parenthesis. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.