The Role of Heterogenous Implementation on the Uptake and Long-Term Diffusion of Agricultural Insurance in a Pastoral Context

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Abstract: To make a difference in lower-income countries, agricultural innovations must be adopted and ultimately diffused across diverse local environments. This study contributes to the ongoing debate about the factors limiting the spread of agricultural innovations by considering the role of heterogenous supply in determining observed demand for the Index-Based Livestock Insurance (IBLI) product, which is a commercial insurance product serving historically uninsured pastoralists in the Horn of Africa. Analysis of sales data from 2010-2020 in Ethiopia and Kenya shows that local conditions can reduce the likelihood of supply channels reaching prospective clients, effectively excluding them from accessing insurance, while other factors can work towards increasing supply of insurance while also decreasing demand for it. Surveys collected from insurance sales agents reveals considerable heterogeneity in their ability to and effort in suppling IBLI. Discussions with IBLI's providers confirms the role of supply constraints in observed demand; the firms consistently point towards the cost of last-mile extension and sales as their largest challenge to increasing sales, and emphasize that it is cost-prohibitive to provide equal access to well-trained insurance agents across the areas that they operate. These findings suggest that current investments aimed at increasing insurance coverage by increasing demand, for example through improved product design or by subsidizing premiums, should be accompanied by investments in developing more cost-effective marketing and distribution processes so that demand can be acted upon. On a broader level, the results highlight a need to consider non-random and incomplete supply as a factor when examining observed uptake of agricultural innovations.

1. Introduction

Insurance has been promoted in a variety of settings to shelter smallholder farmers from weather shocks. While much of the empirical literature on the diffusion of agricultural innovations, including insurance, focuses on characteristics of the technology itself (e.g., Aldana et al. 2012; Bold et al. 2017; Emerick et al. 2016), characteristics of the client (e.g., Foster and Rosenzweig 2010; Suri 2011), or on social learning as a mechanism for transferring familiarity, trust and understanding of the innovation (e.g., Banerjee et al. 2013; BenYishay and Mobarak 2019; Conley and Udry 2010), few assessments take into consideration the many factors that can create heterogeneity in the supply of, and access to, those innovations, such as the costs associated with marketing products to remote regions or competition in the market.

In this paper, we use the example of index based livestock insurance (IBLI) to study the role of supply-side and demand-side factors in the observed patterns of insurance purchases. While there already exists a considerable body of literature examining demand for insurance, there have been no empirical studies of the factors leading to heterogenous supply and access to insurance, both of which are prerequisites for purchasing coverage. Indeed, analysis of demand for insurance are rarely able to speak to the broader patterns of observed insurance uptake, which we hypothesize largely reflect variation in supply-side factors such as the costs and incentives that insurance agents face.

The IBLI product was developed with the objective of mitigating impacts of drought on pastoral households and to reduce constraints regarding productivity-enhancing innovations. IBLI was piloted in 2010 and has now been available to pastoralists in northern Kenya and southern Ethiopia for over ten years. Since its inception, the IBLI contract and index has moved through several iterations in response to client feedback and expert advice, presumably improving the value offered by IBLI coverage. The product has been sold by several insurance firms and has been used as a social protection tool within resilience and development programming by several NGOs and government institutions. By December 2020, over

40,000 policies had been sold directly to pastoralists in northern Kenya and southern Ethiopia, resulting in a total insured value of over USD 12.2 million and USD 1.5 million in indemnity payments. In addition, between 2015 and 2022, the Government of Kenya purchased over 109,000 policies, insuring more than USD 70 million for targeted pastoral households in northern Kenya.[1]

While the availability of IBLI spread from 63,000km^2 in 2010 to well over 406,000km^2 in 2020, the rate of purchases by pastoralists has neither been consistent across time or space, nor has there been an obvious growth trajectory in the percent of households purchasing coverage. Rather, it seems that there are smaller pockets of market growth and decline that, for the most part, cannot be explained by the existing literature on adoption of agricultural insurance, which mainly points towards risk aversion, price, trust, product experience, product quality, peer imitation, and knowledge as main drivers of insurance uptake (e.g., Cai, De Janvry, and Sadoulet 2015; Cole et al. 2013; Cole, Stein, and Tobacman 2014; Hill et al. 2019; Hill, Hoddinott, and Kumar 2013; Jensen, Mude, and Barrett 2018; Karlan et al. 2014; Mobarak and Rosenzweig 2012; Stoeffler and Opuz 2022; Moritz, Kuhn, and Bobojonov, 2023), thereby focusing on product and demand characteristics. After more than a decade of working with insurance firms selling IBLI, we hypothesize that the observed variation in insurance purchases across time and space has been, to a great degree, driven by variation in the supply of insurance, a side of the insurance market that has historically been left under-studied by research on insurance specifically and by most studies on the diffusion of agricultural technologies more generally.

[1] In this study, we are unable to include insurance coverage provided by programs from which appropriate data were not available. These include the Satellite Index Insurance for Pastoralists in Ethiopia (SIIPE) program implemented by the World Food Program (WFP), which is active in Ethiopia and Zambia, a pilot study by the International Committee of the Red Cross in East Hararghe, Ethiopia, and a pilot by Catholic Agency for Overseas Development (CAFOD), Scottish Catholic International Aid Fund (SCIAF) and Trócaire in Dassenech, Ethiopia.

Because IBLI is one of the most successfully scaled, commercially provided agricultural index insurance products in a rural and lower income setting to date, it offers a unique opportunity for studying the dynamics that drive changes to supply and demand for insurance. In addition, the extended period of time and the considerable geographic area over which IBLI has been promoted allow for the investigation of factors that most studies of adoption are unable to empirically consider, such as how changes to contract design or characteristics of insurance units have impacted purchases, because of their more limited scope. Combining data from various, often very different, levels and sources was made possible by aggregating them at the insurance unit level, which is the spatial unit at which premium rates are set, policies are sold, the drought index values are calculated, and for which payouts are determined.

We use these data to study the importance of supply in the dynamics of diffusion. We leverage the fact that IBLI purchases could only have taken place if prospective clients had access to an insurance agent, to isolate the role of supply in observed demand for IBLI. This work is distinguished from the existing literature on agricultural insurance in its scale and scope; it includes purchase data from 115 insurance units across 20 insurance sales seasons, resulting in a total of 1,360 observations; it assesses factors that limit and support access to insurance, a side of the insurance market that has previously remained under-studied in the development sector; and it studies actual insurance markets “in the wild”, rather than only the demand for a product within a project context and among a project-related sub-sample of the population.

The remainder of this paper is organized as follows. Section 2 provides a brief background by way of a conceptual model for the supply of IBLI and a description of the context. Sections 3 and 4 describe the methods and data used for the analysis, respectively. Section 5 presents the results. We end with a discussion of the implications of the results in Section 6.

2. Background

Conceptual Framework and Hypothesis

The conventional literature concerning insurance has been premised on the strong assumption that the quantity and quality of services is determined purely by the point on the demand curve chosen by the informed, utility-maximizing consumer. Through prices, supply is assumed to both maximize profits for the firms while also fully accommodating demand. However, insurance firms face incentives, constraints and costs that can limit their investments in supply channels even when they could sell insurance at a profit, or that can cause them to continue selling insurance even when it is unprofitable. Further, those factors can change with space and time, so that in one period a region may be profitable while its neighbour is not, and in another period their profitability has swapped. While most models assume that firms can respond to such dynamics by adjusting price, prices are not always easily changed. So-called sticky prices are common in many markets, and there are specific reasons, which we will discuss, to believe that they apply here.

We begin by considering an insurance firm that aims to maximize profit (Π_{ut}) in each insurance unit *u* and period *t* by adjusting the premium rate (P_{ut}) and their expenses in supplying insurance (I_{ut}) (Equation 1). Firms generate revenue in each insurance unit as a function of the amount of insurance sold (S_{ut}) and the premium rate.

The firm has two types of expenses. The first are the indemnity payments (γ_{ut}), which are multiplied by the amount of insurance sold. Because future indemnity payouts are unknown to the firm, they optimize sales using the expected payout rate (E[γ_{ut}]). Investments are the second expense. To offer insurance, the insurance firm must invest in its supply chain, which includes making a fixed reoccurring investment to develop and maintain a supply channel (I_{ut}^{F}) that must at least meet threshold T_u and variable investments (I_{ut}^{V}), which include (re)training, supporting and motivating insurance agents as well as supporting outreach activities such as radio campaigns.

$$\max_{P,I} \Pi_{it} = S_{ut}(P_{ut} - E[\gamma_u]) - I_{ut}^{F} - I_{ut}^{V} \quad (1)$$

The amount of insurance sold is a function of demand (latent and fulfilled) for this type of insurance product (D_{ut}), its price (P_{ut}), and prospective clients' awareness of, knowledge about, and access to the product (combined into A_{ut}). Insurance companies can increase A_{ut}, and therefore sales, by increasing investments ($\frac{\partial S_{ut}}{\partial I_{ut}^{V}} \geq 0$) but there are decreasing marginal returns to those investments ($\frac{\partial^2 S_{ut}}{\partial (I_{ut}^{V})^2} \leq 0$), at a minimum because the populations in each insurance unit are finite so that the market can be saturated. Equation (2) describes the relationships between insurance sold and these factors of demand.

$$S_{ut} = \begin{matrix} 0 & if\ I_{ut}^{F} < \mathrm{T}_u \\ f(D_{ut}, P_{ut}, A_{ut}) & if\ I_{ut}^{F} \geq \mathrm{T}_u \end{matrix} \quad (2)$$

Where:

$$\frac{\partial S_{ut}}{\partial D_{ut}} \geq 0\ ; \frac{\partial S_{ut}}{\partial P_{ut}} \leq 0;\ \frac{\partial S_{ut}}{\partial A_{ut}} \geq 0\ ;\ \frac{\partial A_{ut}}{\partial I_{ut}^{V}} \geq 0\ ;\ \forall\ S_{ut}, D_{ut}, P_{ut}, A_{ut}, I_{ut}^{V} > 0 \mid I_{ut}^{F} \geq \mathrm{T}_u$$

While insurance firms can change premium rates, those selling IBLI have done so infrequently (the average is less than every 5 years between 2010 and 2020). Such changes require costly re-assessments and renegotiations with their reinsurers, expenses related to changing and republishing all materials and retraining insurance agents, and can cause reputational damage if premium rates are increased.[2] Historically, when the firms that sell IBLI have updated premium rates, they have adjusted the rates across all insurance units to reflect their updated estimates of the risk ($E[\gamma_u]$) and updated rates from the reinsurers. Importantly, the insurance firms selling IBLI have not made season by season adjustments to premium rates. While premium rates have appeared sticky, firms can also impact their profits (or losses) through their expenses and the number of policies sold; they can adjust their investments in selling insurance, which can mean ceasing investments in insurance units that are unprofitable at the current premium levels. The plausibility of this model is illustrated by the relatively common occurrence in which insurance firms did not provide agent (re)trainings in certain regions, or even pulled out of the IBLI market all together, rather than raising premium rates in real time to reflect losses.

Insurance agents are in a position that is similar to that of the insurance firm (Equation 3). Individuals are incentivized to become an insurance agent through fixed stipends provided during periodic (usually annual) agent trainings (t_{ut}), and commissions, which are the product of the amount of insurance they sell (s_{ut}) and their commission rate (c_{ut}), are meant to incentivize agents to perform (costly) outreach efforts. To sell any insurance agents must make a fixed investment (i^F_{ut}) and can increase the amount of insurance that they sell by making variable investments (i^V_{ut}) in awareness creation, extension and in making themselves accessible to prospective clients. The majority of these tangible investments are in transportation and the agent's time, but there are also intangible investments, such as entering risky

[2] Practically speaking it is also not easy for firms to know when they should change prices and to what levels. The combination of short time series and the threat of changing weather make risk estimates uncertain, especially when projected into the future.

environments and drawing on social capital. The agents' variable investments have decreasing marginal impacts on sales for the same reasons that the firms' investments do.

The agent maximizes their profits as an agent by adjusting their investments.

$$\max_{i} \pi_{it} = s_{ut} * c_{ut} + t_{ut} - i_{ut}^{F} - i_{ut}^{V} \tag{3}$$

$$s_{ut} = \begin{matrix} 0 & if\ i_{ut}^{F} < \tau_u \\ f(D_{ut}, P_{ut}, A_{ut}) & if\ i_{ut}^{F} \geq \tau_u \end{matrix}$$

$$\frac{\partial s_{ut}}{\partial D_{ut}} \geq 0\ ; \frac{\partial s_{ut}}{\partial P_{ut}} \leq 0;\ \frac{\partial s_{ut}}{\partial A_{ut}} \geq 0\ ;\ \frac{\partial A_{ut}}{\partial i_{ut}^{V}} \geq 0\ ; \frac{\partial s_{ut}}{\partial i_{ut}^{V}} \geq 0;\ \forall\ D_{ut}, P_{ut}, A_{ut}, i_{ut}^{V} > 0 \mid I_{ut}^{F} \geq \tau_u$$

The payoff from attending training combined with the fixed and variable costs of selling insurance can mean that insurance agents maximize their profits by attending trainings without making any investments to sell insurance. Or, in cases in which an agent is responsible for several insurance units whose demand and costs associated with selling insurance vary, agents may sell insurance in some insurance units while remaining absent from others.[3]

This conceptual model highlights that there are several factors that can limit supply. The two main findings— (1) that when firms cannot easily adjust prices, they respond by adjusting supply, sometimes

[3] Here we note that the firm's profits are not considered in agent's optimization problem, which, in this case, means that it is possible for firms to support supply while agents do not.

to zero, and (2) that agents face costs and incentives that can impact supply of insurance—lead us to our hypothesis.

Hypothesis: Heterogenous supply of IBLI can constrain purchases of IBLI so that observed variations in purchases are not exclusively a function of demand.

A confirmation of our hypothesis would suggest that researchers and policy makers wishing to support insurance markets should consider allocating resources to improving the profitability of insurance, perhaps by helping firms overcome the costs of supplying the product. Further, if supply-side dynamics are resulting in non-random heterogenous access to insurance, it could bring into question the results of studies on demand that do not account for selection into supply. A rejection of our hypothesis would suggest a continued focus on demand-side factors and that research on insurance purchases can continue to focus on observed demand. Finally, because of the unambiguous nature of the relationships in the models, they can help us understand the role of several factors that are believed to impact observed demand strongly, but whose relationship is conceptually ambiguous.[4]

While the conclusions of the conceptual model and hypothesis may not be novel, there is good reason to consider them in these circumstances. Doing so could help shed light onto the market forces that have resulted in the plethora of research for development innovations that prove effective and profitable in pilot but fail to scale (Kosmowski et al. 2020; Woltering et al. 2019). Many such failures lead to studies on

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[4] The Kenya Livestock Insurance Program (KLIP), which provided a 100% subsidy for insurance for up to five cattle to a relatively large proportion of the dryland population in Kenya between 2015 and 2022, is an example of one such factor. While we expect that the KLIP program impacts commercial demand for IBLI, *a-priori*, we do not have any reason to believe that it is more likely to compete with commercial insurance or strengthen the commercial insurance market by providing exposure and familiarity to the product.

why demand had failed, assuming that market forces would have ensured that supply had met any demand. In this case, we have the rare opportunity to test if an innovation's supply seems to be limiting purchases and therefore determining observed demand.

Index-Based Livestock Insurance—From Development to Scale

Drought has been identified as one of the main causes of poverty among pastoralists. IBLI was first piloted in Marsabit County, Kenya in 2010 with the objective of mitigating the impacts of drought on pastoral households. At that time, the IBLI insurance policy was based on an index of predicted area-average livestock mortality rate, which relied on the Normalized Difference Vegetation Index (NDVI) as a signal of vegetation conditions. The index was calibrated using monthly household data collected by the Government of Kenya's Arid Land Resource Management Project between 2000 and 2008 and had been shown to have good predictive power in out-of-sample testing using quarterly panel data collected by USAID's Global Livestock Collaborative Research Support Program Pastoral Risk Management (Chantarat et al. 2013).

The IBLI pilot in Marsabit County was launched with a considerable monitoring and evaluation infrastructure aimed at assessing and improving the IBLI contract. As preliminary evidence showing the value of IBLI began to mount, demand for scaling beyond Marsabit County grew. While a lack of mortality data outside of Marsabit County prevented scaling the original product, a new product was developed that focused on forage anomalies rather than livestock losses. Because the NDVI data are globally available and are a proven indicator of forage availability in the rangelands (Borowik et al. 2013), such a contract could be scaled to any rangeland region. Further, NDVI data have a reasonably long archive, which allowed scientists to determine that NDVI values during the rainy season could accurately be used to predict forage scarcity at the end of the following dry season, opening the door for a new product that made payouts in anticipation of coming forage scarcity (Vrieling et al. 2016). This new product has been called an asset protection policy, presumably because clients could use payouts to prevent loss of their livestock, to distinguish it from the original policy that made payments after drought, when livestock were already lost.

Since its inception in 2010, IBLI has seen tremendous growth. IBLI has commercially scaled to eight arid counties in Kenya—Garissa, Mandera, Marsabit, Isiolo, Samburu, Tana River, Turkana, and Wajir—and to the Borena Zone of Ethiopia. In 2015, the Government of Kenya began using IBLI to provide a safety net to targeted beneficiaries in the Arid and Semi-Arid Lands (ASALs) of Kenya. Between 2017 and 2021, the Kenya Livestock Insurance Program (KLIP) provided IBLI coverage to over 18,000 pastoral households annually. At the same time, the World Food Program has started using an IBLI-based product to support resilience building for 15,500 targeted pastoralists in the Somali Region of Ethiopia (World Food Program 2021). There have also been, and continue to be, several collaborations between NGOs and the insurance providers through which subsidies are provided to targeted participants of NGO programming as a way to support their development and humanitarian objectives. Just recently, a collaboration between the World Bank Group and several countries in the Horn of Africa called the De-risking, Inclusion, and Value Enhancement of Pastoral Economies (DRIVE) Project has dedicated tens of millions USD to increasing IBLI coverage in the region while other stakeholders have commissioned feasibility studies for several additional countries in the Sahel.

Figure 1 illustrates the total sum insured through IBLI between 2010 and 2020 through direct purchases by pastoralists; non-commercial purchases, such as those by the Kenya Government through KLIP or those supported by WFP through Satellite Index Insurance for Pastoralists in Ethiopia (SIIPE) are omitted from this figure.

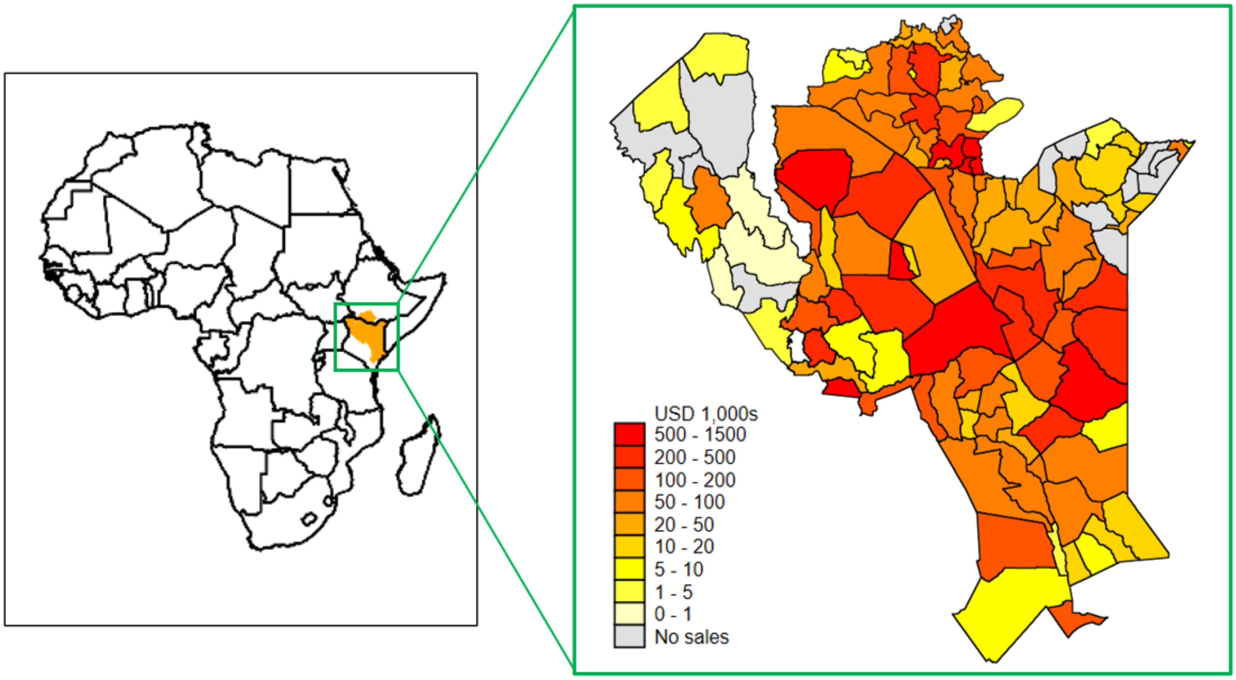

Figure 1. Total sum insured in each insurance unit through direct purchases of IBLI by pastoralists in Kenya and Ethiopia between 2010 and 2020.

IBLI's Distribution Channels

Growth in the supply of IBLI has been irregular in space and time, and has even run backwards at times. Since IBLI was first piloted in Marsabit County insurance firms in Kenya have used the administrative level-1 boundaries—counties—to define their areas of operations, rolling into or out of counties as a unit, rather than choosing to sell or not sell IBLI in the smaller insurance units, of which counties are composed. This decision to use counties programmatically was made to simplify logistics—many of the insurance firms' operations were managed at a county level. For example, insurance agents' trainings usually took place at the county level, county managers or field coordinators were often used to manage county teams of insurance agents, and informational materials on the insurance policies were customized for each county. The result is that Kenyan insurance firms generally entered or exited a county all at once. Once active in a county, the insurance firms remained active in that county for an average of 4.7 years. While the decision to exit or enter a county were made infrequently, insurance firms' investments between and within each county could vary dramatically each season. This mode of operating will be important as we analyze the patterns of IBLI sales.

Kenyan insurance firms have employed several different strategies for selling IBLI. All firms have always used local sales agents and commissions, but who those agents were, how commissions were structured, and the configuration of those agents has changed within insurance firm over time and has varied between insurance firms. For example, in several circumstances, insurance firms used networks of younger, more educated, individuals as their agents, with the idea that these individuals are looking for work and could easily understand the insurance concepts. But this model frequently faced high turnover rates and little commitment from agents as they were searching for, and often finding, more lucrative or more stable opportunities. More recently, a structure relying on local business owners, mostly small store owners, has been favored by one firm because these individuals are less likely to move on to other locations and can sell insurance as part of their activities in their store. Further, the physical location of a store may have several other advantages, such as physically tying agents to a location, and making them easier to locate for potential and current clients.

In Ethiopia, the supply of IBLI was less spatially determined and more strongly determined by interest from the local cooperatives through which IBLI was sold there. These formal cooperatives are required to work with the insurance firm to put in place the necessary infrastructure (e.g., sign agreements, formally designate specific cooperative members for roles related to selling IBLI, train individuals on IBLI, how to register clients, and on how to collect premiums) and the cooperatives sell insurance to their members within their catchment area. In most cases, cooperatives designated individuals to act as Village Insurance Promotors, which we will call agents for consistency, whose jobs is to provide outreach to the communities in their cooperative's catchment area and recruit clients. Since its launch in 2012, the local insurance firm has expressed willingness and availability to sell insurance in any of the kebeles in the Borena Zone, as long as there was a cooperative operating there that was willing to set up the necessary infrastructure. At the same time, there are many kebeles without active distribution processes in place in any given year. In some cases, there has never been any active cooperative, in others, cooperatives started selling IBLI and then stopped for various reasons.

The insurance policies themselves have always been and continue to be developed at the insurance unit level, so that the policies could be activated or deactivated each season at this level. In Section 4, we will return to an important implication of the tension between the larger spatial and lower temporal resolution at which firms make decisions and the smaller spatial and higher temporal resolution at which insurance agents and clients operate at.

In both Ethiopia and Kenya, some form of commission has always been used by the commercial firms to incentivize outreach and sales by their agents. At the same time, the agent structures and commission schedules have been adjusted by the insurance firms several times in an effort to reduce costs or increase sales. Most often, the firms set up a hierarchy in the distribution channel, under which there is a country coordinator/lead agent (Kenya) or cooperative (Ethiopia) that manages and aggregates clients, and these are served by some form of promoter or sub-agent that performs outreach. In Kenya, those promotors, often called agents or sub-agents, are commonly able to register and collect premiums from clients directly, while in Ethiopia agents perform outreach to prospective clients in the communities but those interested in purchasing IBLI are then referred to the cooperative to register and pay premiums. These differences reflect variation in the two environments, such as those caused by differences in access to mobile banking as well as regulatory restrictions on requirements for registering insurance clients. Importantly, the commissions received by insurance agents could change when their management structure changed. In both Kenya and Ethiopia, the expenses of providing outreach (e.g., transportation to villages, mobilization of prospective clients) have been the responsibility of the agents, except in special circumstances.

3. Empirical Methods

The relationships between individuals' characteristics and their observed demand for index insurance is well studied in the economic development literature (Cai et al. 2015; Cole et al. 2013, 2014; Hill et al. 2019, 2013; Jensen et al. 2018; Karlan et al. 2014; Mobarak and Rosenzweig 2012; Moritz, Kuhn, and Bobojonov 2023; Stoeffler and Opuz 2022). We extend this literature by recognizing that observed demand is also a function of supply and that studies of demand for insurance may have drawn inaccurate conclusions if supply did not fully meet demand in some communities. While we have little doubt that those performing the existing studies recognized the importance of supply channels, indeed several studies examine how factors in the supply chain impact individual insurance purchases, few, if any, assessments of demand allow or account for potential shortfalls in supply. If a selection process on the supply-side does impact observed demand and is not accounted for, analysis aimed at determining factors that impact demand could generate biased estimates.

Put in econometric terms, we propose that observed demand is the result of a selection process on the supply side. When there is no supply, we do not observe demand. While the contrary, that if we do not observe demand there is no supply, does not necessarily follow, there are strong reasons to believe that this is true in this case. Those reasons are discussed in detail in the section on administrative data.

When purchases are observed ($S_{ut} > 0$), those purchases are an indicator that there is some supply ($I_{ut}^F \geq \mathrm{T}_u$ and $i_{ut}^F \geq \tau_u$ from the conceptual model) and some demand, but we cannot determine which, if either, is constraining further purchases because we cannot observe the level of investment in supply or latent demand and the two cannot be disentangled because there are factors that play important roles in both the supply and demand of technologies. Indeed, supply of products is often modeled as a function of expected demand.

Heckman proposed that such selection could be framed as a missing variables problem and be addressed by controlling for the process of selection (Heckman 1979). Using supply as the selection equation, Heckman's approach allows for separate but correlated processes to generate observed demand while also accounting for its conditionality.[5] Testing for correlation in the error terms between the two models is one approach to testing if supply selection plays a role in observed demand but this test alone does not provide guidance on the economic importance or policy relevance of accounting for the selection process in the coefficient estimates.

To determine the importance of accounting for selection, we assess the factors related to observed demand with and without accounting for a prospective selection process. The Heckman selection model is used for the selection case and a Tobit model for the non-selection case. The Tobit model provides a relevant counterfactual because it assumes that a single process is used to generate the entire set of observations, which is inconsistence with our hypothesis that in some cases observed purchases reflect both supply and demand processes.

We then test for differences between the coefficient estimates of the two models, paying attention to both the relative magnitude and statistical significance of the differences, and discuss the economic and policy relevance of those magnitudes. The magnitudes of the differences are expressed in terms of a

[5] While several studies of demand for insurance use a selection process in their study (e.g., (Bageant and Barrett 2017; Jensen, Mude, and Barrett 2018), those studies modelled the amount of insurance purchases as being conditional on an individual's (selection) decision to purchase any insurance, while this manuscript moves beyond the clients' sphere of influence to the supply chain itself.

proportional difference in coefficient estimates and the statistical significance of the differences are tested using a χ^2 test.

Drawing on the conceptual framework, we use a reduced form model of supply that integrates the firm's (Equation 1) and the agents' (Equation 3) incentives and costs as the selection equation (Equation 4). Firms are assumed to adjust their investments in their supply chains for an insurance unit in response to their historic profits there. Agents maximize the benefit of being an agent by investing more in those areas that are likely to have higher demand at less cost to the agent. Here we note that while there could be more than one firm selling insurance in the same period in the same insurance unit, agents only worked for one firm at a time and sometimes several agents working for the same firms could have overlapping catchment areas. Therefore, all analysis is performed at the firm-index unit-season level, even when considering costs and benefits to the agents.

$$y_{fut} = \beta^0 + \beta^1 Profit_{fut} + \beta^2 Costs_{ut} + \beta^3 Benefits_{fut} + \beta^4 T_t + \delta_u + \varepsilon_{fut} \qquad (4)$$

- y_{fut} is a binary indicator that is one if insurance was actively sold by firm *f* in insurance unit *u* during sales window *t*, and zero otherwise;
- $Profit_{fut}$ is a is measure of cumulative profits (+) or losses (-) that insurance firm *f* has generated in insurance unit *u* in the seasons leading up to the current sales window *t*;
- $Costs_{ut}$ is a vector capturing insurance unit factors that are associated with the agents' costs of marketing and sales activities in an insurance unit, and does not vary between firms in the insurance unit in the same period;

- $Benefits_{fut}$ is a vector of factors that are related to the benefits that an agent could capture by visiting in insurance unit in a specific insurance window, and does vary between firms in that same insurance unit and season;
- T_t is a vector controlling for time trends in y_{fut};
- δ_u is a vector of location fixed effects;
- and ε_{fut} is the normal error.

The coefficient estimates for Equation (4) are estimated using a Probit model with robust errors clustered at the insurance unit level.

For the second step in the analysis, we consider the substantive body of literature on the factors that contribute to demand for insurance when prospective clients have access to sales channels. Most of that literature uses household data to examine variation in purchases between individuals. We draw on that literature but add to our analysis factors that vary at higher levels as well, such as contract type, potential substitutes/competition, and characteristics of the insurance unit.

Using the number of policies sold as our indicator of demand, we estimate demand as a function of product characteristics (P_{ut}), environmental conditions (E_{ut}), marketing and distribution characteristics (I_{fut}), and local characteristics (L_{ut}). In the selection case, we control for the Inverse Mills Ratio calculated from Equation (4). We also control for non-linear time trends and district fixed effects.

$$y_{fut} = \beta^0 + \beta^1 P_{ut} + \beta^2 E_{ut} + \beta^3 I_{fut} + \beta^4 L_{ut} + \beta^5 T_t + \delta_u + \varepsilon_{ut} \tag{5}$$

Here:

- y_{fut} is the number of policies purchased from insurance firm *f*, within the insurance unit *u* during sales season *t*;
- P_{ut} is a vector of characteristics of the new technology (e.g., price, contract type);
- E_{ut} is a vector of current and preceding environmental conditions that are relevant for the product and a seasonal indicator;
- I_{fut} is a vector of marketing and distribution characteristics;
- L_{ut} is a vector of insurance unit characteristics, such as overall drought risk or population size;
- T_t is a vector controlling for time trends in diffusion;
- δ_u is a location fixed effect;
- and ε_{ut} is the normal error.

The coefficient estimates for Equation (5) are estimated using the sub-sample of observations for which y_{fut} >0 using OLS and robust errors are clustered at the insurance unit level.

To provide unbiased and robust estimates in the second stage, the Heckman selection model requires at least one "excluded" variable that both contributes to the selection model and, conditional on controls, is not related to the outcome except through the selection. We employ a set of excluded variables that are directly related to the supply of insurance but are not directly related to demand.

All statistical analysis were performed using Stata version 18.0. The Tobit model was estimated using the *tobit* command with zero as the lower bound and the Heckman selection model was estimated using the *heckman* command and the maximum likelihood option.

Data

Administrative data and outcome variables

The outcome variables of this study are developed from the administrative data of insurance firms that sold IBLI. Insurance firms varied in when and where they offered the IBLI product; moving into and out of regions (counties in Kenya and woredas in Ethiopia) as they saw fit. In some cases, multiple insurance firms offered the IBLI product in the same insurance unit and in the same period. In other cases, a firm might start selling IBLI in a region, then stop, leaving the population without access to IBLI, and then start selling again several years later. In 2021, the International Livestock Research Institute (ILRI) worked with all four insurance firms that had ever sold IBLI, to structure and collate their sales data from sales seasons between 2010 and 2020. The data were aggregated to the insurance unit-season level.

While working with the insurance firms to structure and collate their sales data, it was observed that there were many cases in which firms' documentation implied that they were offering insurance in an insurance unit, but there were no sales. The firms commonly attributed such instances to a lack of effort in marketing by their agents. Indeed, in several cases, firms mentioned that sometimes agents attended trainings but had never sold any insurance.[6] At the same time, conversations with agents often returned to the need for greater support from the insurance firms to pay for outreach activities (e.g., for the agent's transportation to remote sites).

We leverage this information to shed light onto the dynamics of IBLI's supply. First, it is clear that an active insurance agent is needed for there to be any insurance purchases; if there are sales, an agent performed marketing activities in that insurance unit in that season. Second, if there are no sales in an insurance unit

[6] Agents were paid transportation, a stipend and provided with food and lodging to attend training, which made the trainings themselves a profitable experience for agents.

in a season that the firm’s documents or policies imply that insurance was available, the most likely cause is lack of agent marketing activities. While the second proposition cannot be proven with the data that we have, there is strong circumstantial evidence to support it. First, the firms themselves consistently identify agents’ lack of marketing and effort as the reason for these situations. Second, although purchase rates have been relatively low and variable across the IBLI region, there has been a proven and persistent demand for IBLI across this extensive area of operation for over ten years. Third, the insurance units contain populations that range from several thousand to hundreds of thousands of pastoralists with a wide range of risk profiles and financial circumstances, which makes it unlikely that an insurance unit does not include a single individual whose risk profile would benefit from IBLI. Finally, a single policy can be purchased for as little as approximately USD1 and there are many instances of households purchasing this small amount of coverage.

With these two assumptions—that positive sales indicate marketing and sales activities by an agent, and that no sales indicate that the agent did not perform marketing and sales activities—we can study the extent to which a lack of marketing and sales activities—i.e., supply—by agents impacted observed demand.

IBLI policies were purchased in 816 (60%) of the 1,360 insurance unit-season observations in which there is strong reason to believe that IBLI were offered, at least on paper. Figure 2 illustrates the distribution of purchases, including observations with zero purchases in the left panel and excluding them in the right panel. The distribution of policies purchased does not transition smoothly from very few purchases to zero policies purchased. Rather, there is an extremely large jump from the number of insurance unit-seasons with 1 policy sold (N=39), which is the second most common observation, and zero polices sold (N=589). The severity of this jump suggests that there are differences in the processes determining whether any policies are sold and how many policies are sold, conditional on there being any policies sold.

This paper assumes that the former reflects incentives faced by the insurance firms and their agents and the latter reflects a combination of those forces and client demand.

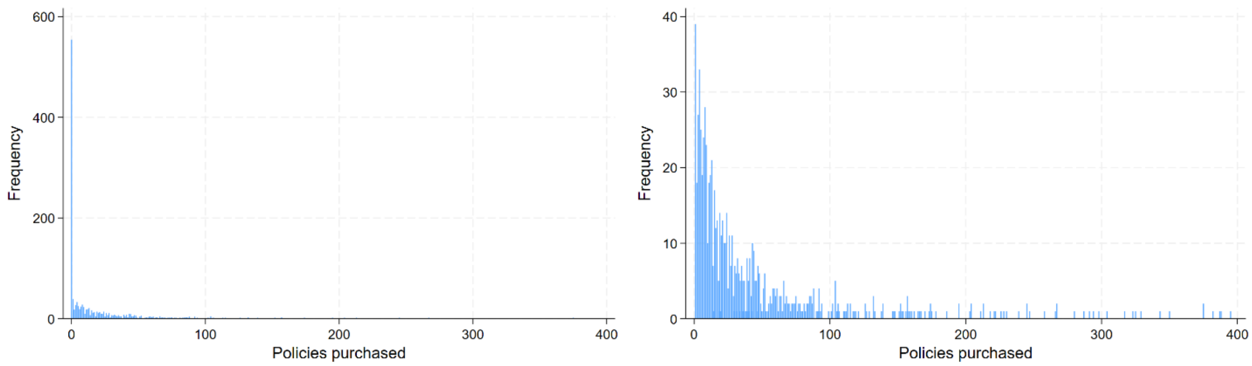

Figure 2. The distribution of policies purchases including (left) and excluding (right) those observations with zero purchases. 11 observations with more than 400 policies are not included in these figures.

Explanatory variables

In the following section, we start by providing a summary of the variables that fit into the supply side categories described in the conceptual framework—firm profits, agent benefits, and agent costs—and then do the same for demand-side factors. There is a potential overlap between these two groups, which we allow for. The full description of each variable and how it was constructed can be found in Appendix A.

Supply

Firm profit: This variable is calculated for each firm in each insurance unit and season that IBLI was offered by cumulating the premiums collected and the payouts made. The resulting variable is a proxy for the profits or losses (Π_{ut}) that the specific insurance unit generated for that specific firm up until the current sales window. Note that the researchers did not have access to, nor could we account for, any non-payout expenditures (e.g., I^F_{ut}, I^V_{ut}).

Agent costs: This is a set of variables calculated at the index unit level that consider the remoteness, as indicated by distance to a large town, and the risk of violence, as measured by the number of fatalities from violence during the five months preceding the sales season as captured in the ACLED data (Clionadh et al. 2010), as factors that the agent might consider in their calculation of costs when considering performing extension and sales activities.

Agent benefits: This is a set of variables broadly associated with commission structure (c_{ut}), latent demand (D_{ut} in the conceptual model) and external activities that could affect prospective clients' awareness of, knowledge about and access to the product (combined into A_{ut} in the conceptual model). For example, the livelihood zone and population could impact latent demand, while subsidies or external marketing support provided by research projects could impact prospective clients' awareness of, and knowledge about, the product at no cost to the agent.

Excluded variables: We identified two variables from the above list that directly impact supply of IBLI to an insurance unit but, conditional on observables, do not directly impact demand.

1) The profits made by the insurance firm are known by the firms and determine their interest in providing IBLI in an insurance unit but are unknown by potential clients because they do not observe the total amount of insurance coverage purchased by the thousands of residents of their insurance unit or the cumulative payouts over the years.

2) The structure of the agent network, which changed between and within firms and impacts the commission rates that agents received, impacts the agents' marginal benefit from investing in sales and outreach. We understand that prospective clients were generally unaware of the agents' management and commission structure.

We include these excluded variables in the Tobit model and the selection component of the Heckman model but exclude them from the demand component of the Heckman model.

Demand

As discussed earlier, demand for insurance has been well studied. We draw on the existing literature to develop a minimal list of factors that were likely to be related to demand. Note that many of the existing studies focus on individual-level factors, which we cannot study here because this study is at the insurance unit level. However, this level of aggregation offers us the opportunity to examine several novel factors.

Technology characteristics: This set of variables intends to capture product characteristics from the perspective of prospective clients. Specifically, the set includes the premium rate, calculated as a percentage of the total sum insured, and the contract type (asset replacement vs. asset protection).

Environmental conditions: This group of variables includes indicators of the environmental conditions during the current sales season and the previous season and whether the sales were taking place at the end of the long or short dry season. The rangeland conditions during the insurance season before the current sales window (i.e., the previous wet and dry season) were captured by an NVDI-based index of relative forage availability using the methods described in Vrieling et al (2016). All else being equal, one might expect that previous conditions could impact current liquidity. Conditions during the current sales window relied on a similar process as those capturing the previous season but were restricted to observations captured during the sales window. Importantly, this second index would have been sensitive to early rains that could theoretically lead to intertemporal adverse selection as herders responded to signs of a good season unfolding.

Marketing and distribution: Product awareness and understanding is reported by pastoralists and the firms selling IBLI to be a large barrier to demand. This group of variables contains a set of indicators of events and actions, such as free insurance being offered through KLIP, *ex gratia* or index-based payouts, and additional marketing activities performed by partner organizations, that could have impacted demand through increased product awareness, trust or understanding.

Insurance unit characteristics: IBLI is now available in a large region that, while all arid or semi-arid, is quite heterogenous. This set of insurance unit characteristics aim to capture the relevance of drought risk for households in the insurance unit through livelihood zone, average NDVI value, risk of conflict, and the total possible demand through human population.

Summary statistics of the explanatory variables are provided in Table 1. There are a few notable characteristics that deserve being highlighted. The region where IBLI has been offered falls mostly in the pastoral livelihood zone (80%), but some index units are agro-pastoral (13%) and there are also several lake-side index units designated as fishing communities and several index units that are mostly copping. The region has an average population density of less than 40 people per km^2, and about 43% of the insurance units experienced at least on conflict-related fatality in the five months leading up to an insurance season at least once during the study period (calculation available on request).

Insurance premium rates and payouts are often studied in the insurance demand literature. The overall average premium rate was 10% for 12 months of coverage. Payouts were made in approximately 22% of the payout periods and ex gratia payments were made in an additional 26 cases.[7] Profits ranged from negative USD104,700 to positive USD44,660. The negative profits are, in part, due to a series of large

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[7] While 26 positive observations do not create great deal of variation, *ex gratia* payments are a contentious issue so we have decided to maintain them assuming that any estimates of their impacts will be imprecise.

payouts during the droughts in 2016-2017 and again in 2017-2019, which resulted in a large increase in average premium rates that took effect in August 2020, the last sales season considered in this research.[8]

Several IBLI impact evaluations provided subsides to a subset of their participants by distributing discount coupons. Discounts were provided to study participants between 2010 and 2014 in Marsabit County in Kenya and Borena Zone of Ethiopia, and then in Samburu County in Kenya in 2018-20220. It total, these subsidies were distributed in 10% of the index-unit-season observations. While the portion of the population in each insurance unit that received a subsidy was very small (~0.1%), the individual-level subsidies were accompanied by community engagements that could have impacted uptake among a much larger portion of the population. For example, it was common for the project field teams to hold open outreach activities about the research project and about the IBLI product in the communities that the surveys were being collected in. In some cases, these activities even included transporting the insurance agent to the communities so that they could be part of the discussions. The result is that the subsidy indicator is actually an indicator for both individual-level subsidies and community-level marketing support. We keep this indicator separate from the external marketing support indicator because they were two fundamentally different activities; one was a firm-led activity aimed at increasing sales and the second was a project funded intervention with several activities and objectives.

Table 1. Summary statistics of the pooled season, firm and insurance unit data.

VARIABLES	N	Mean	Min	Max
External marketing support (=1 if yes)	1,360	0.0419	0	1

[8] These dynamics reflect one of the fundamental challenges of offering weather insurance; the actuarially fare rate can be extremely sensitive to the periods used to calculate it. Using longer periods to estimate risk should generate more stable estimates but concerns that climate change is changing the risks that households and insurance firms face favor a focus on more recent periods, which are presumably a better reflection of current risk.

KLIP (=1 if KLIP was there)	1,360	0.587	0	1
Payouts last season from the index [1]	1,360	0.218	0	1
Ex gratia payouts last season [2]	1,360	0.0191	0	1
Contract (=1 if asset protection)	1,360	0.824	0	1
Premium rate (percent of total sum insured)	1,360	0.101	0.0347	0.372
Subsidies (=1 if yes)	1,360	0.104	0	1
Index during sales season (higher=greener)	1,360	0.00159	-2.17	4.90
Index during previous season (higher=greener)	1,360	-0.0263	-3.02	3.40
Fatalities from violence [last 5 months]	1,360	0.301	0	10
Average NDVI [3]	115	0.336	0.142	0.572
Distance to markets (km) [3]	115	11.1	0	53.5
Livelihood: Pastoral [3]	115	0.800	0	1
Livelihood: Agropastoral [3]	115	0.130	0	1
Livelihood: Cropping or fishing [3]	115	0.0696	0	1
Human population (10,000s)	115	5.03	0.241	23.3
Firm's cumulative profit preceding current season (USD1,000s)	1,360	-1.15	-105	44.7
Insurance agent structure				
- Coordinator, Agents	1,360	0.0331	0	1
- Coordinator, Lead agents, Shop-agents	1,360	0.434	0	1
- Coordinator, Lead agents, Sub-agents	1,360	0.188	0	1
- Field coordinators, Lead agents, Agents	1,360	0.0934	0	1
- Field coordinators, Supervisors, VIPs	1,360	0.0382	0	1
- Cooperative, Agents, VIP	1,360	0.191	0	1
- Master trainers, VIPS	1,360	0.0221	0	1

[1] Payouts were triggered by the index and made to all the clients in an insurance unit in 297 of the 1,370 observations.
[2] Ex gratia payouts were made to all the clients in an insurance unit 26 different times.
[3] The sample size reflects that the indicator is calculated as a fixed characteristic of each insurance unit.

Supplementary data

While the administrative and environmental data can provide insight into the broad relationships between factors related to supply and observed demand, they can do little to illustrate how those factors manifest on the ground among agents and clients, or in the board-room of insurance firms. We employ two alternative sources of information to better understand the supply chain.

Agent survey data

In 2017, ILRI collaborated with one of the insurance firms selling IBLI, to conduct a study on how knowledgeable their IBLI-agents were in regards to the IBLI product. In October 2017, just after the

August-September sales window, ILRI attempted to survey all 63 sales agents that were registered to sell IBLI for that firm during the August-September sales season. The tool used to survey those agents included questions about their training, a quiz on the IBLI product to test their knowledge and questions about their outreach and sales activities. The survey was collected in local languages by enumerators in Nairobi through phone.

The survey data show the extent to which a fairly large sub-set of insurance agents were being provided with and were providing much-needed information on the IBLI product. While this manuscript focuses on supply a binary indicator of access, there is clearly room for a spectrum of access. For example, one may have easy access to an agent who themselves does not understand the product but little access to an agent with a strong understanding of the product. We will use the data from these phone surveys to illustrate the extent that we can observe such scenarios.

Key informant interviews

We have had several wide-ranging engagements with staff at each of the insurance firms selling IBLI. Those engagements varied from spending weeks training and working with insurance agent trainers in the field, to meetings and workshops with the CEOs and senior staff of insurance firms. While most of the content from those discussions is not well documented, we have drawn from them to inform the research questions, analysis, and discussion of the findings. We have briefed staff from these firms of our findings and have integrated their thoughts into the discussion on the implications of our quantitative analysis.

4. Results

A primary motivation for this research was the observation that in some cases there was no access to formal information or sales channels within the insurance units and this was true even within regions that insurance firms were supposedly selling IBLI while, at the same time, studies of demand for IBLI (or other supposedly helpful innovations) commonly focused on demand as the main constraint to diffusion. Figure 3 illustrates the ratio of seasons that clients had access to insurance (indicated by positive sales), to the number of seasons that IBLI was theoretically offered, for each insurance unit between 2010 and 2020. For example, in the insurance units that are coloured dark green there have been IBLI sales in over 80% of the seasons that firms offered insurance, while in the insurance units that are coloured the lightest colour there have been purchases in less than 20% of the seasons that IBLI was offered. We propose that it is inaccurate to assume that these patterns perfectly reflect demand and that studies that do so, could draw inaccurate conclusions.

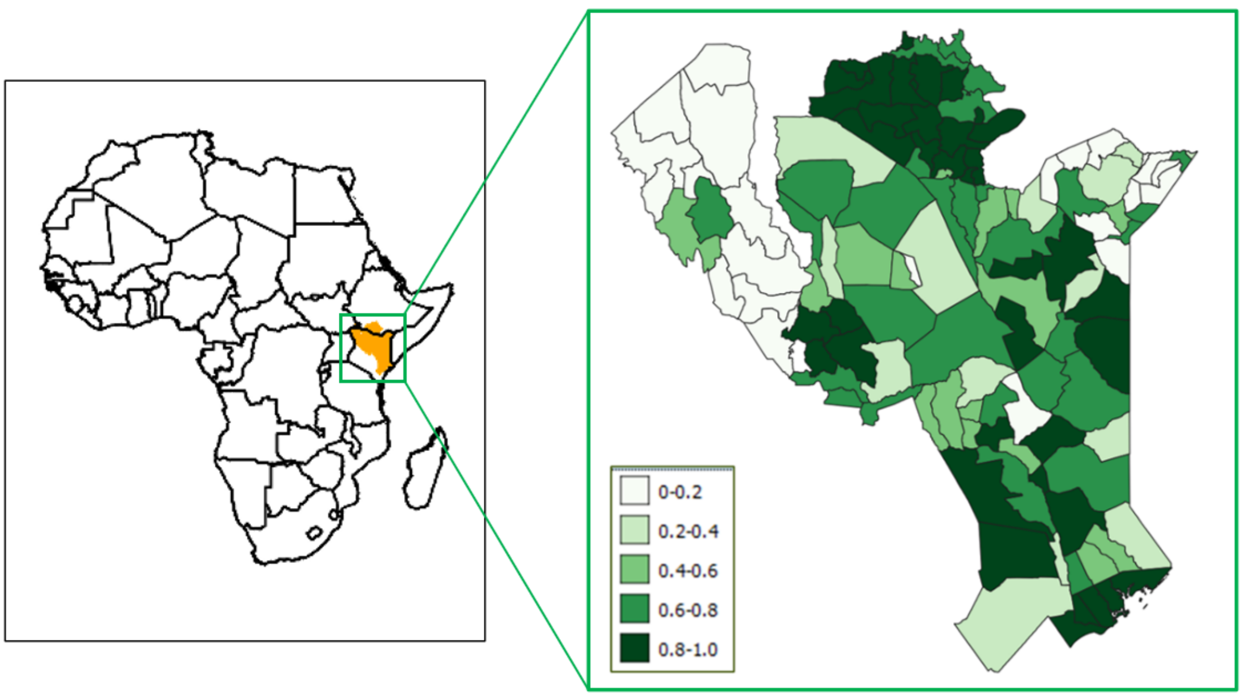

Figure 3. The ratio of seasons that clients had access to insurance to the total number of seasons that insurance was theoretically available.

Table 1 provides a truncated list of coefficients and their estimates for the first stage of the Heckman selection model (column 1), the second stage of the Heckman selection model (column 2) and the Tobit model (column 3).[9] The Wald test for independent equations within the Heckman selection model rejects the null hypothesis that the equations are independent (χ^2=6.42, p-value=0.01). This alone verifies that there is a selection process but does not provide guidance on its practical relevance for studying diffusion. To test for the relevance of controlling for the selection process generated by non-random supply when examining observed demand, we compare the coefficient estimates from the intensive margin of the selection model (column 2) to the estimates from the Tobit model, which assumes no-supply selection (column 3). In column 4, we calculate the differences between the coefficient estimates from these two models and test those differences for statistical significate to focus on those differences that are precisely estimated. We also indicate the percent difference between the two coefficient estimates as an indicator of practical relevance of those differences for the question of how these factors are related to purchases (column 5).

We start by highlighting those variables with the most important differences; those for whom differences between the models are statistically significant and in which there is a sign change. There are three such factors: external marketing support (i.e., by non-agent actors), premium rate, and the index during the previous season. The coefficient estimates for these same three factors all change signs also between the selection and level processes in the selection model, indicating that they play opposing roles in supply and demand for IBLI.

Starting with external marketing support; the results from the Tobit model indicate that external marketing support leads to greater purchases, which from a demand-perspective could easily be interpreted as implying that prospective clients were information constrained. However, the selection

[9] The full results for the Heckman selection model and the Tobit model are provided in Appendix B.

model paints a different picture. The results of the selection equation show that agents were more much likely to visit and sell insurance in locations that have had external marketing campaigns, presumably because that campaign had made it easier, or had lowered their costs, to visit and/or sell insurance there. Conditional on supply, the external campaign did not increase purchases. While we cannot observe why external campaigns did not increase purchases, one plausible explanation is that, without external marketing, the insurance agent must perform those marketing activities on their own if they were to sell insurance. That is, the external and agent-led campaigns are substitutes for each other.

The results reflect similar conflicting dynamics related to premium rates, where agents are less likely to visit locations with high premium rates, premium rates themselves have a positive relationship with the amount of insurance purchased when they do visit. While the positive relationship between price and purchases may seem unreasonable, the conceptual model highlights that even in this second stage, the amount of insurance purchased is a function of demand and supply. It is not implausible that if insurance agents made the (relatively rare) decision to invest in selling insurance in locations with higher premium rates, they did so with more rigour because their commission from each unit of coverage sold was higher in these insurance units with higher premium rates. The Tobit model presents a weighted average of these two dynamics, which could lead to the inaccurate conclusion that higher premium rates necessarily lead to less coverage being purchased.

Index in the previous season is the third variable with both a sign change and a statistically significant difference between models. The selection model show that agents are more likely to supply insurance to regions that have just completed a relatively better season, but that demand actually decreases in those same seasons. While we are unable to empirically unpack this dynamic, the researchers were working with one of the insurance firms in 2022 in Ethiopia and observed that the insurance agents (rightly) refused to visit locations that were experiencing famine at that time, because they said it was unethical and felt that they would lose considerable social capital by trying to sell insurance coverage to individuals that could not afford to purchase food. In these seasons with dry conditions, those that do purchase, purchase more insurance on average than do purchasers coming after good conditions. Importantly, the Tobit model does not present any of this nuance.

Table 2. Coefficient estimates from the Heckman selection model that accounts for non-random variation in supply, the Tobit model that assumes supply always fulfills demand, and differences between the two.

	Heckman		**Tobit**	**Difference**	
				Tobit - Heckman	
Variables	Any Purchase	Policies	Polices	Level	Percent
External marketing support (=1 if yes)	0.742***	-8.507	14.92	23.4***	-275%
	(0.243)	(12.04)	(13.49)		
KLIP (=1 if KLIP was there)	-0.150	-22.53*	-33.11***	-10.6	47%
	(0.169)	(13.02)	(10.99)		
Payouts last season from the index	0.313**	27.33***	32.37***	5.04	18%
	(0.125)	(8.911)	(9.407)		
Ex gratia payouts last season	-0.470**	27.28**	15.70	-11.6	-42%
	(0.207)	(12.76)	(15.12)		
Contract (=1 if asset protection)	0.313	44.21***	66.13***	21.9*	50%
	(0.280)	(13.40)	(17.79)		
Premium rate (percent of total sum insured)	-2.345	109.2	-86.64	-195*	-179%
	(1.592)	(131.0)	(144.8)		
Subsidies (=1 if yes)	0.820*	17.76	34.32**	16.6	93%
	(0.434)	(13.52)	(17.21)		
Index during sales season (higher=greener)	-0.134**	7.235	0.710	-6.53	-90%
	(0.0664)	(9.507)	(8.101)		
Index during previous season (higher=greener)	0.370***	-11.25	10.44	21.7***	-193%
	(0.0670)	(9.716)	(7.841)		
Fatalities from violence (last 5 months)	0.0243	-0.571	2.320	2.89	-506%
	(0.0569)	(3.672)	(3.788)		
Average NDVI	-2.692***	-69.64	-181.1***	-111*	160%
	(0.855)	(76.66)	(70.16)		
Distance to markets (km)	8.40e-06	-0.159	-0.129	0.0301	-19%
	(0.00380)	(0.278)	(0.284)		
Livelihood: Pastoral[1]	0.301*	29.70***	41.16***	11.5	39%
	(0.179)	(11.44)	(13.54)		
Livelihood: Agropastoral[1]	0.152	12.13	18.85	6.72	55%
	(0.232)	(15.72)	(16.26)		
Human population (10,000s)	0.0167	0.743	0.984	0.241	32%
	(0.0176)	(1.163)	(1.158)		
Test of independent equations: χ^2		6.42**			
Test of equity across all coefficients: χ^2				58.2***	

[1]The omitted category is "cropping or fishing" (N=4). The first stage of the Heckman selection model (column 1) and the Tobit model (column 3) also included firm profits and the sales agent structure. All models also included controls for district, and a polynomial of time (Time Time^2 Time^3). Standard errors are robust and clustered by insurance unit. *** p<0.01, ** p<0.05, * p<0.1

There are also several factors whose signs are the same between models but whose magnitudes differ significantly. Again, these indicate the importance of the supply selection process in determining observed demand. We also test for equity across the full set of shared coefficient estimates, which is rejected (χ^2=58.2, p-value<0.01). We note that in many cases, these large differences are related to factors whose coefficients have opposing signs in the selection and purchasing components of the selection model. For example, agents are less likely to offer any sales in units that have just received ex gratia payments but, when offered insurance, the people there purchase more insurance. One might suspect that the agent is deciding to avoid those insurance units in which the ex gratia process did not satisfy clients in favor of those in which it did. Importantly for this research, the change in sign between the two components of observed purchases for ex gratia payments, as well as several other factors, highlight the need for considering both supply and demand dynamics.

Robustness

The validity of our excluded variables—firm profits and agent structure—can also be probed. To test the robustness of our results when dropping the exclusion assumption, we re-estimate the Heckman model including the excluded variables in both stages of the selection model (Appendix C, Table C1). Including the excluded variables, the ability of Heckman selection models to control for prospective selection is weak. In this case, this manifests in a reduction of the χ^2 test for independent equations from 6.42 to 2.60. At the same time, the regression coeffects are all qualitatively the same in magnitude and statistical significance as in the original model. The results continue to indicate that a selection effect continues to play an important role in observed demand.

Agent survey results

The team successfully surveyed 37 of the 63 registered sales agents. Of those, 16% had never received any training and an additional 32% had received training in the past but no training for at least a year. Those that had never received any training scored on average of 24 percentage points (p-value=0.02) lower on the IBLI product quiz, where the mean score was 89%.

The agents' own efforts to provide outreach and education was also incomplete. While 62% reported performing at least one group-level education and outreach activity in the previous sales season, 33% reported performing only one-on-one activities, which we assume limited the opportunities that prospective clients had to learn about and purchase insurance, and 5% reported no outreach activities at all.

Due to the administrative processes used by the insurance firms, we are unable to link individual sales agents to their sales. But the above statistics show clearly that there were some sales agents that had received no training on the product and that those without training were much less likely to have a firm grasp of the product's details. Further, about 40% of agents did not perform group-level outreach activities of the type that would be required to educate and provide access to thousands of pastoralists that lived in each agent's catchment area.

5. Policy Implications

The results from our main analysis make a strong argument in favour or our hypothesis; that heterogenous supply of IBLI has constrained purchases of IBLI so that purchases are not exclusively a function of demand. While the mechanisms relating the factors studied with observed demand that we discussed are speculative, they highlight the importance of considering the role of the supply channel when examining observed demand. Policy makers aiming to increase insurance coverage, such as those that supported

KLIP or those currently supporting the DRIVE project, would be wise to consider the role that their policies will have, not only on demand for insurance by the client, but also on the incentives affecting the firms offering insurance and on the agents that they depend on to recruit clients. As illustrated in the results, some factors may have opposing roles in each of these domains, which could lead to ineffective policy recommendations if only demand is considered. At the same time, there could be factors that encourage or discourage supply and demand simultaneously. While our discussion in the results section focused on those factors with seemingly contradictory roles, KLIP, payouts in the previous season, an improved contract, subsidies, and livelihood zone all had consistent impacts across both supply and demand. Such agreement may indicate areas where policies could be especially effective.

Although this study was unable to observe exactly how supply is practically varied on the ground, the costs associated with last mile of service delivery have consistently been identified as a key challenge to greater market penetration by insurance firms and researchers (Chelang'a, Banerjee, and Mude 2015; Fava et al. 2021). The assessments of the phone survey data on agent-level training, knowledge and outreach all confirmed that there are considerable gaps in last mile domain. Insurance firms, often with the support of researchers and donor funding, have experimented with several approaches for improving the cost-effectiveness of last mile activities, for example through adjusting insurance agent structures (e.g., St. Claire and Banerjee 2019), using eLearning, mLearning, and gamification platforms to train, certify and maintain agents (e.g., Taye and Jensen 2019; Wandera 2015), and radio and mobile based extension platforms targeted directly at prospective clients (Tessema, Hobbs, and Jensen 2021). In some cases, these strategies have been mainlined by insurance firms but in many cases, they remain ad-hoc or are dropped altogether when funding runs out.

Discussions with insurance companies revealed that they also felt that investments in last mile delivery had been successful in the past, but continued investments were needed to improve long-term adoption rates. These firms reported that when there are sufficient funds to retrain and reinvigorate insurance agents each season, and to provide agents with funds for transportation or to host information events, they can be quite successful. But these actions are expensive and are only common when supported by a development project. In the absence of project support, insurance firms often work to reduce overhead costs, for example by: shifting to a training of trainers strategy, which can mean a loss of quality and monitoring; reducing trainings all together; reducing the number of insurance agents and therefore access to insurance for some; and by eliminating funds for agents to use for their commercialization activates beyond the commissions, which can also reduce access for those that do not live near the remaining agents. IBLI's providers also mentioned that KLIP undermined their investments in developing a strong outreach and sales channel because KLIP provided insurance coverage to a large portion of their client base while circumventing their agents completely. This dynamic is supported by the data, which showed that presence of KLIP is one of only a few factors that both reduced the likelihood of any commercial sales in an insurance unit and the amount of coverage purchased in those locations.

In light of these insights, questions arise about how to most sustainably provide access to IBLI. Recruiting, training, and maintaining agents within each insurance unit is desirable but expensive. There are ways to reduce those costs, but they can result in reduced access to accurate information about the product for prospective clients. Further, attempts to keep premiums low for clients translate into lower commission rates for agents, which increases agent turnover and reduces incentives for the remaining agents to expend efforts in actively promoting sales. The resulting dynamics can reduce access to information on the product and mean fewer purchase points for prospective clients.

We suggest that projects aiming to increase insurance coverage in the drylands move away from directly subsidizing premium rates or the last-mile delivery of services, both of which are effective approaches to increasing short-term uptake but seem to leave little lasting effect on the market, towards activities that improve the sustainability and/or efficiency of outreach and service delivery. One such opportunity is to train local government field officers on financial concepts so that they can provide a trusted source of information and in turn build local capacity, leaving prospective clients in a better position to make informed decisions related to seeking out more information about IBLI and other financial tools. Such investments could have large impacts across the industry, both reducing the costs of service delivery for providers and increasing access to accurate information for prospective clients.

Moving forward, it is also important that more is learned from the insurance firms about which strategies they have employed and how effective they have been. For example, the authors are aware of several important interventions made by insurance firms and their partners that aimed to improve marketing or coverage, but for which no comprehensive information or assessments are available. We believe that structured knowledge sharing between insurance firms could be very useful in this space. Since less than 1% of the population are purchasing IBLI in any specific sales window, we expect that the gains of sharing knowledge would be higher than any competitive loss.

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Appendix A: Variable Construction and Theorized Role in Diffusion

This appendix provides additional details on the variables used in the analysis contained in the main text of this manuscript. The first step in developing this database was to determine when and where each firm had offered insurance. This was not fully observed because the firms only documented positive sales. To supplement the list of locations with positive sales, we used the firms' own documentation and processes, documentation and field reports generated by ILRI staff, and interview with field agents. In Kenya, the insurance companies implemented insurance agent recruitment, agent training activities and sales at the county-season level; meaning that if there were any insurance sales within a county during a specific sales season, there was an active insurance agent network in that county and season responsible for selling insurance across the entire county.[10] This process for identifying seasons during which IBLI was available in Kenya but no sales were made, has been discussed with, and vetted by, staff at firms underwriting IBLI in Kenya and by ILRI field teams that worked closely with them in the region.

Ethiopia required a different strategy to identify IBLI availability when there were zero sales because the insurance rollout did not take place in the same fashion. Here, the firm signed formal agreements with local cooperatives, who then identified agents to perform outreach and marketing campaigns in their catchment regions. Interested individuals then purchase IBLI coverage by attending a cooperative meeting, during which they register and pay their premium to the designated IBLI treasurer. Unfortunately, the cooperatives' and agents' catchment regions are not well delineated or known by the researchers, but we do know that the process for developing formal agreements with the firm to sell insurance takes time and effort. For example, to sell insurance, the cooperatives were required to identify

[10] At the same time, we suspect that insurance agents did not always provide extension or outreach services to all the insurance units in their catchment area.

specific individuals for administrative roles, such as treasurers and agents, and those individuals had to be vetted and trained by the firm. We argue that these processes created frictions to market entry and exit which meant that cooperatives were unlikely to formally enter and exit the IBLI market frequently. Rather, once engaged, cooperatives continue to offer insurance in their catchment region but the degree to which marketing and outreach activities are performed is up to the agent. The data are consistent with individual agents playing a large role in sales; sales within insurance units over time are highly variable and punctuated with by occasional seasons with zero sales. Occasionally, it is clear that a cooperative has deactivate permanently and stopped selling insurance all-together. We therefore assume that, in Ethiopia, once policies start being sold in an insurance unit, they continue to be offered for purchase until the last sales season in the insurance unit with any sales.[11] This policy for identifying seasons during which IBLI was offered but in which no sales were made, has been vetted with ILRI field teams that worked closely with the firm in the region.

[11] For example, we observe positive sales in the insurance unit Malbe Yabello during every season between 2012 and 2020 except during the January/February 2019 sales season. Here we assume that insurance was theoretically available for purchase in Malbe Yabello during the January/February 2019 sales season—that the cooperative could have sold IBLI coverage—but that there were no sales. On the other hand, if we had not seen any sales in Malbe Yabello after 2018, we would assume that IBLI was not available there in 2019 or 2020.

Name	Details
Condition for inclusion into analysis	
Insurance available	An indicator that is equal to one if insurance was available in that insurance unit in that season. When sales are greater than zero in an insurance unit, we know it was available there in that season. When sales are zero in an insurance unit, we know that insurance was still available in that insurance unit if this is consistent with insurance firm or field documents. In addition, in Ethiopia, we assume that insurance was available in insurance units in seasons in which there were sales in the season preceding the current season and in the season after the current season. In Kenya, insurance was rolled out by county, so that if there were insurance sales within a county it means that insurance was available for all insurance units in that county.
Outcomes	
Any sales	This is an indicator that is equal to one if there was a positive number of insurance sales in the insurance unit in that season. This variable is distinct from the "insurance available" variable in cases where there was insurance available programmatically but that sales were zero, which we argue indicate that it was not practically available.
Number of Policies	The total number of policies sold in each insurance unit by each firm in each sales season.
Explanatory Variables	
External marketing support	This is a binary variable that is equal to one in seasons during which the insurance firms or ILRI documented the provision of extra-ordinary external marketing support in that insurance unit. The extra-ordinary external marketing support ranged from large radio campaigns, to traveling insurance outreach events, to large payout ceremonies. Unfortunately, there were no record maintained on the types of marketing campaigns and any information we have on the types of activities performed during specific campaigns is incomplete, which is why we have settled on a binary indicator instead of studying the effectiveness of certain types of campaign activities.
KLIP	An indicator variable that is equal to one if KLIP was providing insurance transfers to households in the county.
Payouts last season from the index	This is a binary variable that is equal to one if the index triggered a payout in the season preceding the current sales season.
Ex gratia payouts last season	This is a binary variable that is equal to one if IBLI made *ex gratia* payouts in the season preceding the current sales season.
Contract	This is a binary variable that is equal to one if the contract for sale was the earlier-paying asset protection contract and zero if it was the later-paying asset replacement contract.
Premium rate	The percent of the value insured charged as a premium rate.
Contract type	This is a binary variable that is equal to one if the firm was selling the asset protection contract. The alternative contract was an asset replacement version, which made payouts 1-3 months later than the asset protection contract.
Premium rate	The percent of the value insured charged as a premium rate
Subsidies	This is a binary variable that is equal to one if there were subsidies offered in that insurance unit in that season.
Forage during the sales season	An NDVI-based indicator for forage anomalies during the insurance sales season.
Forage conditions during the previous season	An NDVI-based indicator for forage anomalies during the previous season.
Fatalities from violence	A count of the number of fatalities due to violent conflicts that took place within the insurance unit in the 3 months leading up to the insurance sales window and during the window. These data are acquired from ACLED (Raleigh et al. 2010)
Average NDVI	The ten year average NDVI value.

Distance to markets	This is the Euclidean distance from the center of the insurance unit to the nearest town mapped in towns layer developed by IRLI but hosted and downloaded from ICPAC at https://geoportal.icpac.net/ (ILRI and ICPAC 2017).
Livelihood zone	The majority livelihood of the insurance unit developed using FEWSNET's livelihood shapefiles downloaded from https://fews.net/data/livelihood-zones.
Human population	The total number of people living in the insurance unit. Population data are obtained at the county level from Rose et al. (2018) and imputed at the insurance unit level assuming uniform population distributions across the units.
Season	A binary variable that is equal to one during the August/September sales season. The alternative is the January/February sales season.
Cumulative firm profit preceding current season	This variable is calculated by cumulating the premiums collected and the payouts made. The resulting variable is a proxy for the profits or losses that the specific insurance unit generated for that specific firm up until the current sales window. Note that the researchers did not have access to, nor could we account for, any non-payout expenditures.
Insurance agent structure	The insurance firms created their own agent networks and hierarchies to sell insurance. Most firms have experimented with more than one structure as they work to improve the cost effectiveness of their agents. There have been seven structures employed thus far and although they seem quite similar, there were differences in employment status, training and commissions between them. The structures employed thus far are as follows: Coordinator, Agents; Coordinator, Lead agents, Shop-agents; Coordinator, Lead agents, Sub-agents; Field coordinators, Lead agents, Agents; Field coordinators, Supervisors, VIPs; Cooperative, agents, VIP; Master trainers, VIPS

Appendix B: Full model results

Table B1. Coefficient estimates from the Heckman selection model.

VARIABLES	Any Purchase	Number of Policies
External marketing support (=1 if yes)	0.742***	-8.507
	(0.243)	(12.04)
KLIP (=1 if KLIP was there)	-0.150	-22.53*
	(0.169)	(13.02)
Payouts last season from the index	0.313**	27.33***
	(0.125)	(8.911)
Ex gratia payouts last season	-0.470**	27.28**
	(0.207)	(12.76)
Contract (=1 if asset protection)	0.313	44.21***
	(0.280)	(13.40)
Premium rate (percent of total sum insured)	-2.345	109.2
	(1.592)	(131.0)
Subsidies (=1 if yes)	0.820*	17.76
	(0.434)	(13.52)
Index during sales season (higher=greener)	-0.134**	7.235
	(0.0664)	(9.507)
Index during previous season (higher=greener)	0.370***	-11.25
	(0.0670)	(9.716)
Fatalities from violence (last 5 months)	0.0243	-0.571
	(0.0569)	(3.672)
Average NDVI	-2.692***	-69.64
	(0.855)	(76.66)
Distance to markets (km)	8.40e-06	-0.159
	(0.00380)	(0.278)
Livelihood: Pastoral[1]	0.301*	29.70***
	(0.179)	(11.44)
Livelihood: Agropastoral[1]	0.152	12.13
	(0.232)	(15.72)
Human population (10,000s)	0.0167	0.743
	(0.0176)	(1.163)
Excluded variables		
Cumulative firm profit preceding current season (USD1000s)	-0.00835**	
	(0.00369)	
Insurance agent structure: [2]		
- Coordinator, Lead agents, Shop-agents	1.299***	
	(0.435)	
- Coordinator, Lead agents, Sub-agents	0.810**	
	(0.403)	
- Field coordinators, Lead agents, Agents	0.0857	
	(0.514)	
- Field coordinators, Supervisors, VIPs	-1.114**	
	(0.465)	
- Cooperative, Agents, VIP	2.694***	
	(0.439)	
- Master trainers, VIPS	1.104	
	(0.954)	
Observations	1,360	
Wald test of independent equations χ^2	6.417	
Wald test of independent equations p-value	0.0113	

[1] "Cropping or fishing" is the omitted category. [2] "Coordinator, Agents" is the omitted category. Regressions also included a constant, district fixed effects and a 3rd order polynomial of time (time, time^2, time^3). Standard errors are robust and clustered within insurance unit. *** p<0.01, ** p<0.05, * p<0.1

Table B2. Coefficient estimates from the Tobit model.

VARIABLES	Number of Policies
External marketing support (=1 if yes)	14.92
	(13.49)
KLIP (=1 if KLIP was there)	-33.11***
	(10.99)
Payouts last season from the index	32.37***
	(9.407)
Ex gratia payouts last season	15.70
	(15.12)
Contract (=1 if asset protection)	66.13***
	(17.79)
Premium rate (percent of total sum insured)	-86.64
	(144.8)
Subsidies (=1 if yes)	34.32**
	(17.21)
Index during sales season (higher=greener)	0.710
	(8.101)
Index during previous season (higher=greener)	10.44
	(7.841)
Fatalities from violence (last 5 months)	2.320
	(3.788)
Average NDVI	-181.1***
	(70.16)
Distance to markets (km)	-0.129
	(0.284)
Livelihood: Pastoral[1]	41.16***
	(13.54)
Livelihood: Agropastoral[1]	18.85
	(16.26)
Human population (10,000s)	0.984
	(1.158)
Cumulative firm profit preceding current season (USD1000s)	-2.056***
	(0.347)
Sales agent structure: [2]	
- Coordinator, Lead agents, Shop-agents	2.168
	(27.23)
- Coordinator, Lead agents, Sub-agents	8.434
	(20.75)
- Field coordinators, Lead agents, Agents	-30.93
	(25.88)
- Field coordinators, Supervisors, VIPs	-24.25
	(21.57)
- Cooperative, Agents, VIP	66.88***
	(25.29)
- Master trainers, VIPS	81.96***
	(29.20)
.	
Observations	1,360

[1] "Cropping or fishing" is the omitted category. [2] "Coordinator, Agents" is the omitted category. Regressions also included a constant, district fixed effects and a 3rd order polynomial of time (time, time^2, time^3). Standard errors are robust and clustered within insurance unit. *** p<0.01, ** p<0.05, * p<0.1

Appendix C: Robustness check

Table C1. Coefficient estimates from the Heckman selection model with firm profits and insurance agent structure included in both stages.

VARIABLES	Any Purchase	Number of Policies
External marketing support (=1 if yes)	0.745***	-9.250
	(0.244)	(11.54)
KLIP (=1 if KLIP was there)	-0.166	-9.280
	(0.169)	(10.09)
Payouts last season from the index	0.325***	20.02**
	(0.124)	(8.390)
Ex gratia payouts last season	-0.462**	34.31**
	(0.210)	(14.75)
Contract (=1 if asset protection)	0.301	46.55***
	(0.283)	(16.05)
Premium rate (percent of total sum insured)	-2.406	112.8
	(1.598)	(134.3)
Subsidies (=1 if yes)	0.795*	26.40
	(0.430)	(16.26)
Index during sales season (higher=greener)	-0.139**	5.686
	(0.0662)	(9.619)
Index during previous season (higher=greener)	0.374***	-9.605
	(0.0664)	(9.401)
Number of fatalities from violence (last 5 months)	0.0227	1.071
	(0.0574)	(3.818)
Average NDVI	-2.670***	-71.87
	(0.860)	(72.03)
Distance to markets (km)	2.78e-05	-0.152
	(0.00378)	(0.279)
Livelihood: Pastoral[1]	0.302*	34.76***
	(0.181)	(10.77)
Livelihood: Agropastoral[1]	0.155	16.54
	(0.235)	(13.26)
Human population (10,000s)	0.0173	0.194
	(0.0179)	(0.836)
Cumulative firm profit preceding current season (USD1000s)	-0.00625*	-2.254***
	(0.00361)	(0.477)
Insurance agent structure: [2]		
- Coordinator, Lead agents, Shop-agents	1.137**	-22.61
	(0.445)	(27.89)
- Coordinator, Lead agents, Sub-agents	0.663	-5.692
	(0.419)	(21.06)
- Field coordinators, Lead agents, Agents	-0.0902	-9.885
	(0.507)	(23.70)
- Field coordinators, Supervisors, VIPs	-1.276***	8.828
	(0.483)	(20.96)
- Cooperative, Agents, VIP	2.431***	13.20
	(0.434)	(23.14)
- Master trainers, VIPS	0.158	14.29
	(0.674)	(27.96)
.		
Observations	1,370	
Wald test of independent equations χ^2	2.599	
Wald test of independent equations p-value	0.107	

[1] "Cropping or fishing" is the omitted category. [2] "Coordinator, Agents" is the omitted category. Regressions also included a constant, district fixed effects and a 3rd order polynomial of time (time, time^2, time^3). Standard errors are robust and clustered within insurance unit. *** p<0.01, ** p<0.05, * p<0.1