The Role of Experience in Learning for Index Insurance Products: Evidence from Rural Kenya

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Abstract

This research focuses on understanding the role of experience in learning for index insurance products, using data from Index Based Livestock Insurance (IBLI), Kenya. More specifically, I analyze the possible heterogeneity of effects in terms of subsidy and knowledge treatment groups on both demand and knowledge for the product, separately. The final results support a model of *rational* behaviour, where payout experience leads to increase in both demand and learning, but disaster experience, more frequently observed in the data, leads to an increase in demand with no associated learning effect. This can explain the decreasing demand associated with the product over sales periods. With respect to the exogenous treatments, I find discount treatments to be most effective in channelling a positive learning effect from the payout experience and, argue for a policy that compliments both type of treatments to increase demand in the short and long run.

Sub-Saharan African agriculture has been characterized by its low rate of technological adoption and associated low performance [1], making agriculture in these regions highly vulnerable to weather shocks. This volatility, combined with the lack of access to formal credit and insurance markets, leads to investment in low risk-low return activities, pushing the risk-averse low-income households living in these countries further into the poverty trap

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[1]Source: "Sub-standard quality of fertilisers and hybrid seeds makes adoption of modern inputs unprofitable".

(Azariadis and Stachurski, 2005). The lack of access to insurance markets is attributable to the fact that the provision of traditional insurance schemes are costly, much higher than the willingness (or ability) to pay for it (Binswanger-Mkhize, 2012). This high cost is due to a combination of highly volatile environment and the asymmetric information problems of moral hazard and adverse selection that characterizes any indemnity insurance scheme[2]. In recent decades, researchers and policymakers advocated index based insurance as a potential solution (Carter et al., 2014). The idea is to condition the insurance payoff on some objectively observed index[3], which is highly correlated with individual specific outcome but cannot be influenced by the actions taken by these individuals. As a result, index based insurance sidesteps the asymmetric information problems and helps provide insurance to households living in high weather risk environments (Barnett, Barrett and Skees, 2008). We know these insurance schemes to be helping vulnerable rural population out of poverty trap (Janzen, Carter and Ikegami, 2020), improving ex-ante risk-management decisions (Karlan et al., 2014; Cai et al., 2015; Cole, Giné and Vickery, 2017; Gebrekidan et al., 2019; Matsuda, Takahashi and Ikegami, 2019), as well as ex-post risk-coping strategies (Janzen and Carter, 2019; Bertram-Huemmer and Kraehnert, 2018; Hill et al., 2019). According to Jensen, Barrett and Mude (2017) index based insurance is also more cost-effective than direct cash transfers. However, despite the low cost of such insurance and the purportedly high associated benefits, the take-up and renewal of such insurance policies remain surprisingly low (Platteau, De Bock and Gelade, 2017).

The existing literature explores *learning by doing and learning from others* as a potential solution to this problem of low take-up rates following the seminal contributions of Foster and Rosenzweig (1995) and, Besley and Case (1993; 1994) on agricultural technology adoption. *Learning* has been advocated as a potential solution for improving the agents' subjective perception of the product, increasing the associated demand. However, relatively less attention has been paid to understanding the effect of experience in forming the agents'

[2]**Asymmetric Information Problems:** When the insurance buyer has more information about his/her exposure to risk than the insurer. Formal definitions of **moral hazard and adverse selection**, along with some examples can be found in Mas-Colell et al. (1995). According to Investopedia: "***Indemnity insurance*** *is a contractual agreement in which one party guarantees compensation for actual or potential losses or damages sustained by another party.*"

[3]See Miranda and Farrin (2012) for examples.

subjective perceptions.

In this research, I focus on exploring the role of experience in forming households' subjective perception about an index insurance product in rural Kenya. Subjective perceptions play an important part in explaining the low demand for index insurance products and the associated policy responses. The key idea to keep in mind is that even though the design of index insurance ensures relying on some *objective measure* that does not vary at an individual level, individuals' subjective perception about this measure can and do vary. As a result, we see factors like basis risk [4], knowledge, trust and, behavioral biases explaining the level of demand in the existing literature. Each of these factors inherently influences the economic agent's subjective belief about the usefulness of the product. The related literature; that advocates learning as a potential solution, focuses on improving these beliefs via experience obtained by repeated use of the product. This can be the economic agent's own repeated use (learning-by-doing) or the repeated use of other agent's in his/her network (learning from others). I deviate from the existing literature and make contributions by:

- Providing evidence in terms of the effect of past experience separately on the present demand and; on the level of learning associated with Index Based Livestock Insurance (IBLI), Kenya.
- Formulating a theoretical framework to understand the role of past experience in forming the agents' subjective perceptions and; interpret my results.
- Exploring the possibility of heterogeneous effects of past experiences in terms of exogenous subsidy and knowledge treatments. This informs policy recommendations to increase either the demand or; the level of learning associated with the product (or; both).

To conduct the analysis, I use balanced panel data on 820 households collected over 5 rounds of household survey for tracking the progress of Index Based Livestock Insurance (IBLI), Kenya pilot. The pilot took place in the Marsabit district of northern Kenya that

[4] Captures the probability that an individual, who is covered by the insurance and incurred a loss, end up not getting a payout as the index did not trigger a loss.

has a significant proportion of population depending on livestock for their main livelihood and, has a history of adverse weather events over the past few decades. The 5 rounds of the survey used in this study covers a baseline and 4 follow-up surveys that track a total of 6 IBLI sales periods. I analyze the effect of two types of past experience that has been identified in the literature for having significant impact on the final demand[5], namely payout and disaster experience. Empirically, the objective is to assess the impact of these experiences on the demand for the product, as well as on the level of learning associated with the product. I also explore the possible heterogeneity of these effects with respect to two types of exogenous treatments: a sales period specific discount treatment and a one-time knowledge treatment.

My results show payout experience to be improving both demand and knowledge about the product (used here as a proxy for the level of learning associated with the product). The increase in demand is found to be around 183-209% compared to the control group means, with no heterogeneity in terms of exogenous treatment groups. This is a large effect of 0.5 standard deviations. However, the result is significant only at 10% level and not robust to an alternative specification. The payout experience is found to be improving the knowledge associated with the product by only around 6% compared to the control group means. However, in this regard I observe heterogeneity in terms of treatment groups. The payout experience conditional on receiving no treatment seems to be decreasing the respondents' performance in knowledge questions, while it is found to have a positive impact for those that received the discount treatment, both significant at 5% level and robust to alternative specifications. No significant heterogeneity is observed with respect to the knowledge treatment. On the other hand, the unconditional disaster experience is found to have a positive impact on demand, with no impact on households' performance in the knowledge questions. The impact on demand is found to vary by treatment groups. For the group that received no treatment, the disaster experience decreased the demand by 46-51% compared to the control group means and, 0.1 points compared to the control group standard deviation. On the contrary, for the group that received discount treatment,

[5]More details on the associated literature can be found in section 1.

the effect is a 54-59% increase compared to the control group means and 0.1-0.2 points increase compared to the control group standard deviations. Unfortunately, the results are not robust to an alternative specification. Again, no significant heterogeneity is observed with respect to the knowledge treatment.

The rest of this paper proceeds as follows. In section 1 I review the selected literature and the associated research gap that motivates this study. Section 2 discusses the dataset used for my analysis in detail. Section 3 presents a theoretical framework and forms the hypotheses that I test in this study and, section 4 discusses the associated empirical strategy. In section 5, I present my results and in section 6, I present some evidence regarding the robustness of those results. I discuss the results and conclude in section 7.

1 Relevant Literature

This research makes contribution to three different streams of literature. They are:

- The literature that focuses on understanding the low demand associated with index insurance products.
- Literature advocating *learning by doing and learning from others* as a potential solution to the problem of low demand.
- The literature that assesses the role of experience in learning about the product.

In this section, I start by reviewing the literature on selected possible factors behind the low take-up rate of index insurance products[6], that are interesting from the perspective of the current study. Next, I introduce the studies that argue learning as a potential solution to this problem and, identify the research gap that influences the specific research questions that this paper aims to answer. Finally, I discuss selected existing works that focus on the role of past experience on the demand and learning associated with the product.

[6] For a more comprehensive review, consult Platteau, De Bock and Gelade (2017).

1.1 Factors behind the Low Demand for Index Insurance

I begin by presenting theoretical and empirical evidence of different possible factors that are found to be responsible for low take-up of index insurance products. For this part the focus is on the factors that are related to the economic agents' subjective perceptions. It should be noted that there are other factors, like poor quality of contract, credit and, liquidity constraints, that are found to be relevant in explaining the puzzle of low demand but beyond the scope of this literature review. I focus on factors related to subjective perceptions instead as these are the ones relevant for my research.

1.1.1 Basis Risk

Basis risk represents the difference between the realized individual loss and the loss predicted by the objectively observed index, according to which index insurance payouts are made. It captures the probability that an individual, who is covered by the insurance and incurred a loss, end up not getting a payout as the index did not trigger a loss. This may happen if the quality of index is not good enough (i.e. the index does not perfectly capture the risk it represents) , so that the correlation between the index and individual realization of loss is very low. Alternatively, this may also happen when the individual's source of loss is not the one covered by the index insurance, and so not represented by the index. High basis risk associated with an index insurance product can explain the observed low demand.

Clarke (2016) develops a theory of rational demand for index insurance. His model rationalized the low demand for index insurance product as a response to high associated basis risk. Using a simplified version of his theoretical framework, Hill, Robles and Ceballos (2016) analyze the demand for a rainfall-based weather insurance product among farmers in rural India using data from a randomized control trial (RCT). In their study price discounts, additional training about the insurance product and, placement of weather stations were randomized. Using an objective measure for basis risk, they showed the predictions of Clarke's model to be true. Moving away from the use of hypothetical objective measures, Jensen, Mude and Barrett (2018) use data from Index Based Livestock

Insurance (IBLI) Kenya pilot to construct a measure for realized basis risk. They observe increased basis risk to be associated with low demand, with the effect being stronger for households that experimentally obtain more knowledge about the product. More recently Janzen et al. (2020) use a lab-in-the-field experiment with farmers in rural Kenya to clearly identify the causal link between basis risk and the demand for a weather index insurance product. They randomize two versions of the same product: one with high objective basis risk, another with low and; show that the low basis risk product has high preferred coverage in an auction than the high basis risk product.

These results suggest that improving the product quality and knowledge about the product can influence the demand for index insurance through its impact on objective and subjective basis risk.

1.1.2 Knowledge and Trust

Another important factor that is argued to be a reason behind low uptake of index insurance product is the consumers' knowledge base. This can be the overall lack of financial literacy, knowledge about how the product works and, also the level of trust in the insurer that comes with it.

Cole et al. (2013), using a series of randomized field experiments in rural India, test the importance of price and non-price factors in the adoption of a rainfall index insurance product. Their evidence suggest limited trust in the insurer and, little understanding about the product being the main non-price factors limiting the demand. To investigate the causal impact of trust, Stern (2019) randomizes the endorsement of a rainfall index insurance product in Kenya that increases trust. He finds strong evidence that trust improves the take-up for the product. In terms of financial literacy, Awel and Azomahou (2015), using cross-sectional household data from Ethiopia, find positive impact of financial literacy on demand for index insurance. Diving more specifically into the effect of product comprehension, Patt, Suarez and Hess (2010) investigate farmers' understanding and the effectiveness of a role-playing game at improving their understanding of how insurance operates in Ethiopia and Malawi. Their results suggest that farmers do not understand many of the core concepts of insurance that would be necessary to make a fully informed and educated choice, even after learning about index insurance through a simulation game or a more conventional education session. Additionally, they find that farmers who better understood how insurance operated were more likely to express a preference for it. However, contradictory results have been found in Takahashi et al. (2016), who explore the purchase patterns of IBLI Ethiopia pilot, focusing on the role of accurate product comprehension and price. They observe randomly distributed learning kits to improve the pastoralists' knowledge of the products, without any strong evidence that this improved knowledge increases product uptake.

In essence, the role of knowledge and trust in improving the demand for index insurance is still under-explored. On one hand, further research is needed to understand the causal relationship between improved knowledge about the optimal use of the product and, an increase in demand. On the other hand, even though there is limited evidence of trust improving demand in the short-run, the long-run implications have not been evaluated.

1.1.3 Behavioral Factors

Lastly, I focus on the rapidly expanding literature arguing for behavioral factors in explaining the demand for index insurance contracts. Elabed and Carter (2015) argue that the low demand is due to the compound lottery structure of index insurance contracts. Their experimental results from Mali show that around 60% of farmers are compound-risk averse, and that this behaviour can potentially cut in half the demand for standard index insurance contracts. Similarly, Elabed et al. (2013), simulating the impact of basis risk on the demand for index insurance for Malian cotton farmers, show that compound risk aversion decreases demand for an index insurance contract around 13 percentage points below what would be predicted by on risk aversion alone. Compound risk aversion, however, is not the only behavioral factor we observe in the literature. Serfilippi, Carter and Guirkinger (2015) argue that discontinuous preference over certain and uncertain outcomes is responsible for dampening the demand for index insurance. They design games to identify agents with such preferences and play them with the cotton farmers in Burkina

Faso. The study show that the farmers are willing to pay more for a given contract if the cost of insurance is artificially made uncertain by being directly deducted from indemnity payments. Arguing for uncertainty aversion being one of the plausible factors behind the low demand puzzle, Belissa, Lensink and van Asseldonk (2019) conduct a lab-in-the-field experiment in Ethiopia to study the effect of risk and uncertainty aversion on an actual index based insurance product uptake decision. They find evidence that an increase in risk aversion speeds-up the uptake of the product, while an increase in uncertainty aversion delays it.

Even though the overall theme of this literature is that behavioral factors like compound risk aversion, ambiguity aversion and, discontinuous preference over certain and uncertain outcomes lead to a decrease in the demand for index insurance, there is evidence against it as well. Clarke and Kalani (2011) use data collected from an artefactual field experiment among poor subjects from rural Ethiopia. Using insurance games, they find the shape of demand for index insurance to be consistent with decreasing absolute risk aversion (DARA) expected utility theory (EUT), i.e. high demand from subjects with intermediate level of wealth but, low demand from the poorest and richest subjects. However, they find the level of demand to be higher than that predicted by EUT. In other words, they observe the behavioral factors to be increasing the demand for index insurance.

To summarize, there is no consensus on the type and number of behavioral factors one need to consider in analyzing the low demand for index insurance. However, it is important to keep in mind the existence of such factors in designing the product.

Having discussed some of the possible factors that can influence the demand for index insurance products through its effect on individuals' perception, now I turn to a solution that has been advocated in the literature.

1.2 Learning as a Solution

In this subsection, I argue learning to be a potential solution to the problem of low demand for index insurance products. The reason behind this argument is twofold:

1. The full potential of an insurance policy can be realized only through experience.

Thus the reason for expecting learning to be a potential solution.

2. Repeated use of the product can improve households' perception about it. This has the potential to improve their subjective believes on basis risk associated with the product, improve their knowledge about the product and, trust on the insurer. The persistent use of the product also has the potential of improving the uncertainty around this type of insurance in the consumers' minds.

In their seminal paper, Foster and Rosenzweig (1995) argue in favour of *learning by doing and learning from others* about optimal input use in agricultural technology adoption. In their model, the best use of the inputs is unknown and stochastic under the new technology. Around the same time, Besley and Case (1993; 1994) argue for another similar model where the profitability of the new technology is assumed to be uncertain and exogenous. Though different from a modelling perspective, both of these studies argue in favour of learning-by-doing from experience. Their argument for expecting a learning-by-doing effect is applicable for index insurance products as well, since insurance is an experience good. In addition, the added complexity of an index insurance contract with respect to a traditional insurance scheme, together with the low financial literacy level of farmers in the developing and underdeveloped regions of the world, makes the case in favour of a learning-by-doing effect even stronger.

This is already recognized in the existing literature, that focuses on demonstrating learning-by-doing (Cole, Stein and Tobacman, 2014; Takahashi et al., 2020), or learning from others (Giné, Karlan and Ngatia, 2014; Dercon et al., 2014; Cai, De Janvry and Sadoulet, 2015; Takahashi, Barrett and Ikegami, 2019), or both (Santeramo, 2019; Cai, de Janvry and Sadoulet, 2020). However, the main focus of the literature has always been improving the final demand for index insurance products. Less attention has been paid to improving the level of learning with respect to the optimal use of the product. As significant amount of focus has been given to improving the quality of the product[7], it has been implicitly assumed in the literature that improved level of learning about the

[7] Consult Chantarat et al. (2013), Vrieling et al. (2014) and, Woodard, Shee and Mude (2016) for some example and related literature.

product goes hand-in-hand with increasing its demand.

In this study, I focus on exploring the role of personal experience in forming the agents' subjective perceptions regarding the product. More specifically, I argue for differential effect of these experiences on the demand and, the level of learning of the product. In other words, I explore the possibility that some experiences increase the demand for the product without improving the associated level of learning and while other experiences have the exact opposite effect. In addition to this, I also focus on analyzing the role of exogenous subsidy and knowledge treatments in magnifying/ reducing these effects. This second type of analysis in part is motivated by the existing literature[8] that argues in favour of *smart subsidies* to increase the uptake of index insurance products. Assuming the positive impact of learning-by-doing and learning from others on the demand, the idea is to give more agents access to the product through a subsidized price at the early stages, getting them to learn about the product enough so that the subsidies can be removed later on without decreasing the demand. However, this procedure may fail to work due to different reasons. The literature argues for the possibility of attention effect[9] and price anchoring effect[10] in this scenario. The main problem is that, if giving access to the product through high subsidies at the early stage does not lead to long-term learning effects, smart subsidies will not work and a direct knowledge treatment may be a better option. Even though existing literature focuses on assessing the impact of smart subsidies and designing optimal subsidy schemes (an example is Cai, de Janvry and Sadoulet, 2020.), the focus is only on demand and, it does not explore the role of personal experience in forming the associated subjective perceptions. The current study proposes to fill in this gap in the literature.

1.3 Role of Experience

I focus on exploring the effect of personal experience on the agents' subjective perception. The existing literature suggests two types of personal experience that has the potential of

[8] See Cai, de Janvry and Sadoulet (2020) for a discussion.

[9] When less attention is given to the product that has a lower price. Consult Ashraf, Berry and Shapiro (2010) for similar concepts.

[10] When lower reference price dampens subsequent demand for a product. See Fischer et al. (2019) for an application.

affecting the demand and associated level of learning of index insurance products. These are the disaster and payout experience.

1.3.1 Disaster Experience

As many index based insurance products cover low probability-high risk events, it has been argued that the lack of demand for such insurance comes from the lack of experience with such "disasters". Cai and Song (2017) use randomized experiment in China to separate the effects of personal experience with disaster and, knowledge of the payout probability on the demand for a crop index insurance product. In a game setting, substituting real disaster experience with hypothetical experience, they observe a 46% increase relative to the baseline take-up rate. Bjerge and Trifkovic (2018) explore whether farmers' decision to buy insurance is sensitive to the type of weather shock experienced, for a rainfall index insurance product in India. They find that excessive rainfall in previous years during the harvest increases the insurance demand, with no effect of lack of rainfall in the planting and growing periods. They attribute their results to access to an irrigation system, underscoring the importance of context in interpreting the results.

1.3.2 Payout Experience

The existing literature has recognized payout experience as one of the key factors in improving the demand for index insurance schemes. Karlan et al. (2014) analyze the impact of a rainfall based index insurance product in Ghana. They note that the demand for insurance is strongly increasing with farmers' own receipt of payout and; the receipt of payout by others in the farmers' social network for the previous year. Analyzing a rainfall index insurance product in India, Cole et al. (2013) calculate that the demand will increase by 36-66% if the product can be priced at payout ratios similar to US retail insurance contracts. They also observe that demand is higher in villages that previously experienced a payout. Using data from Indian microfinance institution BASIX, Stein (2018) find that customers who received an insurance payout are 9-22% more likely to repurchase in the following year than customers who did not receive any insurance payments. He argues for trust and learning about the product being the key factors behind this effect. However, his empirical analysis does not support this hypothesis. On the contrary, Timu et al. (2018) find that receiving an indemnity payout by itself did not necessarily improve uptake for IBLI, Ethiopia. They also do not find any evidence of social learning due to the payout experience in one's network.

Thus, there is no consensus in the literature regarding the extent and mechanism through which payout experience may affect the final demand. By analysing the effect of payout experience separately on demand and knowledge regarding the product and, exploring the possible heterogeneity in terms of exogenous treatment groups, I intend to make contribution in terms of improved understanding on this.

2 Data Description

2.1 Background

Index Based Livestock Insurance (IBLI) was introduced as a pilot in the Marsabit district of Northern Kenya and the Borena Zone of Southern Ethiopia in 2010 and 2012, respectively[11]. IBLI uses Normalized Differenced Vegetation Index (NDVI) as the objectively observable measure of greenness of a region to insure pastoralist households against drought related livestock mortality [12]. For the purpose of this study, the focus is on the Kenyan pilot, where the survey and implementations were conducted by International Livestock Research Institute (ILRI), Cornell University, the BASIS Research Program at the University of California, Davis and Syracuse University together with their implementing partners Equity Bank, UAP Insurance Company, APA Insurance Company, and Takaful Insurance of Africa.

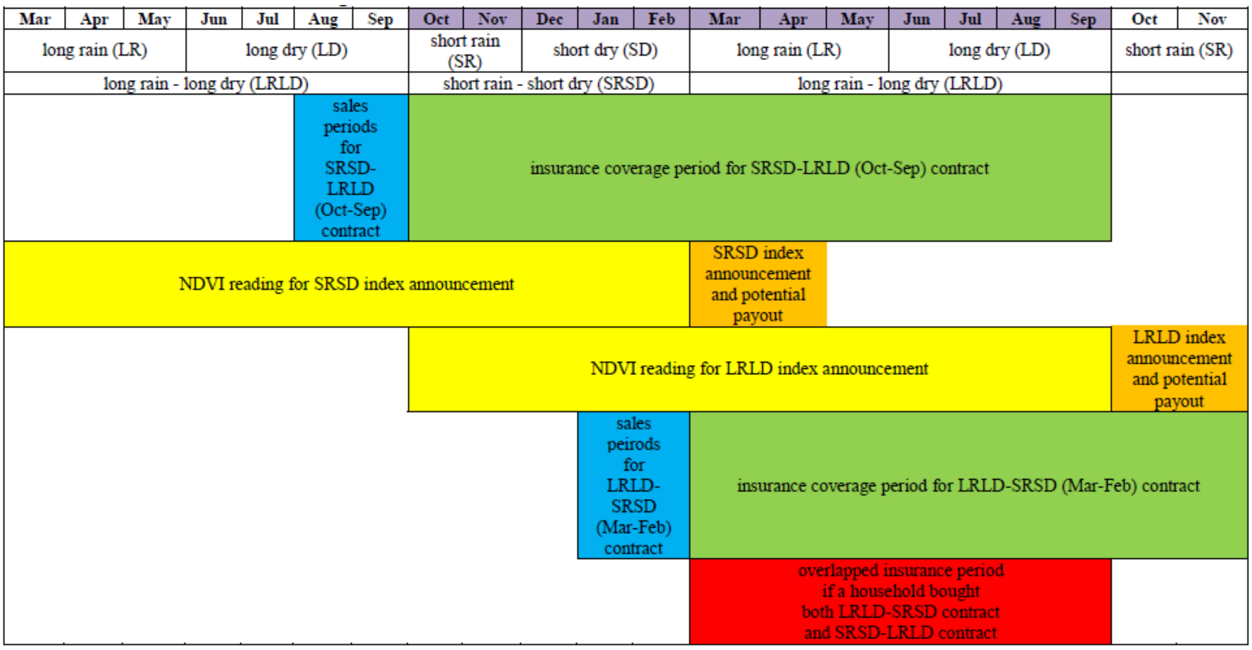
Marsabit district was divided into five index regions[13] for the purpose of IBLI distribution. The insurance was available to all households in these regions, who could self-select themselves into getting a contract.

[11]Details regarding the project can be found in: `https://ibli.ilri.org/index/`.

[12]Chantarat et al. (2013) discusses in detail about the construction of the index insurance product.

[13]Premium rates and NDVI readings vary at the index area level.

The region is characterized by its bi-modal rain pattern. The insurance was also designed to be offered twice in every year, before each rainy season, with each insurance contract being valid for a whole year. This design generated the possibility of overlapping payouts for some seasons. This structure of overlapping contracts was intended to reduce credit and liquidity constraints of the households[14]. Figure 1 demonstrates the bi-modal rain pattern observed in the region, IBLI sales periods, coverage periods and the possibility of overlapping payout.



Source: IBLI Marsabit Household Survey Codebook.

Figure 1: Figure 1: Time Structure of IBLI Marsabit

The NDVI was used as the main input to calculate area-average livestock mortality rate for each index region [15]. If the calculated area-average livestock mortality in an index-region was higher than a certain threshold[16] payouts were made to all households who was covered by the insurance in that region. The total payout to a household depended on the amount of coverage bought by the household (household specific) and the difference of the calculated livestock mortality from the threshold (index-area specific).

[14]Chantarat et al. (2013).

[15]Details regarding the calculation can be found in Chantarat et al. (2013) and Jensen, Mude and Barrett (2018).

[16]This threshold was 15% for the first 5 sales periods. After that, consumers were given the option to choose between 10% and 15% threshold levels, with different associated premium rates.

In practice, however, the overlapping structure of contracts was not possible every year, as a result some years had two sales periods as intended, while some had only one (shown in Figure 2).

2.2 Survey and Intervention

Although IBLI was introduced to all five index-regions of Marsabit, the survey only covered four of them. The primary geographic region of the survey was “sub-locations". Each index-area contained multiple sub-locations, with the 4 index-regions surveyed containing a total of 16 sub-locations. From each of this sub-location, a sample size of around 11% was set to be drawn proportional to the 1999 Kenya Population and Housing Census. Then, a minimum size of 30 and a maximum of 100 households were set per sub-location to decide the final sample size[17]. This resulted in a final sample of 924 households.

Figure 2 outlines the details about the timing of household survey round. The baseline survey was conducted in 2009, with annual follow-up rounds after the introduction of the product in 2010-2013. In 2015, two years after the survey round 5 in 2013, survey round 6 was conducted. For the purpose of this study, I focus on the first 5 rounds of household survey. The reason behind this is twofold:

1. The exogenous discount intervention was effective until the 6th IBLI sales period, i.e., it got discontinued following household survey round 5. As the product is highly price sensitive (as shown in the results), this led to a huge drop in the associated demand. If included, this can highly bias my results.

2. The reference period hugely differs for survey round 6, compared to the past survey rounds. This can potentially lead to a reference period bias if I include survey round 6 for my analysis.

The sample size of 924 households were originally intended to be repeated in each round of survey, to be able to construct a panel of these households. However, some households could not be traced down in later periods and, as a result, replacement households were

[17]Details can be found in IBLI Marsabit household survey codebook.

Date	Activity
October-November 2009	Household survey round 1
January-February 2010	1st IBLI sales period
October-November 2010	Household survey round 2
January-February 2011	2nd IBLI sales period
August-September 2011	3rd IBLI sales period
October-November 2011	Household survey round 3
October-November 2011	1st IBLI indemnity payout
March-April 2012	2nd IBLI indemnity payout
August-September 2012	4th IBLI sales period
October-November 2012	Household survey round 4
January-February 2013	5th IBLI sales period
August-September 2013	6th IBLI sales period
March-April 2013	3rd IBLI indemnity payout
October-November 2013	Household survey round 5
January-February 2014	7th IBLI sales period
March-April 2014	4th IBLI indemnity payout
August-September 2014	8th IBLI sales period
October-November 2014	5th IBLI indemnity payout
January-February 2015	9th IBLI sales period
March-April 2015	6th IBLI indemnity payout
August 2015	7th IBLI indemnity payout
August-September 2015	10th IBLI sales period
October-November 2015	Household survey round 6

Source: IBLI Marsabit Household Survey Codebook.

Figure 2: Figure 2: Timeline for IBLI Marsabit

found. For the purpose of this study, however, my focus in on the balanced panel of 820 households for which the information are available in all 5 rounds of survey[18].

The IBLI product was made available to all households in the Marsabit district. However, for impact evaluation purposes, exogenous knowledge and discount treatments were randomly distributed in the surveyed regions. The knowledge treatment was implemented in the form of a IBLI knowledge game that was randomized and implemented only once just before the first sales period. The discount treatment came in terms of discount coupons, which were randomized independently in each sales period and was only valid for the sales period it was distributed.

The indemnity payouts, as can be seen from Figure 2, occurred 3 times during the first 5 rounds of survey. However, since I do not consider the survey round 6, my focus is on the effects of first two indemnity payouts that took place in October-November, 2011 and

[18]An analysis of the related attrition can be found in Jensen, Mude and Barrett (2018).

March-April, 2012.

2.3 Relevance for the Current Study

The dataset is rich in terms of its variables. The following information from the dataset are particularly useful for the current study:

- Households' purchase decisions. This involves not only the decision to buy/not buy the insurance, but also the type and number of animals insured conditional on the purchase of the insurance.

- Their knowledge about the insurance product as reflected by their answers to knowledge questions and its evolution over time.

- Their livestock holding. This includes information about livestock intake and offtake over time, reasons behind the death of the animals.

- Household specific time-invariant and time-varying characteristics. This includes some information on their perceptions and expectations. It also includes information regarding their permanent and transitory income.

- Risk preferences generated by a Binswanger (1980) type of incentivized game.

- As can be seen from the Figure 2, a shock occurred and, as a result, payout has been made for October-November, 2011 and, March-April, 2012. The dataset has 3 survey rounds available both before and after this shock. Which helps me to asses both short and long run effect.

3 Theoretical Framework

In this section, I first present a theoretical model of index insurance following Janzen, Carter and Ikegami (2020). After presenting their basic framework, I relax some simplifying assumptions of the model to introduce the possibility of learning, which is discussed next.

3.1 Index Insurance without Learning

Consider a representative household that has a given asset holding A_t at period t and decides between how much to consume at this period (c_t) and how much to save as assets for the next period (A_{t+1}). The household is credit constrained: $c_t \leq A_t + f(A_t)$, where $f(\cdot)$ is a fixed production function that does not change over time[19]. They face two types of shocks: a covariate shock θ that is common to all other households living in the same region as them[20], and an idiosyncratic shock ϵ that is household-specific. In terms of the dataset used here, $1 \geq \theta \geq 0$ can be interpreted as being the actual area-average livestock mortality, with $1 \geq \epsilon \geq 0$ being the individual level deviation from it. Consequently, $\mu = (\theta + \epsilon)(\in [0, 1])$ denotes the livestock mortality at the household level.[21]

So, at any period t, the household chooses their consumption (c_t). After that they realize the composite shock $\mu_{t+1} = (\theta_{t+1} + \epsilon_{t+1})$, which determines their next period's asset holding $A_{t+1} = (A_t + f(A_t) - c_t)(1 - \mu_{t+1})$. Thus, their optimization problem can be represented as:

$$
\begin{aligned}
& max_{c_t} E_\mu \sum_{t=0}^{\infty} \beta^t u(c_t) \\
& subject\ to: \\
& c_t \leq A_t + f(A_t) \\
& A_{t+1} = (A_t + f(A_t) - c_t)(1 - \mu_{t+1}) \\
& A_t \geq 0
\end{aligned} \tag{1}
$$

where $u(\cdot)$ represents the household's period-specific utility function, with β being the discount factor.

Now, suppose that there exists an index insurance product that insures the household against the covariate shock θ but not the idiosyncratic shock ϵ. The index insurance

[19] In Janzen, Carter and Ikegami (2020), $f(A_t) = \max\{f^H(A_t), f^L(A_t)\}$ as their model focuses on the role of index insurance in escaping poverty trap. Here, simplification has been made for my purpose.

[20] This *region* can be interpreted as being the index-area for my analysis.

[21] Following the assumption in Janzen, Carter and Ikegami (2020), I have also considered the shocks to be negative shocks only. By construction, this assumption helps capture the negative basis risk associated with the product, while ignoring the positive basis risk events. However, the empirical analysis relaxes this assumption.

product makes the payout based on some objectively observed index $i(\theta)$ that represents the covariate shock. Payout $\delta(\theta)$ is positive iff $i(\theta)$ is higher than some strike point $s \geq 0$, i.e. $\delta(\theta) = \max\{i(\theta) - s, 0\}$.

With the index insurance product available, the household now decides how much to consume (c_t) and how much to insure (I_t) at each period t. The per unit price of the index insurance product is assumed to be fixed at p. The household's optimization problem becomes:

$$
\begin{aligned}
& max_{c_t, 0 \leq I_t \leq A_t} E_{\theta,\epsilon} \sum_{t=0}^{\infty} \beta^t u(c_t) \\
& subject\ to: \\
& c_t + pI_t \leq A_t + f(A_t) \\
& A_{t+1} = (A_t + f(A_t) - c_t)(1 - \mu_{t+1}) + (\delta_{t+1} - p)I_t \\
& \delta_{t+1} = \delta(\theta_{t+1}) = \max\{(i(\theta_{t+1}) - s), 0\} \\
& I_t, A_t \geq 0
\end{aligned} \tag{2}
$$

For their purpose, Janzen, Carter and Ikegami (2020) assumed: $i(\theta) = \theta$ and it is a common knowledge, which implies:

- For the insurer, the index perfectly observes the covariate risk, without any error. In terms of the terminology used in Elabed et al. (2013); this means that there is no *design risk* associated with the product[22].

- The consumers also believe the index to represent the covariate risk perfectly. More importantly, there is no deviation between the objective value of $i(\theta)$ and its subjective perception to the consumer.

- The basis risk associated with the product, for both the insurer and insurees, are represented by the household specific idiosyncratic risk ϵ.

Under these assumptions, the household have perfect information regarding the basis risk associated with the product and makes their decisions accordingly. In the next subsection,

[22] *Design risk* is represented by the prediction error of the index in capturing the covariate risk.

I relax these assumptions, which creates a possibility of learning for the household, in terms of the product's basis risk. I argue that the lack of information on the actual basis risk is (one of the main factors) responsible for dampening the demand for the product and learning from experience improves the household's information set, which can in turn result in higher demand.

3.2 Index Insurance with Learning

For $I > 0$, I assume the per-unit return δ', to be depending on the index $\iota(\theta) = \gamma^*\theta$, following the non-linear function:

$$\delta' = \delta'(\theta) = \begin{cases} \gamma^*\theta - s & if\ \iota(\theta) \geq s \\ 0 & otherwise \end{cases} \tag{3}$$

where s is the pre-determined strike point, which is common knowledge to everyone. In terms of the dataset, $\iota(\theta)$ can be interpreted as the predicted area-average livestock mortality. So, essentially, here I assume the predicted value of area-average livestock mortality to be a linear function of its actual value.

Here $\gamma^* \in [0, 1]$ is a latent variable for the insurer that maps households' covariate risk to the index $\iota(\theta)$. The insurer does not observe θ, so makes the payout contingent on $\iota(\theta)$.

First, I assume that the household observe θ, so they can figure out γ^* from the realization of $\iota(\theta)$. For now, I also assume that the covariate shock $\theta \sim F_\theta$ and the household specific idiosyncratic shock $\epsilon \sim F_\epsilon$ are independent draws at each time period. The distributions are also known to the household[23]. However, only after the making the decisions on c_t and I_t, the household is able to observe the shocks ϵ_{t+1} and θ_{t+1}. Thus, the

[23]The distributions do not need to be known to the households for the model to be true. However, they need to have some beliefs about the distributions. Additionally, I will just need to make the assumption that they believe F_θ to be monotonic (explained below).

household's problem becomes:

$$
\begin{aligned}
& max_{c_t, 0 \leq I_t \leq A_t} E_{\theta,\epsilon} \sum_{t=0}^{\infty} \beta^t u(c_t) \\
& subject\ to: \\
& c_t + pI_t \leq A_t + f(A_t) \\
& A_{t+1} = (A_t + f(A_t) - c_t)(1 - \mu_{t+1}) + (\delta'_{t+1} - p)I_t \\
& \delta'_{t+1} = \delta'(\theta_{t+1}) = \max\{(\iota(\theta_{t+1}) - s), 0\} \\
& I_t, A_t \geq 0
\end{aligned} \tag{4}
$$

Note that at this stage problem (4) is just a general version of problem (2), i.e., if $\gamma^* = 1$ problem (4) reduces to problem (2). There is no need for learning for the household, as the correlation between the index function and the covariate risk (i.e., γ^*) is known to them[24].

Now, I consider the scenario where the realized value of θ is not observable to the household. Instead, they can only observe the realized value of the composite shock $\mu = (\theta + \epsilon)$, the distribution of which (F_μ) is also known to them prior to making their decisions. I argue that, in this scenario, the household's belief about γ^* determine their demand.

Consider that, at any period t, the household believe $\gamma^* \in [0, 1]$ to be some $\gamma_t \in [0, 1]$. Given γ^*, the objective probability of receiving a payout upon purchasing the product is:

$$Prob(\theta \geq s/\gamma^*) = 1 - Prob(\theta < s/\gamma^*) = 1 - F_\theta(s/\gamma^*)$$

However, the subjective counterpart of this probability is $(1 - F_\theta(s/\gamma_t))$. If $\gamma_t < \gamma^*$, then under monotonicity of F_θ:

$$F_\theta(s/\gamma^*) < F_\theta(s/\gamma_t) \Rightarrow (1 - F_\theta(s/\gamma_t)) < (1 - F_\theta(s/\gamma^*))$$

In other words, the household is less likely to purchase the product than under perfect

[24]As the household observes θ, I assume that they are able to figure out γ^* after using the product for a fairly small number of rounds.

information regarding γ^*. This is because, given $\gamma_t < \gamma^*$, the subjective basis risk associated with the product is higher than its objective counterpart.

Under this framework, given price (p), if the household do not purchase the product then, absent knowledge spillovers, they do not learn anything new about the product in the next period. However, under the same assumptions, even if the household purchase the product in this period, absent any payouts they do not learn anything new about the product as well since $\theta < s/\gamma^* \Rightarrow \theta < s/\gamma$. Thus, in this scenario, the possibility of learning arises only when a payout has been made, as $\theta \geq s/\gamma^* \not\Rightarrow \theta \geq s/\gamma$. This leads to my first hypothesis:

Hypothesis 1: *Ceteris paribus, receiving a payout improves the level of learning about the product. This may or may not increase the demand for the product.*

This is a deviation from the existing literature that assumes higher level of learning will lead to high demand. This postulated positive relationship may fail to hold for products with high objective basis risk (i.e., low γ^*). If the basis risk associated with the product is high (implies low product quality) and, consumers initially had higher than optimal demand due to incomplete information on γ^* (more specifically, due to $\gamma_t > \gamma^*$), learning about the true value of γ^* can actually lead to a decrease in demand. To allow for this possibility, I measure the effect of household level experience separately on demand and, level of learning about the product. In other words, I aim to indirectly test the positive relationship between demand and learning, taking presence of high basis risk as the possible explanation for this relationship to not hold.

I now focus on the heterogeneity of these effects with respect to exogenous subsidy and knowledge treatments, through the lens of my theoretical framework. For an exogenous knowledge treatment that has been received before the first ever sales period, the payout experience should not induce any additional learning effect as the household should already have complete information about γ^*[25]. Hence, for the knowledge treatment group, neither level of learning nor the associated demand should be impacted. For the period specific

[25] This assumes that the knowledge treatment is effective at communicating full information about γ^*. References needed to justify this assumption.

discount treatment, however, no similar predictions can be made without making additional assumptions. If receiving a payout does indeed increase (decrease) the demand associated with the product, it should be higher (lower) for people that receive a discount coupon in addition to receiving a payout. This is because; for these people, lower price creates an additional incentive to purchase the product. The associated effect on level of learning will also be heterogeneously greater(smaller) for this group of people if the increase in demand leads to some kind of *learning-by-doing*(or, lack of attention) effect[26]. However, whether these assumptions actually hold in practice is an empirical question. This leads to my next hypothesis:

Hypothesis 2: *The payout experience has the following heterogeneous effects in terms of exogenous treatment groups:*

1. *For those who received the sales period specific discount treatment, the payout experience disproportionately increases the associated demand, provided the payout experience increases demand. For the same group, the payout experience increases level-of-learning associated with the product if there exists some 'learning-by-doing' effect.*

2. *For those receiving a one-time knowledge treatment, the payout experience does not induce any additional learning effect.*

Next, I relax the assumption of independent draws of θ and ϵ at each time period. In real world, the shocks are more likely to be correlated over time. Consider the situation where high μ_t makes μ_{t+1} more likely to be high as well[27]. As θ is never perfectly observed and μ serves as a noisy indicator of θ, high μ is also an indicator of high θ. If that is the case, ceteris paribus, the importance of the product improve. This should increase the demand for the product, without inducing any associated learning. Which leads to the following hypothesis:

[26] More explanation needed here.
[27] Assumes a Markov 1 process.

Hypothesis 3: *Experiencing high μ in the last period increases the demand for the product in this period, without improving the level of learning associated with the product, absent any knowledge spillovers.*

In terms of the knowledge treatment, a high μ in the last period should not increase the demand and its associated level of learning of the product. This is because the knowledge treatment group should know better not to respond to a transitory shock. However, for the discount treatment, high μ in the previous period should mechanically increase demand, without increasing the level of learning. So, I hypothesize the following:

Hypothesis 4: *The disaster experience has the following heterogeneous effects in terms of exogenous treatment groups:*

1. *For those who received the sales period specific discount treatment, the disaster experience should disproportionately increase demand, without improving the level of learning associated with the product.*

2. *For those receiving a one-time knowledge treatment, the disaster experience should neither improve level of learning nor increase the associated demand.*

Having discussed my theoretical framework and the associated hypotheses, next, I move to the empirical strategy used for testing these hypotheses.

4 Empirical Strategy

In this section, I discuss the empirical strategy used in this study for testing the hypotheses mentioned in the last section. This discussion is divided into three subsections. First two sub sections focus on testing hypotheses related to payout experience and disaster experience, respectively. For the last sub section, the focus is on past experience in general, which includes both the payout and disaster experience.

For each of the following regressions the main objective is to understand the effect on sales period specific demand and the level of learning. In the dataset used, I am able to observe the sales period specific decision to buy or not buy the insurance, as well as the number of animals insured for each category: camel, cattle or shoat[28]. However, no information has been collected that directly captures the sales period specific level of learning with respect to optimal usage of the product. For this purpose, I use the respondents'[29] answers to knowledge questions that tests them regarding their understanding of how the product works, as a proxy for their level of learning. These questions are asked consistently throughout all four rounds of survey that I focus here (no questions were asked in the baseline survey, as the product was not introduced yet). There is a total of 12 knowledge questions asked during these 4 rounds of survey. However, only 3 out of these 12 questions are asked in all 4 rounds, and so I focus on these 3 questions only. For each of these three questions, I convert the answers into a right (1) or wrong (0) binary outcome and then take a simple average per household per round to get an index of performance in the knowledge questions. I postpone the detailed description of these knowledge questions, as well as their possible answers to the Appendix A.

As the response to knowledge questions are only available per survey round, for year's that contain more than one sales period, the knowledge variable, that can be measured only by the end of the year, takes the same value for these two sales periods.

4.1 Payout Experience

In order to explore the effect of payout experience on the demand and level of learning associated with the product, I run the following set of regressions:

$$Demand_{ijt} = \alpha_1^D T_{ijt} + \alpha_2^D Payout_{ijt} + \alpha_3^D T_{ijt} \times Payout_{ijt} + \alpha_4^D X_{ijt} + u_{1ijt}^D \quad (5)$$

$$Knowledge_{ijt} = \alpha_1^K T_{ijt} + \alpha_2^K Payout_{ijt} + \alpha_3^K T_{ijt} \times Payout_{ijt} + \alpha_4^K X_{ijt} + u_{1ijt}^K \quad (6)$$

Here i denotes household, j stands for the index-area and t is the time period. $Demand_{ijt}$ represents the binary decision to purchase the product while $Knowledge_{ijt}$ captures the household's performance in the knowledge questions. The treatment T_{ijt} is a 2×1 vector $T_{ijt} = (d_{ijt}, k_{ij})'$, where d_{ijt} captures whether the household received sales period specific

[28]The term is used to indicate sheep/goat.

[29]This information is collected at the household level.

discount coupon and, k_{ij} captures whether they received the one-time knowledge treatment. The $Payout_{ijt}$ variable captures whether the household i from index area j had a payout experience prior to the sales period t. So, the variable is designed to capture both the short and long term effects of receiving a payout. X_{ijt} controls for both time-invariant and time-varying household characteristics[30]. I provide a detailed description of these variables in Appendix B. The treatments are randomly distributed, as mentioned in section 2. The payout experience depends on:

- Normalized Differenced Vegetation Index (NDVI), which can easily argued to be exogenous.
- Whether the household made a purchase in the sales period where the payout has been made. This lagged purchase decision can be correlated to the demand and knowledge observed in the current period and hence, if not controlled for, can lead to omitted variable bias. To control for this, I include the lagged demand in X_{ijt}.

Jensen, Mude and Barrett (2018) also argue for spatiotemporal adverse selection[31] for the dataset. I control for this by including index-area specific fixed effects in the regressions, that are part of u^D_{1ijt} and u^K_{1ijt}. The error terms also includes survey round fixed effects. After controlling for the fixed effects, the reminder of the error terms are assumed to be uncorrelated to the explanatory variables.

4.2 Disaster Experience

To asses the impact of disaster experience, I replace the $Payout_{ijt}$ variable in the regressions (5) and (6) with the variable DE_{ijt}. This DE_{ijt} (DE stands for Disaster Experience) is a dummy variable that captures whether the household lost any livestock due to drought anytime during a period of one year prior to the sales period. This leads us to the following

[30] The time-invariant variables are constructed using information from the baseline survey.

[31] When the insurance buyer has more information about the covariate risk than the insurer, which is not internalized by the insurance premium.

two regression equations:

$$Demand_{ijt} = \beta_1^D T_{ijt} + \beta_2^D DE_{ijt} + \beta_3^D T_{ijt} \times DE_{ijt} + \beta_4^D X_{ijt} + u_{2ijt}^D \quad (7)$$

$$Knowledge_{ijt} = \beta_1^K T_{ijt} + \beta_2^K DE_{ijt} + \beta_3^K T_{ijt} \times DE_{ijt} + \beta_4^K X_{ijt} + u_{2ijt}^K \quad (8)$$

Whether the household had a disaster experience during the one year prior to a sales period depends on:

- Whether they experienced any drought at the household level. This can argued to be exogenous.
- Whether the household had any livestock at that time. Not controlling for this information can create a omitted variable bias as it can also argued to be influencing the household's decision to make a purchase, as well as their knowledge about the product (through interest in the product). Thus, I include the flow variable herd size (measured in tropical livestock units:TLU[32]) of the household during one year prior to a sales period in X_{ijt} to control for this. This replaces controlling for lagged purchase in regressions (5)-(6).

The other variables are the same as in the regressions (5)-(6). Similarly, I also include index-area and survey round specific fixed effects in the error term.

4.3 Past Experience

Finally, I turn to the analysis of understanding the effect of past experience on present perceptions. Here, I consider both payout and, disaster experience to run the following set

[32]As mentioned in the Marsabit household survey codebook: *1 TLU is equivalent to 1 cow, 0.7 camel, 10 goat, or 10 sheep/goats.*

of regressions:

$$
\begin{aligned}
Demand_{ijt} =& \gamma_1^D T_{ijt} + \gamma_2^D Payout_{ijt} + \gamma_3^D DE_{ijt} + \gamma_4^D T_{ijt} \times Payout_{ijt} \\
&+ \gamma_5^D T_{ijt} \times DE_{ijt} + \gamma_6^D X_{ijt} + u_{3ijt}^D \qquad (9)\\
Knowledge_{ijt} =& \gamma_1^K T_{ijt} + \gamma_2^K Payout_{ijt} + \gamma_3^K DE_{ijt} + \gamma_4^K T_{ijt} \times Payout_{ijt} \\
&+ \gamma_5^K T_{ijt} \times DE_{ijt} + \gamma_6^K X_{ijt} + u_{3ijt}^K \qquad (10)
\end{aligned}
$$

The $Payout_{ijt}$ and DE_{ijt} variables are both representing livestock death due to drought. The $Payout_{ijt}$ variable is representing this loss at the index-area level, where DE_{ijt} represents it at the household level. By design of the index insurance product, there should be high correlation between these two variables, if measured in the same reference period. In the regressions (5)-(8), I ignore the possibility of this correlation since $Payout_{ijt}$ and DE_{ijt} variables have different reference periods. In regressions (9) and (10), I control for this possibility.

5 Results

5.1 Descriptive Statistics

I begin with the description of baseline summary statistics of the households surveyed. For this purpose, my focus is on the 820 balanced panel households that have been interviewed in all first five rounds of survey.

As can be observed from Table 1, the average household in the survey has a household head aged around 48 years, who completed around 1 year of education. The survey has slight over-representation of male headed households. The asset index is an average of the binary variables on whether the households own poultry, own donkey, own land, has the walls of their main dwelling predominantly made of bricks/block/cement, has their floor made of cement/tiles and, has a toilet facility. The index can take values between 0 and 1. As, can be seen, for the sample here, the households on average said yes to only 1 out of the 6 asset questions mentioned above. In terms of risk aversion, 44% of the sample is

Table 1: Table 1: Baseline Summary Statistics

Variables	Mean	SD
Age*	47.92	18.53
Gender (Female=1)	0.38	0.48
Years of Education**	1.03	2.95
Asset Index	0.19	0.19
Extreme Risk Aversion (=1)	0.27	0.44
Moderate Risk Aversion (=1)	0.44	0.50
Risk Neutral (=1)	0.29	0.45
No. of Observations		820

* Based on 819 observations. ** Based on 818 observations.
Age, Gender and Years of Education are calculated for household head.

moderately risk averse, with 27% and 29% being extreme risk averse and, risk neutral, respectively.

Having discussed the baseline household characteristics, next I present the trends observed in the dataset over time. For this purpose, the focus is on the dependent variables of my analysis: $Demand_{ijt}$ and $Knowledge_{ijt}$. The following Figure 3 shows the demand for the product over time. As the figure shows, over the course of six sales periods the

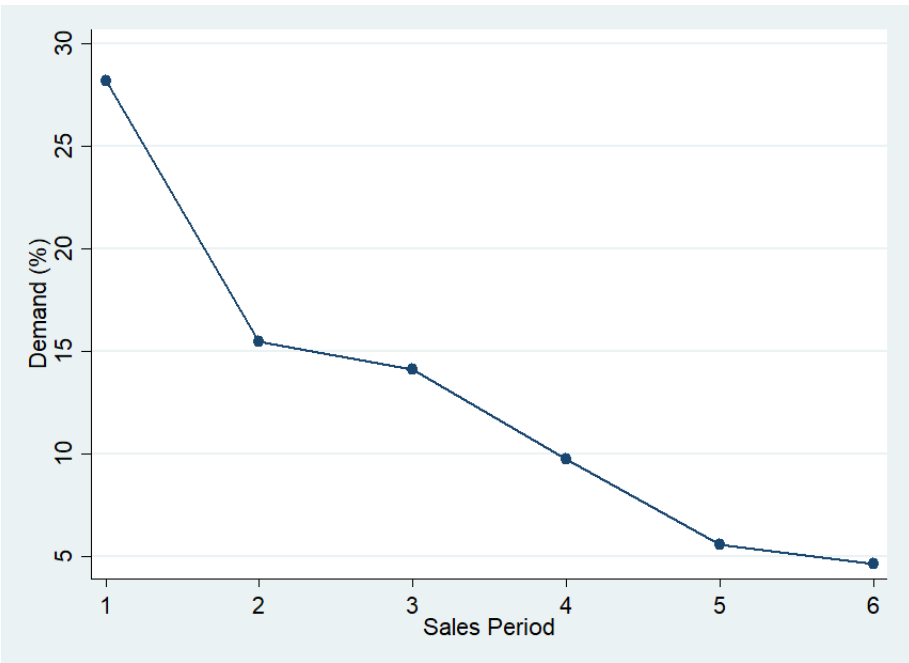


Figure 3: Figure 3: Demand Over Sales Periods

demand dropped drastically from around 28% to less than 5%. However, this figure hides the possible heterogeneity in terms of the treatment groups. This is depicted in Figure 4. To construct Figure 4, I calculated the percentage share demanded by four different

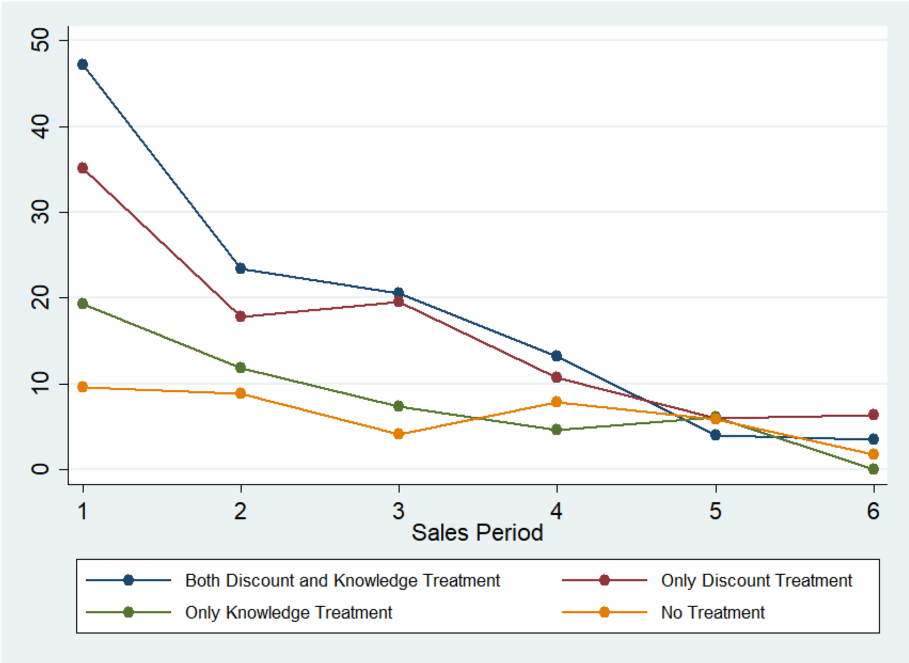


Figure 4: Figure 4: Demand Over Sales Periods by Treatment Groups

treatment groups:

- The 'control group' that received no treatment.
- The 'only discount group' that only received sales period specific discount coupon but not the one time knowledge treatment.
- The 'only knowledge group' that received the one-time knowledge treatment, but not the sales period specific discount treatment.
- Finally, the 'Discount and Knowledge' group that received both the period specific discount coupon as well as the one-time knowledge treatment.

Note that the treatment groups are constructed by each sales period, which means, for each of these groups, the number of members and their identity are not fixed over time. What we observe in this figure, is a convergence by all these different treatment groups over time, in terms of demand. This can be because of the following reasons:

- Spatiotemporal adverse selection already documented for this dataset[33]. Index-area specific fixed effects should control for that in the regressions.

- There can be *learning-by-doing and learning from others* over time together with high objective basis risk associated with the product.

- It can be due to the lack of payout experience in the data, that can channel long term learning effect, increasing demand in the long run. More frequently observed disaster experience, on the other hand, probably stimulated demand in the short run, creating no long term learning effect, thus no long run increase in demand. This is something I test in my analysis.

Moving on, Figure 5 shows the household's performance in knowledge questions over survey rounds. Similar to the demand, it documents gradual decrease over time. Looking for heterogeneity in terms of treatments, Figure 6 documents the households' performance in knowledge questions by the four treatment groups mentioned above.

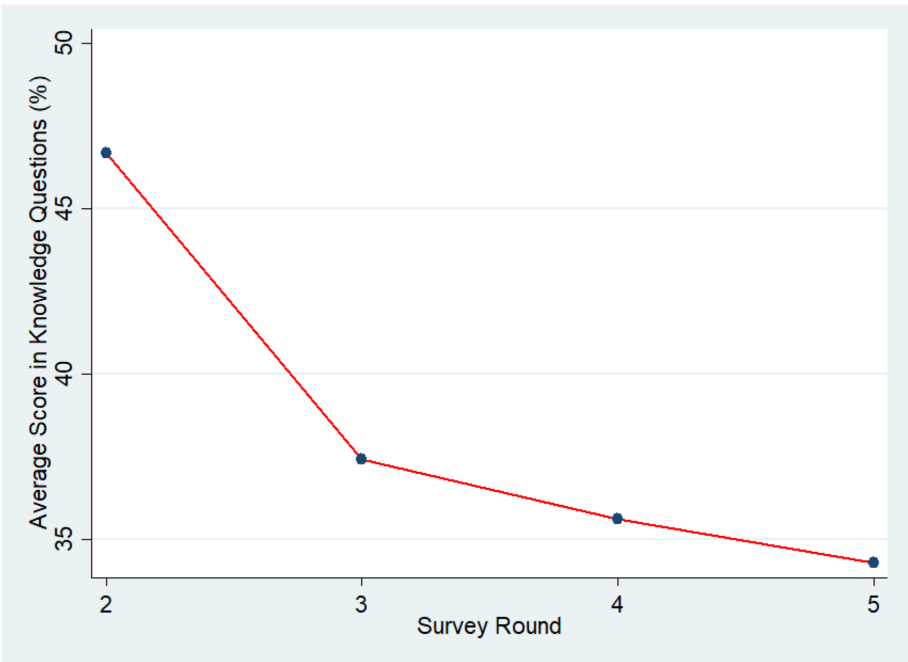


Figure 5: Figure 5: Performance in Knowledge Questions Over Survey Rounds

[33]In Jensen, Mude and Barrett (2018).

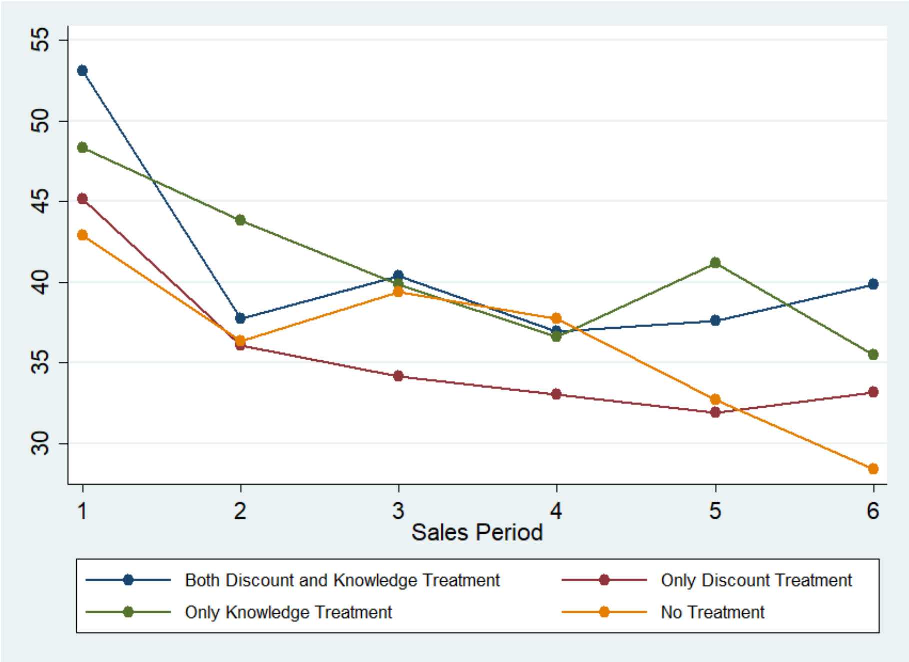


Figure 6: Figure 6: Performance in Knowledge Questions Over Sales Periods by Treatment Groups

5.2 Estimation Results

Here, I present the main results of my analysis. These are the estimates of regression equations (5)-(10), as described in section 4. The 'control group' of comparison varies by each column in the tables. The definition of the control group remains the same though: the group that received neither of the exogenous treatments (discount coupon and knowledge treatment), as well as did not experience the particular event of concern (payout, disaster or both).

I begin with Table 2. It presents the ordinary least square (OLS) regression results where the outcome variable is $Demand_{ijt}$. The columns (1), (2) and, (3) in the table represents the estimation results for regression equations (5), (7) and, (9), respectively. In other words, column (1) presents the effect of payout experience, column (2) presents the effect of disaster experience and, column (3) presents the effect of both.

For all the results presented in Table 2, the sales period specific discount treatment seems to be improving the probability of purchase, where the one time knowledge treatment does not. The coefficients associated to the discount treatment ranges from 0.046-0.063. The effect is always statistically significant at 1% level. This corresponds to a 67.6-114.5%

Table 2: Table 2: OLS Regression Results for Demand

Variables	(1)	(2)	(3)
Discount Coupon	0.063***	0.046***	0.047***
(=1 if recipient)	(0.010)	(0.013)	(0.013)
Knowledge Game	0.010	0.019	0.015
(=1 if participant)	(0.012)	(0.017)	(0.015)
Reported Payout	0.115*		0.108*
	(0.061)		(0.061)
Reported Payout × Discount Coupon	-0.035		-0.026
	(0.071)		(0.071)
Reported Payout × Knowledge Game	-0.047		-0.049
	(0.061)		(0.060)
Disaster Experience		-0.031*	-0.030*
		(0.016)	(0.015)
Disaster Experience × Discount Coupon		0.037**	0.035**
		(0.018)	(0.018)
Disaster Experience × Knowledge Game		-0.013	-0.012
		(0.022)	(0.021)
Lagged Uptake	0.122***		0.123***
	(0.019)		(0.019)
Herd Size		0.000	0.000
		(0.000)	(0.000)
Constant	0.044	0.067	0.053
	(0.041)	(0.048)	(0.042)
Household Characteristics	Yes	Yes	Yes
Index-Area Fixed Effects	Yes	Yes	Yes
Survey Round Fixed Effects	Yes	Yes	Yes
Control Group Mean	0.055	0.068	0.059
(SD)	(0.228)	(0.252)	(0.236)
Observations	3858	3858	3858
R-squared	0.07	0.05	0.07

* p<0.10, ** p<0.05, *** p<0.01.

Robust standard errors clustered at the household level are in parentheses.

increase over the control group means, considering the control group means are in the range 0.055-0.068. This also corresponds to a 0.2-0.3 standard deviation increase with respect to the control groups, considering the standard deviation for the control groups are in the range 0.228-0.252. This can be considered as a small to medium size effect. On the other hand, the coefficients associated with the one time knowledge treatment are always statistically insignificant.

Having discussed the effect of exogenous treatments on the probability of purchase, next I turn to one of the main focus of my analysis: the effect of payout experience. For this type of experience, I do not observe any heterogeneity in terms of exogenous treatments. The payout experience seems to be improving the probability of purchase by 0.108-0.115 units, even though the results are only significant at the 10% level. This corresponds to a 183.1-209.1% increase over the control group means, which corresponds to around 0.5 standard deviation increase. This can be considered as a medium size effect. Moving on to the effect of disaster experience, unconditional on the exogenous treatments, it increases the probability of purchase by only 0.005-0.006 units, at 10% level of significance. This corresponds to a small increase of 8.5-8.8% and 0.02 standard deviation over the control group means and standard deviations, respectively. However, conditional on receiving a discount coupon, the effect is much larger and significant at 5% level. The effect size is 0.035-0.037 units. Which is a 54.4-59.3% increase over the control group means and, corresponds to a standard deviation increase of around 0.2, which is medium. No significant heterogeneous effect of disaster experience can be observed in terms of the one-time knowledge treatment.

Apart from the effects described above, I also report the coefficients corresponding to lagged demand, herd size and, a constant. No statistically significant effect can be observed in terms of the herd size and the constant for these regressions. In terms of the lagged purchase, it increases the probability of purchase in the current period by 0.122-0.123 points. These are a 208.5-221.8% increase with respect to the control group means. This also correspond to a medium increase of 0.5 standard deviations with respect to the control groups.

Table 3: Table 3: OLS Regression Results for Knowledge

Variables	(4)	(5)	(6)
Discount Coupon	-0.018	-0.003	-0.010
(=1 if recipient)	(0.011)	(0.015)	(0.015)
Knowledge Game	0.049***	0.043**	0.045**
(=1 if participant)	(0.017)	(0.021)	(0.021)
Reported Payout	-0.086**		-0.086**
	(0.042)		(0.042)
Reported Payout × Discount Coupon	0.109**		0.105**
	(0.048)		(0.048)
Reported Payout × Knowledge Game	-0.072		-0.063
	(0.074)		(0.076)
Disaster Experience		0.022	0.019
		(0.019)	(0.019)
Disaster Experience × Discount Coupon		-0.021	-0.017
		(0.022)	(0.021)
Disaster Experience × Knowledge Game		0.008	0.006
		(0.027)	(0.027)
Lagged Uptake	0.064***		0.065***
	(0.017)		(0.017)
Herd Size		0.001	0.001
		(0.000)	(0.000)
Constant	0.335***	0.327***	0.316***
	(0.068)	(0.069)	(0.068)
Household Characteristics	Yes	Yes	Yes
Index-Area Fixed Effects	Yes	Yes	Yes
Survey Round Fixed Effects	Yes	Yes	Yes
Control Group Mean	0.356	0.343	0.344
(SD)	(0.312)	(0.308)	(0.312)
Observations	3522	3522	3522
R-squared	0.07	0.07	0.07

* p<0.10, ** p<0.05, *** p<0.01.

Robust standard errors clustered at the household level are in parentheses.

Next, I move to Table 3, which presents the ordinary least square (OLS) regression results for the outcome variable $Knowledge_{ijt}$. In this table, column (4) presents the effect of payout experience, column (5) presents the effect of disaster experience and, column (6) presents the effect of both. That is, the columns (4), (5) and, (6) in this table represents the estimation results for regression equations (6), (8) and, (10), respectively. In terms of the exogenous treatments, the discount treatment does not seem to have any significant effect on the households' performance in the knowledge question, where the one-time knowledge treatment does. One time participation in the knowledge game associated with the product seems to be improving their performance in answering the knowledge questions by 0.043-0.049 points. The results are all significant at least at the 5% level. This is a 12.5-13.8% increase compared to the control group means that is in the range 0.343-0.356. It is also a 0.1-0.2 standard deviation increase compared to the control group whose standard deviations range in 0.308-0.312. This is a small effect.

The payout experience, unconditional on the exogenous treatment received, seems to be improving the households' performance in the knowledge questions by 0.019-0.023 points. This is significant at the 5% level. This is a 5.5-6.5% increase compared to the control group means. Which can be characterized as a small increase of 0.1 standard deviations. When it comes to heterogeneity of this payout experience in terms of the exogenous discount treatment, the increase is much larger and at the range 0.105-0.109 points. This result is also significant at the 5% level. This increase is around 30.5% compared to the control group means. In terms of the control group standard deviations, this means an increase of 0.3-0.4 points, which is a medium level effect. However, I observe no significant heterogeneous effect of the payout experience in terms on the one-time knowledge treatment. In terms of the disaster experience, conditional or unconditional on the exogenous treatments, no effect can be observed on the participants' performance in the knowledge questions.

Apart from the variables mentioned above, for Table 3, I also report the coefficients for lagged purchase, herd size and a constant term. No significant effect can be observed in terms of the herd size. The lagged purchase improves performance in the knowledge question by 0.064-0.065 points, which is significant at the 1% level. This is a 18-18.9% increase compared to the control group means. Which is also a medium size increase of 0.2 standard deviations. In terms of the constant, the effect is much larger and in the range 0.316-0.335. This is also significant at the 1% level. It characterizes a 91.9-94.1% increase compared to the control group mean, and a large increase of around 1-1.1 standard deviations.

6 Robustness Checks

The objective of this section is to check the robustness of my results, discussed in the last section, with respect to some major concerns.

6.1 Heterogeneity of Discount Treatments

The first major concern arises in terms of the possible heterogeneity of effects with respect to the different discount treatments. For the analysis presented above, the discount treatment is just taken to be whether the household received a sales period specific discount coupon or not. However, the associated discount rate varied between 0-60% for the first 4 sales periods and between 0-80% for the fifth and sixth sales periods. On one hand, without controlling for this heterogeneity in discount rate can lead to some bias in the results. On the other hand, the small sample size may fail to capture the heterogeneity in terms of the discount rate. To shed more light on this issue, I run the regressions (5)-(10), replacing the dummy variable discount coupon with the continuous variable discount rate. The results are presented in Tables 4 and 5.

Table 4 is the counterpart of Table 2, with the variable discount rate instead of discount coupon. Results remain similar with respect to the exogenous treatments. I still do not observe any significant effect with respect to the knowledge treatment and observe positive effect with respect to the discount treatment that is significant at 1% level. However, when controlling for the heterogeneity in discount rates, I observe only a 1.4-1.8% increase in the probability of purchase with respect to the control group means. This is much lower

Table 4: Table 4: OLS Regression Results for Demand (with Discount Rate)

Variables	(1)	(2)	(3)
Discount Rate	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)
Knowledge Game	0.009	0.018	0.014
(=1 if participant)	(0.011)	(0.017)	(0.015)
Reported Payout	0.113**		0.109**
	(0.051)		(0.052)
Reported Payout × Discount Rate	-0.001		-0.001
	(0.001)		(0.001)
Reported Payout × Knowledge Game	-0.046		-0.048
	(0.060)		(0.060)
Disaster Experience		-0.019	-0.018
		(0.015)	(0.014)
Disaster Experience × Discount Rate		0.000	0.000
		(0.000)	(0.000)
Disaster Experience × Knowledge Game		-0.012	-0.011
		(0.015)	(0.014)
Lagged Uptake	0.123***		0.123***
	(0.019)		(0.019)
Herd Size		0.000	0.000
		(0.000)	(0.000)
Constant	0.056	0.074	0.061
	(0.041)	(0.048)	(0.042)
Household Characteristics	Yes	Yes	Yes
Index-Area Fixed Effects	Yes	Yes	Yes
Survey Round Fixed Effects	Yes	Yes	Yes
Control Group Mean	0.055	0.068	0.059
(SD)	(0.228)	(0.252)	(0.236)
Observations	3858	3858	3858
R-squared	0.07	0.05	0.07

* p<0.10, ** p<0.05, *** p<0.01.

Robust standard errors clustered at the household level are in parentheses.

than the increase I observed with respect of the discount coupons, which was 67.6-114.5%. Similarly, in terms of the control group standard deviations, the increase is only by 0.004 points, much lower than the 0.2-0.3 standard deviation increase observed with the dummy variable discount coupon. This is not surprising, because here the coefficient of discount rate captures the increase in probability of purchase due to 1% increase in discount rates. Which is supposed to be much smaller than the increase in probability of purchase due to receiving a discount coupon, compared to not receiving it.

Moving on to the effect of payout experience, the main result do not change much. I still do not observe any heterogeneity in the effect of receiving a payout with respect to the exogenous treatments. The positive effect of unconditional payout experience also remains robust. However, this effect is now significant at 5% level, better than with the original specification where I observed significance at 10% level. The effect size also does not change much, compared to the specification with dummy variable discount coupon instead of continuous variable discount rate. In this case, I observe 184.7-205.5% increase compared to the control group mean, which was 183.1-209.1% increase in the original specification. This is the same 0.5 standard deviation increase, as observed before. However, when it comes to the effect of disaster experience, the significant effects observed in Table 2 completely vanishes. The results remain the same with respect to lagged demand, herd size and the constant.

Moving on to Table 5, which is the counterpart of Table 3 with the variable discount rate instead of discount coupon. Results remain almost same with respect to the discount and knowledge treatments. Period specific discount still does not significantly improve households' performance in the knowledge questions. Considering discount rate instead of discount coupon actually made the results even stronger in the sense that the coefficients turn out to be extremely negligible. In terms of the households' participation in the knowledge game, the results remain exactly the same as in Table 3.

In terms of the payout experience, however, the results change. Receiving 1% increase in discount rate together with a payout experience improves the households' performance in knowledge questions by 0.002 points, which is significant at 5% level. This is a small 0.6%

Table 5: Table 5: OLS Regression Results for Knowledge (with Discount Rate)

Variables	(1)	(2)	(3)
Discount Rate	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)
Knowledge Game	0.049***	0.043**	0.045**
(=1 if participant)	(0.017)	(0.020)	(0.021)
Reported Payout	-0.065*		-0.065*
	(0.037)		(0.037)
Reported Payout × Discount Rate	0.002**		0.002**
	(0.001)		(0.001)
Reported Payout × Knowledge Game	-0.072		-0.063
	(0.075)		(0.077)
Disaster Experience		0.024	0.022
		(0.017)	(0.017)
Disaster Experience × Discount Rate		-0.001	-0.001
		(0.000)	(0.000)
Disaster Experience × Knowledge Game		0.008	0.005
		(0.027)	(0.027)
Lagged Uptake	0.063***		0.064***
	(0.017)		(0.017)
Herd Size		0.001	0.001
		(0.000)	(0.000)
Constant	0.329***	0.321***	0.308***
	(0.068)	(0.069)	(0.068)
Household Characteristics	Yes	Yes	Yes
Index-Area Fixed Effects	Yes	Yes	Yes
Survey Round Fixed Effects	Yes	Yes	Yes
Control Group Mean	0.356	0.343	0.344
(SD)	(0.312)	(0.308)	(0.312)
Observations	3522	3522	3522
R-squared	0.07	0.07	0.07

* p<0.10, ** p<0.05, *** p<0.01.

Robust standard errors clustered at the household level are in parentheses.

increase compared to the control group means, which also characterizes a 0.01 standard deviation increase. This is much lower than the effect of receiving a discount coupon in addition to a payout experience, which is reported to be a 30.5% increase with respect to the control group means in Table 3. This is not a surprising result, as I expect the discontinuity of receiving a discount coupon with respect to not receiving it to amplify the payout experience more than a continuous 1% increase in discount rate. What is interesting is that the effect of payout experience conditional on not receiving any discount or knowledge treatments, decrease, similar to Table 3, but with slightly less coefficient and significance level. It is a 0.065 points decrease which is significant at the 10% level. It was 0.086 points decrease in Table 3, which was significant at the 5% level. With respect to the control group means this is a 18.3-18.9% decrease, which was 24.2% in Table 3. With respect to the control group standard deviation, this is a 0.2 points decrease, which is medium size. The interesting part is that, now when I calculate the unconditional effect of the payout experience, its a 0.063 points decrease in the households' performance in knowledge questions, contrary to 0.023 points increase that was observed in Table 3. This may seem to be contradictory, but it is simply because the increase in payout experience conditional on receiving a discount coupon is much higher than the increase in payout experience conditional on receiving 1% increase in discount rates. The coefficient of payout experience conditional on receiving a one-time knowledge treatment still remains insignificant. So, the results remain robust with respect to the payout experience. Similar to Table 3, here also I do not observe any significant effect with respect to the disaster experience. The lagged uptake and constant included in the regression continued to have similar coefficients and level of significance as they had on Table 3. There is still no significant effect of herd size.

6.2 Selection into Purchasing

6.3 Controlling for Network Effects

7 Discussion and Conclusions

My results suggest a positive impact of payout experience on both demand and knowledge associated with IBLI, Kenya. On the contrary, the disaster experience is found to have significant positive impact only on the demand and, no significant effect on the knowledge associated with the product. This result is consistent with my theoretical framework. More generally, the results support a model that deals with *rational* consumers. This is in contradiction with a model of *behavioral biases*, that would have a different prediction. However, some results are not strong and robust to alternative specifications, so I am unable to reject an alternative model that integrates *behavioral biases*.

In terms of the exogenous treatments, the sales period specific discount treatments seem to matter a lot, specifically in terms of increasing knowledge from the payout experience. More alarming is the negative impact of the payout experience on knowledge, absent exogenous treatments, even though it increases demand. This suggests that a smart subsidy scheme, that subsidizes heavily at the initial sales periods only to remove it later hoping to trigger a learning effect, may fail to work in reality. A possible way out of this issue is giving people knowledge treatments, as then the experiences may not matter as much, as suggested by my results. However, if the objective is to improve the associated demand, knowledge treatments alone does not seem to be effective at all.Hence, there is need to compliment discount and knowledge treatments in order to improve both demand and learning associated with the product. This is in line with the policy suggestions made in Cai, de Janvry and Sadoulet (2020).

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Appendices

A Knowledge Questions

Knowledge Question 1: How often do you have to pay a premium in order to remain insured?
Answers: Don't Know/ Remain insured until compensated/ Once every two years/ Once every six months/ Once every year
Right Answer: Once every year

Knowledge Question 2: If you did not receive indemnity payout (compensation) from the livestock insurance, would you expect to receive your premium back?
Answers: Don't Know/ Yes/ No
Right Answer: No

Knowledge Question 3: What institution will provide you indemnity payout if there is a payout?

Answers: Don't Know/ Equity Bank/ ILRI/ UAP Insurance/ APA Insurance/ Government/ NGO

Right Answer: UAP Insurance for sales periods 1-3, APA Insurance for sales periods 4-6.

For each knowledge questions, I code 0- Wrong, 1- Right. Then the $Knowledge_{ijt}$ variable is constructed as:

$$Knowledge_{ijt} = 1/3(Knowledge^1_{ijt} + Knowledge^2_{ijt} + Knowledge^3_{ijt})$$

where $Knowledge^m_{ijt}$ represents their performance in Knowledge Question m.

B Description of Household Control Variables

Apart from the variables already mentioned in the empirical strategy section, the following variables are controlled for in the regressions:

- Age and Age-Squared of household head, measured at the baseline.
- Gender and years of education of household head, measured at the baseline.
- Asset index measured at the baseline. This is an average of the binary variables on:
  - Whether the households own poultry.
  - Whether they own any donkey.
  - Whether they own any land.
  - Whether the household has the walls of their main dwelling made of bricks/block/cement.
  - Whether they has their floor made of cement/tiles.
  - Whether the household has a toilet facility at home.
- Dummy variables on extreme risk aversion and moderate risk aversion calculated using an experiment conducted in the baseline following Binswanger (1980). The omitted category is the dummy that captures whether the household is risk-neutral.

- Whether livestock was the main source of income in the baseline.

- Whether drought is the main source of risk faced by the household in the baseline.

- The household's flow of total income, for one-year prior to the sales period.