Experience of shocks and expectation formation –Evidence from smallholder farmers in Kenya

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Abstract

When faced with uncertain events, decision makers form subjective probabilistic expectations regarding the events' occurrence. The drivers, biases, and implications of probabilistic expectation formation are still poorly understood, especially for farm decision makers in developing countries whose incomes are very risky. This paper analyzes the dynamic expectation formation behavior of farmers in a developing country regarding a range of shock events. Our results suggest that famers are more likely to expect any specific adverse shock to occur in the future when they or, independently of themselves, a larger share of village members were recently affected by that shocks or when they were affected by more adverse shocks in total. By applying a novel method of measuring expectation formation bias to our data, we find that, on average, farmers' expectations are biased, overreacting when affected by weather, agricultural, or price-related shocks and underreacting when affected by demographic shocks. Farmers that expect more shocks have a higher likelihood of holding precautionary savings, but do not apply less harmful coping strategies. Acknowledging drivers and biases of expectation formation can help design better risk management instruments that could potentially increase farmers' resilience.

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1. Introduction

When faced with uncertain adverse events or shocks[3], decision makers form probabilistic expectations regarding the events' occurrence. Economists have neglected the individual differences of this forecasting behavior for a long time (Manski, 2004, 2018). While it has been assumed that individuals make, on average, statistically optimal forecasts following the Rational Expectations Hypothesis (Muth, 1961), and, in the case of probabilities, the Bayes' rule (Gallagher, 2014), recent empirical literature, mainly in macroeconomics and finance, has challenged this view (e.g. Bordalo, Gennaioli, & Shleifer, 2018; Coibion, Gorodnichenko, & Kamdar, 2018). Many aspects of the cognitive processes, the decision heuristics, and individual factors that determine the formation of probabilistic expectations are, however, still unknown (Barberis, 2013; Gilboa, Postlewaite, & Schmeidler, 2008). Despite the critical importance of risk, risk perception, and risk response in rural developing economies (Dercon, 2005, 2008; Elbers, Gunning, & Kinsey, 2007), there is little evidence on (probabilistic) expectation formation from developing countries (Attanasio, 2009; Delavande, 2014), as most research on the topic looks at professional forecasters (e.g. Bordalo et al., 2018; Coibion & Gorodnichenko, 2012, 2015; Kucinskas & Peters, 2018). Most secondary datasets generally only include the observable outcomes of subjects' decisions but not the subjective probabilities that may have guided their decision making process (Delavande, Giné, & McKenzie, 2011), which make them unapt for analyzing expectation formation.

There is scarce empirical evidence from farming households suggesting that heterogeneity in subjective probabilities is driven by household as well as farm-specific characteristics (Bellemare, 2009), as well as their access to coping mechanisms (Giné, Townsend, & Vickery, 2009). These studies are however static and do not allow for drawing conclusions regarding

[3] In the following, we refer to the term shock as a "realization of the risky process" as in Dercon (2005), p. 10, that is, in principle, unpredictable.

the *updating* of expectations. Making judgments about the rationality of updating requires at least some knowledge about the "true" data generating process underlying an adverse event, i.e. the objective probabilities of the random event over time, which is rarely observable outside a lab or without long time-series (Kucinskas & Peters, 2018). Furthermore, it is unclear to which degree the rationality in updating probabilistic information might also depend on the type of probabilistic event.

Analysing expectation formation of decision makers in developing countries, and particularly of farmers, is highly relevant for at least two reasons: First of all, because agricultural production and incomes are very risky by nature (e.g. Dercon, 2008). Second, because it allows tracing back observed behavior to preferences and identify behavioral biases, allowing for a better understanding of farming behavior (Delavande, 2014). Furthermore, it is unclear whether expecting a shock leads decision makers to adopt mitigation measures that could make the consequences of experiencing a shock less severe.

We add to a very limited literature analyzing the dynamics of expectation formation in a developing country by looking at expectations of Kenyan smallholder vegetable farmers regarding a range of shock events over time. We elicit detailed information over three consecutive years regarding farmers experience of a wide range of adverse shocks, as well as whether they expect the specific shock to re-occur in the following year. Specifically we ask whether farmers are more likely to update their expectations (1) when they were recently hit by a particular shock, (2) when a larger share of village members was hit by the particular shock, or (3) when they were hit by more other shocks in total. Furthermore, we measure (4) whether it depends on the type of shock encountered whether farmers update their expectation after experiencing a shock. Apart from this, we (5) test whether expectation formation of farmers is irrational, applying a novel method (Kucinskas and Peters 2018) that requires limited information about the true underlying stochastic process of the shock variable. Lastly, we analyze (5) whether farmers who expect a particular adverse shocks to happen use different ex-ante (precautionary savings) and/or ex-post measures (harmful coping strategies) to minimize the negative effects of shocks on their livelihoods. Knowing more about drivers of expectation formation, on the one hand, and behavioral biases, on the other hand, could potentially in designing better risk-management tools that could increase farmers' resilience.

The paper is structured as follows. Section 2 reviews the extant literature and presents our conceptual framework. Section 3 presents country and data descriptions while details of the estimation strategy are explained in Section 4. Both descriptive and econometric results are discussed in Section 5, and Section 6 concludes and gives an outlook for further research.

2. Literature Review and Conceptual Framework

Rational Expectations

Different theories on decision-making under uncertainty coincide in characterizing decisions as a result of preferences and the (subjective) probabilities of different risky states of nature (Giné et al., 2009). The process can be thought of as two-step (Barberis, 2013; Fox & Tversky, 1998): first, an individual makes a subjective assessment of the probability of a rare random event. Second, based on this probability assessment and taking into account her preferences, she makes a decision. The economics literature has long focused on preferences over risks (risk aversion) or probabilities (non-linear probability weighting) as drivers of heterogeneity in decision making under risk. In that context, it was found that the experience of random shocks can alter individual risk preferences (Cassar, Healy, & Kessler, 2017; Gloede, Menkhoff, & Waibel, 2015; Hanaoka, Shigeoka, & Watanabe, 2018; Liebenehm, 2018; Said, Afzal, & Turner, 2015; Voors et al., 2012).

Individual differences in subjective expectations, however, have long been neglected, since probability assessments were assumed to be in line with the Rational Expectation Hypothesis (Lucas & Sargent, 1981; Muth, 1961), stating that decision makers take into account all available information and make, on average, unbiased forecasts. When updating probabilistic expectations over time in the light of new information, this means that they should update according to Bayes' rule. Following Gallagher (2014), a decision makers conditional expectation of their probability p of incurring a specific shock under full information is given as:

$$E(p|S_t, t) = \frac{S_t+\alpha}{t+\alpha+\beta}. \tag{1}$$

Here, t is the number of time periods and $S_t = \sum_{s=1}^{t} v_s$ is the number of observed shock occurrences. The fixed parameters α and β determine prior beliefs over the probability of the shock.

However, there is a range of studies documenting deviations from rationality in expectation formation of macroeconomic fundamentals (see Assenza, Bao, Hommes, & Massaro, 2014; Coibion et al., 2018 for reviews) and probabilities (Barberis, 2013). Detecting deviations from rational expectations in probabilities of shocks that adversely affect decision makers is particularly complicated by the fact that decision makers can influence their own probability of incurring an adverse shock and have unobservable, private information regarding their risk of exposure (Rheinberger & Hammitt, 2018). Empirically, deviation from rational expectations can be detected by the predictability of forecast errors that would be random and unpredictable under rational expectations (Coibion & Gorodnichenko, 2012, 2015; Kucinskas & Peters, 2018). A range of alternative models have been sought out to explain predictability of forecast errors, incorporating information rigidities (e.g. Mankiw & Reis, 2002), behavioral biases

(Kahneman & Tversky, 1972; Tversky & Kahneman, 1973), or related phenomena (see Coibion & Gorodnichenko 2018 for a review).

To date there is little empirical evidence on the individual-specific determinants of expectations, especially in agricultural and development economics. Exceptions are Bellemare (2009), studying the determinants of subjective perceptions of tenure insecurity under different contracting scenarios; Lybbert et al (2007) studying determinants of rainfall expectation formation of pastoralists in Ethiopia and Kenya, and Giné et al. (2009), analyzing how Indian farmers form subjective beliefs regarding the timing of the monsoon rains and their accuracy.

Biases in Expectation Formation

There are several explanations for deviations from rationality in expectation formation. Under information rigidities, decision makers lag behind when incorporating new information to their expectations or perceive new information as noisy (Coibion et al., 2018), which would lead to *underreaction* to current information. However, when forming *probabilistic* expectations, behavioral biases that impair judgments about probabilities lead to *overreaction* to current information. It has been argued that decision makers tend to overestimate the probability of any event when past instances of the event are more easy to recall from their memories, such as recent and more salient events, due to the "availability bias" (Tversky & Kahneman, 1973). Likewise, they overestimate the probability of an event that is more representative for a whole class of events, due to the "representativeness bias" (Kahneman & Tversky, 1972). Emotions can also affect risk perceptions (Baron, Hershey, & Kunreuther, 2000; Loewenstein, Weber, Hsee, & Welch, 2001) such that experiencing adverse shocks may invoke negative emotion and lead to pessimism in the evaluation of probabilities of future adverse events (Blum, Silver, & Poulin, 2014; Botzen, Kunreuther, & Michel-Kerjan, 2015; Brown, Daigneault, Tjernström, & Zou, 2018; Sartore, Kelly, Stain, Albrecht, & Higginbotham, 2008).

These phenomena are supported by empirical evidence from non-farmer subjects suggesting that being struck by an emergency event increases the perceived probability of re-experiencing the same (Brown et al., 2018) or also other adverse events (Blum et al., 2014; Knuth, Kehl, Hulse, & Schmidt, 2014). As becomes evident in multiple period studies, decision makers tend to expose an extrapolative bias by which recent time lags of information are assumed to continue (e.g. Assenza et al., 2014). These considerations lead to our first hypothesis for this study:

> **Hypothesis 1: Reaction to own experience:** Farmers are, on average, more likely to update their expectation of a particular shock if they experienced this shock in the current year.

New information about an adverse shock can be in the form of own experience or from observing other's experience (Gallagher, 2014; Viscusi & Zeckhauser, 2015). Such indirect information, however, is likely to be discounted (Viscusi & Zeckhauser, 2015) depending on one's confidence in the relevance for oneself, which in turn depends on individual specific factors (Rheinberger & Hammitt, 2018; Viscusi, 1989). Assuming that information about risk is private and imperfect, the farmer's reaction when observing other village members' experience of shocks depends on how much he believes to deviate from them in terms of behavioral factors that influence risk. When assuming that village inhabitants perceive themselves to be similar in terms of exposure and self-protective behavior, a farmer's perceived probability of a shock should increase when a larger share of village members is affected by that shock, independently of whether they are affected themselves. This corresponds to our next hypothesis:

Hypothesis 2: Reaction to others' experience: Farmers are, on average more, likely to update their expectation of a particular shock if a larger share of households in their village experienced this shock in the current year.

Blum et al. (2014) argue that repeated experiences of negative events worsens people's general views about the world and its people being benevolent and alters how one projects the likelihood of future negative events based on one's memories. This argument is applied to our context in the next hypothesis:

Hypothesis 3: Other shocks: Farmers are, on average, more likely to update their expectation of a particular shock if they experienced a larger number of shocks in the current year.

Furthermore, we argue that how decision makers change their forecasts of shocks depends on the type of shock encountered. As argued by Rheinberger & Hammitt, (2018), individual-specific factors affect a decision maker's confidence in new information when updating probabilistic expectations. Similarly, we argue that when a decision maker experiences an adverse shock, the confidence in this shock carrying information regarding his future shock affectedness varies by type of shock. The accuracy of any probabilistic forecast, and therefore also the tendency to revise one's expectation, will also depend on how relevant the forecasted variable, in our case the probability of a shock, is to the livelihood of the forecaster (Brunnermeier & Parker, 2005; Giné, Townsend, & Vickery, 2009). Therefore, we would assume that farmers more readily adjust their perceived probability in case of agriculture-related shocks than other type of shocks, where the accuracy of the forecast is less important. This is formulated in our next hypothesis:

Hypothesis 4: Heterogeneous updating. Farmers are more likely to change their probabilistic expectations of an adverse shock in the case of agricultural shocks than other non-agricultural shocks.

In principle, the behavior in Hypotheses 1, 2, and 4 could be rational and reflect Bayesian updating as in equation (1). As an indicator for deviation from rational expectations, one may test for predictability of forecast errors, i.e. the difference between the expectation and realization of a forecasted variable, over time (Coibion & Gorodnichenko, 2012, 2015). Since we have limited information on the true objective probabilities of shocks that our farmers are facing, we apply a novel model that builds on this notion, but without requiring information about the true process underlying the forecasted variable suggested by Kucinskas and Peters (2018). This method relies on exploiting the autocorrelation structure of ex-post forecast errors and is thereby able to capture bias in expectation formation without requiring information about "true" probabilities. Following Kucinskas and Peters (2018), we assume a covariance-stationary process

$$v_t = \sum_{l=0}^{+\infty} \alpha_l \varepsilon_{t-l}, \tag{2}$$

with ε_t being a white noise series. Ex-post forecast errors e at time t are then defined as:

$$e_t = v_t - F_{t-1}(v_t) = -b_0 - \sum_{l=1}^{\infty} sgn(\alpha_l) b_l \varepsilon_{t-l} \tag{3}$$

Here, v_t is the realization of the random variable or process in t, $F_t(v_t)$ is the forecast of that realization in $t-1$, and $sgn(\alpha_l)$ is the sign of the true autocorrelation coefficient, α_t from equation (2). The variable b_l is the bias coefficient for the lag l. The forecast error e_t depends on a time-invariant bias b_0 and the sum of the product of all time-variant bias coefficients b that distorted the reaction to all past realizations l of the random variable ε. The autocorrelation structure of the forecast error serves as an indicator of bias. When expectation formation is unbiased, last year's forecast error should not significantly predict the current year's errors, but errors should just be random noise.

We will apply this approach in order to test whether, on average, the farmers in our sample have unbiased expectations regarding shocks, or tend to over- or underreact to new information. Kucinskas and Peters (2018) state that for a simple test of whether expectations are unbiased one does not need to know $sgn(\alpha_l)$. When we know the sign, however, we can draw conclusions about the direction of bias: If α_l in equation (2) is positive, we would conclude that a decision maker underreacts (overreacts) to new information when his/her forecast errors are positively (negatively) autocorrelated.

Given the prior findings of biases in expectation formation in all sorts of contexts, we also assume that farmers are not immune to these biases and tend to overreact to new information (i.e. when they are affected by a shock) when forecasting the likelihood of future shocks. Therefore, our next hypothesis is:

> **Hypothesis 5: Overreaction.** On average, farmers overreact to own experience of shocks when forming expectations regarding future shocks.

Mitigation and Precautionary Behavior

When people do not anticipate a particular adverse event, they may not engage in strategies to minimize its probability of occurrence and/or ex-post harm, as opposed to when they expect it to occur (assuming that they expect a shock to occur only when they are not able to *fully* mitigate its probability or harm). So from a normative point of view, understanding how vulnerable decision makers form probabilistic expectations of adverse shocks is important *because* one assumes that decision makers will adopt precautionary measures in order to alleviate the risk they perceive to be high – this idea is referred to as the "motivational hypothesis" (Weinstein, Rothman, & Nicolich, 1998). The validity of this hypothesis has been discussed critically, for instance, in the context of health (van der Pligt, 1996) and flood risks (Bubeck, Botzen, & Aerts, 2012). Recent evidence in favor of the hypothesis include Beatty et al. (2019), finding that public disaster forecasts affected both ex-ante and ex-post mitigation behavior, and Gallagher et al. (2014), finding that flood insurance sales increase in flood affected regions. In the agricultural economics literature, it has been found that farmers do not necessarily change their protective behavior when receiving rainfall information (Luseno, McPeak, Barrett, Little, & Gebru, 2003), even though they do update their subjective expectations of rainfall (Lybbert et al., 2007). Lybbert et al. (2007) argue that the more coping strategies one has available ex-post, the lower will be the effect of an adverse event on the ex-post welfare and the lower will be the value of changing behavior ex-ante.

However, ex-post coping strategies can also be harmful, for example when they involve depleting productive assets, taking children out of school, and reducing food or health expenditures (e.g. Dercon, 2002; Kinsey, Burger, & Gunning, 1998; Rosenzweig & Wolpin, 1993). We would expect farmers to avoid these harmful ex-post measures through adoption of less harmful precautionary measures when they expect adverse shocks to occur. Precautionary savings present a strategy to enable consumption smoothing in the face of adverse shocks (Besley, 1995; Karlan, Ratan, & Zinman, 2014). This leads to our final hypothesis:

> **Hypothesis 6: Expectation, mitigation and coping.** The more shocks farmers expect, (1) the more precautionary savings they hold *ex-ante* and (2) the fewer harmful *ex-post* coping strategies they apply when affected by shocks.

3. Country and Data Description

Sampling and Data Collection

We answer the stated research questions with econometric analyses of a balanced panel dataset from the HORTINLEA household survey (Kebede & Bokelmann, 2017) undertaken in rural and peri-urban areas of Kenya in 2014, 2015 and 2016 with African indigenous vegetable (AIV) producers. Even though Kenya is categorized among the lower middle income countries, its economy is based on agriculture which accounts for 26% of GDP, 65% of total exports and more than 18% of the country's formal employment (FAO, 2014). As common in many developing countries, the agricultural sector in Kenya is dominated by smallholder farmers that are prone to adverse shocks which lead to food insecurity and malnutrition, and the use of potentially harmful coping strategies (Mathenge & Tschirley, 2015).

The rural sites of the HORTINLEA study were located in two counties in Western Kenya, Kisii and Kakamega, while the peri-urban sites were in the counties Kiambu, Nakuru, and Kajiado (Figure A1 in the Annex). Households for the survey were selected using multi-stage sampling approach. First the four counties were purposely selected based on prevalence of AIV production. The selection of the sub-counties and divisions was based on information from the respective district agricultural offices on experiences of AIV production. From each division, locations/wards were randomly selected, and in turn households within locations were randomly selected (see Table A1 in the Annex for details of the survey). The survey was carried out through face-to-face interviews with farmers engaged in indigenous vegetable production, marketing, and consumption.

In 2014, the number of households interviewed was 1232. However, this number was reduced to 700 households in the subsequent surveys in 2015 and 2016 for budgetary reasons. However, the households were randomly dropped keeping the proportion of respondents constant with in the counties. As Table A2 in the Annex shows, households that are dropped from the survey after 2014 have similar socio-economic characteristics and are affected by a similar amount of shocks. However, households that are kept on average expected significantly more shocks than those who were dropped. Overall, from 2014 to 2016, the attrition rate is 2.8%. The final balanced sample consists of 684 farmer respondents.[4]

Relevance of the Survey for Research Question

Even though the HORTINLEA survey is not representative at national level, the data provides a comprehensive overview of indigenous vegetable producers in rural and peri-urban areas. Given the randomized sampling method and the relatively large sample size in each county, results of analysis on the survey data can be generalized to indigenous vegetable producers in rural and peri-urban areas in Kenya. The survey has an elaborated module on shocks which elicits binary data on the experience of 24 different shocks every year, as well as binary data on expectations of shocks in the coming year, and some other characteristics of shocks. Shocks can be roughly categorized as weather shocks (such as drought and flood) agricultural production shocks (such as pests); economic shocks (such as job loss and expenditures for festivity); price shocks (such as food and input price increase); and demographic shocks (such as death or illness of household member).

Vegetable production, including indigenous vegetables is a recent phenomenon in Kenya and is associated with high value-added and income generation for farmers (e.g. Rao & Qaim, 2011). As common in other agricultural products, these vegetables are prone to various shocks, such as weather related shocks of drought and shortage of water as well as pests and diseases. Therefore, our sample of indigenous vegetable producers provides the ideal setting to assessing

[4] Very few missing values each year were inputed with values from the values of the past or following surveys, as it applied, such as respondent age (8 cases), highest level of education (48 cases), and asset index (3 cases). One observation had to be dropped.

the exposure to various shocks of vegetable producers and their expectation formation. In addition, this provides us the opportunity to recommend policies that have double effect on both reducing farmers vulnerability by understanding expectation formation determinants.

4. Estimation Strategy

Determinants of Expectations

In order to test hypothesis 1-4, namely the factors affecting the updating of expectations regarding the experience of a range of shocks, we pool the data across shocks and estimate the probability of expecting any particular shock conditional on a range of covariates with linear fixed effects models. Since our outcome variable is binary, a logit estimator would be preferred. However, the incidental parameters problem in non-linear fixed-effects panel models with large cross sections with short time-series would introduce bias (Wooldridge, 2002). Since we have a relatively large cross-section and only a short time series, we prefer to assume a linear relationship and use a linear fixed effects model. Using fixed effects, we can control for unobserved time-invariant heterogeneity such as a farmers general exposure to environmental risks due to, for instance, his plot's location, as well as time-invariant shock specific factors. We also need fixed effects to capture within-variation, meaning what drives farmers to change their expectations over time, not differences between farmers. Our estimation model is:

$$y_{sijt} = \alpha X'_{sijt} + \beta Z'_{ijt} + u_{sij} + e_{sijt} \tag{4}$$

$$\text{with } X'_{sijt} = (y_{sijt-1};\ v_{sijt}\ ;\ \overline{v}_{sjt};\ \textstyle\sum_{s=1}^{24} v_{sijt})$$

Here, y_{sijt} is a binary indicator variable taking the value 1 if a specific shock s is expected to occur in the next 12 months by respondent i of village j in year t. X'_{sijt} is a vector of time-variant, shock-specific regressors. It includes a binary variable v_{sijt} indicating whether i experienced shock s in t, the lagged dependent variable y_{sijt-1} indicating whether shock s was expected in $t-1$, a variable $\bar{v}_{sjt}$ comprised of the average of v_{sijt} by village j (excluding farmer i), and $\sum_{s=1}^{24} v_{sijt}$, the sum of the shock indicators for all 24 shocks that i could have experienced in t. In further specifications testing the heterogeneous effects by shock type, we interact the shock experience variable v_{sijt} with indicators of the type of shock (weather, agriculture, demographic, economic, price). Z'_{ijt} is a vector of individual-specific, shock-unspecific time-variant characteristics varying by estimated model, including household size, land size, and asset ownership. The terms u_{sij} and e_{sijt} denote the time-invariant individual-specific fixed effects by shock and the error term, respectively. In the estimations, standard errors are clustered at the household level to take into account the multiple observations per household.

Forecast Errors

For the forecast errors, we follow the approach suggested in Kucinskas and Peters (2018). First, we calculate the ex-post forecast error e_{sit} as the difference between the shock-affectedness variable v_{sit} and last year's forecast y_{sit-1}:

$$e_{sit} = v_{sit} - y_{sit-1} \tag{5}$$

Due to the binary structure of our shock data the variable e_{sit} has three possible values [-1; 0; 1]. We therefore estimate an ordered logit model for e_{sit} to take into account the categorical structure of the variable. We also assume a linear relationship and estimate a linear autoregressive model for e_{sit}:

$$e_{sit} = c + \alpha e_{sit-1} + \beta X'_{it} + \gamma Z'_{i} + \varepsilon_{sit} \tag{6}$$

To gain information on whether farmers over- or underreact to the experience of shocks when forming expectations, we furthermore estimate a linear autoregressive model for the shock experience v_{sit}:

$$v_{sit} = c + \alpha v_{sit-1} + \beta X'_{it} + \gamma Z'_i + \varepsilon_{sit} \tag{7}$$

In equations (6) and (7), we control for a one-year time lag of the dependent variable and a vector of time-variant (X'_{it}) (age, household size, asset index, land size, total number of shocks, year dummy) and time-invariant covariates (Z'_i) (gender of the respondent, location dummies, highest level of education) that may affect both the forecast errors as well as shock exposure in general. Note that since we only have three years of data, the estimation in equations (6) and (7) are based on two years. Standard errors are always clustered at the household level.

Precautionary Savings and Mitigation Behavior

In order to test for whether expectations of shocks affects precautionary savings behavior, we additionally estimate the following model

$$savings_{it} = \alpha \sum_{s=1}^{24} y_{sit-1} + \beta X'_{it} + \gamma Z'_i + \varepsilon_{it} \tag{8}$$

Here, *savings* refers to (1) either a binary variable indicating whether a farmer holds savings for precautionary motives (given he/she holds any savings at all) or (2) a categorical variable for six intervals of savings amounts ranging from 0 (no savings), 1 (0 to 5,000 KSH), to 5 (100,000 KSH and more). The term $\sum_{s=1}^{24} y_{sijt}$ refers to the sum of all shocks expected by the farmer. The model is estimated as (1) panel logit and (2) ordered logit model with random effects. The control variables are identical to the previous model. To analyze how expectation affects coping, we estimate a random effects logit model of the following form:

$$coping_{sit} = \alpha y_{sit-1} + \beta X'_{it} + \gamma Z'_i + \varepsilon_{sit} \tag{9}$$

Here, *coping* is a binary indicator taking the value 1 if one or more harmful coping strategies[5] are chosen in t in response to a specific shock s, and y_{sit-1} indicated whether the farmers expected the shock to happen.

[5] We define harmful coping strategies as any of these: buying less inputs, taking children out of school, making children work, selling of livestock, land, or storage, switching to lower valued food items, reducing number of meals, eating less diverse foods.

5. Results

5.1. Descriptive Results

Table 1 presents some socio-demographic characteristics of the balanced sample by year. In 2014, the average respondent was 50 years old, owned around 0.8 ha of land, lived in a household with around 6 persons, and has completed secondary education. Most respondents were male (around 80%). On average, they suffered between 2 and 3 shocks a year between 2014 and 2016 and expected on average 1.3, 1,7, and 0.7 shocks to occur in 2014, 2015, and 2016, respectively.

Table 2 describes the farmers' shock experience during the last twelve months prior to the survey as well as their respective shock expectations for the following twelve months separately by shock and survey year for the balanced sample. Drought is the most widespread shock reported by more than 31% of the overall sample across the three years, followed by crop failure. Illness of a household member is reported by about 24% of the households across years, while livestock death and unusually heavy rain are reported by about 21% of the households in the survey. There is substantial variation across years, though. For instance, the proportion of households that reported a drought rose from 18% in 2014 to 45% in 2015 and dropped to 40% in 2016. In general, we find that weather and agricultural production shocks are most dominant among the surveyed households as their livelihood is based on rain-fed agriculture. Demographic shocks apart from illnesses of household members as well as price or economic shocks mostly affected only a small fraction of farmers, with some exceptions, such as food price increases that affected only 7% of households in 2014 and 19% in 2015.

Comparing shock expectations, we find that our sample households seem to be optimistic in a sense that on average, the fraction of farmers experiencing shocks is substantially higher than those expecting them in any given year. This is reflected in the classification of households in Table 3. For example, 26% of farmers never expected a drought throughout the time span of the survey (and regardless of whether they were affected by drought), while only 0.3 percent expected a drought to occur every year. Around 10 percent are realistic in a sense that their drought expectation is confirmed (i.e., their forecast is correct). We observe similar trend for the other shocks as well.

Figure 1 depicts the time trends of three variables: the shares of farmers affected by a particular shock, the share of farmers that expected this shock to re-occur in the next year, and the share of farmers that expected this shock to re-occur conditional on having been affected. The first graph on the upper left presents this trend for drought: In 2014, 18% of the farmers in the sample faced a drought and 16% expected a drought for 2015, while less than half of those were also affected by drought. In 2015, 44% faced drought and the share of farmers expecting a drought for 2016 increased to 28% (with 19% were affected). These descriptive results show that farmers tend to update their expectation based on experience of shocks. This is clearly observed especially for shocks related to agricultural production such as drought, crop failure and unusually heavy rain, and less so for health shocks and death of livestock. As stated earlier, expectations of health related shocks are in general quite low as compared to weather related production shocks. Reasons are most likely cultural in nature, as explicitly expecting such an event might connote an omen of bad luck.

5.2. Estimation Results

Determinants of Expectations

The coefficients from estimating equation (4) (determinants of expectation formation) are reported in Table 4. All models control for time-variant sociodemographics, while in models

(2) and (3) we additionally control for shock severity and a time trend, respectively. Our preferred specification is the full model (3).

First, we find that having been affected by a particular shock in the current year significantly increases farmers' likelihood of expecting the same shock to re-occur in the coming year by around 15% in our preferred specification. This result is in line with hypothesis 1, stating that farmers' expectations react to the experience of shocks, and it is in line with the descriptive findings from Figure 1.

We also find that after controlling for the farmers' own experience of the shock, a larger share of other village inhabitants being affected (excluding the farmer him/herself) increases perceived likelihood of the same shock to re-occur in the coming year. This is in line with hypothesis 2, stating that the farmers do not only update their expectations based on their own, but also to relevant others' experience of a particular shock.

Lastly, the higher the total number of shocks one has experienced in a given year, the higher is his/her perceived likelihood of being affected by any shock in the coming year. This is in line with our hypothesis 3 and reflects the notion in the literature documenting cross-over effects between different shocks and respective expectations and arguing that the more adverse life events one has experienced, the more likely one is to expect other adverse events to occur in the future (Blum et al., 2014; Knuth et al., 2014). However, the effect size is rather small.

In models (4) to (6), we estimate heterogeneous effects of shock affectedness by shock type. The composition of the shock categories can be found in Table 2. We hypothesized that farmers would update their expectations more strongly in response to experiencing shocks that directly relate to their agricultural production. The omitted category in the estimations refers to weather shocks. Relative to weather shocks, farmers are significantly less likely to update expectations when they experienced other agricultural shocks, demographic shocks, or economic shocks.

This only partly reflects our hypothesis (4), assuming expectations to move stronger with experience of shocks that are of direct significance for agricultural production. This is true for expectations about demographic shocks and more general economic shocks, but these, of course, also entail significant economic effects. The difference between general weather shocks and other agricultural shocks seems unclear. The main distinction is that the latter shocks in general occur less frequently.

When looking at our control variables, we find that farmers' expectations are negatively correlated over time, and that higher perceived shock severity (rated on a 4 point scale ranging from 0=”no impact to 3=“high impact”) decreases the perceived likelihood of the shock to re-occur, potentially due to a form of diminishing sensitivity. This result is not straight forward and deserves further investigation.

Forecast Errors

The regression results for the forecast error on its lagged value as in equation (6) are found in Table 5. The columns are alternately showing estimation coefficients for a linear and ordered logit model, respectively. The main result we can draw from models (1) and (2) of this estimation is that, on average, the forecast errors are statistically significant and negatively autocorrelated, controlling for a range of time-variant and –invariant household and shock specific characteristics. This means that farmers' updating of expectation is, on average, biased (Kucinskas and Peters 2018). The magnitudes of the correlations vary by shock type, but they are unambiguously negative, except for demographic and economic shocks, for which we find a positive correlation of forecast errors, however the coefficient for economic shocks is statistically insignificant, suggesting that economic shock expectations are unbiased (or a lack of observations, since relatively few farmers expect any economic shocks, on average).

To make sense of these correlations, we compare them with the results from estimating equation (7), i.e. the autocorrelation structure of shocks, on average and by type of shock. Model (1) in Table 6 shows that on average, the shocks that the farmers face are statistically significant and positively correlated over time. Models (2) to (3) confirm this relationship for all the groups of shocks (although with varying magnitudes). Following the model by Kucinskas and Peters (2018), if the shocks are positively correlated, we can conclude that a decision maker underreacts (overreacts) to new information when his/her forecast errors are positively (negatively) autocorrelated. Our evidence suggests that farmers, on average, overreact when updating their shock expectations in the light of shock experience, but this does not hold for all types of shocks: when updating expectations of demographic shocks (e.g. death or illness of household members), farmers tend to underreact, and for economic shocks (e.g. theft of goods, job loss), they neither over- nor underreact.

This discrepancy deserves further investigation. The underreaction to demographic shocks likely has to do with cultural norms and social desirability, in a sense that stating such expectations is socially inacceptable and may evoke misfortune.

Mitigation and Coping Behavior

Finally, we are interested in which way expectations of shocks, regardless of whether they are biased or not, affect precautionary and coping behavior. Table 7 depicts results from estimating equation (8). Models (1) through (3) show the determinants of the conditional probability of holding precautionary savings, given that a household has any savings at all. The results show that the probability of indicating precautionary motives for holding savings significantly increases with the number of shocks expected. Models (4) through (6) show the determinants of the amount of savings, conditional on saving for precautionary motives. Herein we find that the amount of precautionary savings is not affected by the expectation of shocks.

Furthermore, we asked whether the probability of choosing a bad coping strategy lower when expecting a shock. The results from estimating the respective equation (9) are depicted in Table 8. We defined “bad coping strategies” as any response to a shock that potentially negatively affects productivity on the long run and may lock households in a poverty trap (i.e. by lowering human capital or physical investments): buying less inputs; eating lower quantity, diversity, or lower quality food; taking children out of school; making children work; selling livestock or land. We could think that when a farmer expects a shock (given that he/she cannot fully mitigate it ex-ante), he/she is better prepared for it and less likely to use one or more of the mentioned harmful coping strategies. However, looking at the probabilities of choosing at least one harmful coping strategy conditional on having been affected by a specific shock and controlling for a range of household and shock characteristics (Table 8), we do not find that farmers are less likely to choose a bad coping strategy when expecting a shock before, not on average and not for specific types of shocks. In fact, in the case of economic shocks (e.g. theft of assets), farmers are even more likely to adopt harmful coping strategies in response to such a shock when they expected it than when they did not expect it. This result seems counterintuitive and will deserve further investigation.

6. Conclusion

Rural households in developing countries are faced with multiple adverse events. In this paper we used a large three-wave panel survey of Kenyan vegetable farmers with detailed information on a wide range of shock events and shock expectations to explore the question how farmers form expectations about such events. While on average relatively few farmers expect shocks to occur, we find that famers update their expectation of a future shock upon experiencing that shock or observing other village members experiencing it. Also, the more shocks a farmer experiences in total the more strongly he or she believes that any shock will affect them the future, likely due to an increased perceived vulnerability and more pessimism about the future.

Applying a novel method (Kucinskas and Peters 2018), we find that farmers' expectations are on average biased: farmers overestimate the probability of a shock to re-occur in the coming 12 months when they were personally affected by it. When looking at specific type of shocks, we find that while for most shocks with direct impact on livelihoods (weather, other production shocks, price shocks) they consistently overreact to their own experience of that shock, they underreact to own experience of demographic shocks, such as illnesses of household members. Likely, this result has to do with social norms that proscribe expressing such expectations.

Biased shock expectations could have harmful consequences when they result in a biased timing of the adoption and dis-adoption of precautionary behavior. When looking at behavior, however, we do not find that farmers significantly increase neither their amount of precautionary savings when expecting more adverse shocks in total, nor reduce their use of negative coping strategies upon expecting a specific shock.

This is in line with the findings from Lybbert et al. (2007), who do not report behavioral change even though farmers updated their rainfall expectations after receiving weather forecast information. It is also in line with findings from other disciplines, often finding that expecting an adverse event does not lead to an increased adoption of precautionary measured. Bubeck et al. (2012) stress that apart from risk perception, a necessary condition is "coping appraisal" (Bubeck et al. 2012, p. 1485), which describes the confidence of an individual in specific risk reduction mechanisms, personal efficacy, and response cost. As laid out by Lybbert et al. (2007), the more coping mechanisms a farmer has available, harmful or not, the lower might be the perceived benefit of ex-ante behavioral change and the higher is the perceived response cost. Regarding confidence in protective measures and self-efficacy, more research is needed that explicitly elicits these attitudes.

Finally, some words on the limitation of the study are in order. First, our paper would of course benefit from having more waves of data. Nevertheless, this is one of the very few datasets that elicits shock expectations over time and presents a good start. Second, we only have binary information regarding shocks, while it would be beneficial to have more detailed subjective probabilities about shocks. Third, validating the accuracy of expectations of weather shocks with rainfall data is also considered as a next step in this research.

Table 1: Socio-economic characteristics of respondents' households (balanced sample)

	2014		2015		2016	
	mean	sd	mean	sd	mean	sd
Highest level of education of farmer	2.71	.81	2.70	.82	2.71	.82
Respondent age; years	50.12	12.58	51.67	12.55	52.73	12.64
Farmer is female; dummy	.20	.40	.18	.38	.18	.39
Household size	5.60	2.35	5.92	2.33	6.11	2.37
Asset index	.21	.14	.23	.16	.276	.18
Land size; ha	.78	.84	.99	1.39	.99	1.34
Total no. of shocks affected	1.95	1.31	3.00	2.10	1.90	1.15
Total no. of shocks expected	1.27	1.42	1.73	2.28	.68	1.07
Observations	684		684		684	

Asset index is based on standardized principal component analysis scores for ownership of around 50 assets.
Education is a categorical variable with referring to completion of 1="Preschool or lower"; 2="Primary"; 3="Secondary"; 4="Tertiary"; 5="University".

Table 2: Shock affectedness and expectations by year and type of shock for balanced sample

	2014			2015			2016		
	Affected in t	Expected in t+1	Affected in t AND expected in t+1	Affected in t	Expected in t+1	Affected in t AND expected in t+1	Affected in t	Expected in t+1	Affected in t AND expected in t+1
Weather shocks									
Drought	0.177	0.159	0.070	0.447	0.287	0.190	0.402	0.208	0.129
Shortage of water	0.096	0.057	0.035	0.213	0.120	0.056	0.079	0.051	0.018
Flood	0.020	0.031	0.016	0.053	0.048	0.012	0.012	0.018	0.004
Unusually heavy rain	0.189	0.156	0.094	0.259	0.183	0.083	0.130	0.072	0.019
Land slide/erosion	0.020	0.018	0.012	0.048	0.045	0.025	0.007	0.006	0.000
Storm	0.050	0.031	0.013	0.051	0.034	0.013	0.047	0.015	0.001
Agricultural production shocks									
Crop failure	0.263	0.143	0.096	0.392	0.159	0.094	0.279	0.032	0.020
Pests on livestock	0.028	0.034	0.020	0.048	0.054	0.016	0.020	0.010	0.000
Pests on crops	0.102	0.050	0.026	0.099	0.085	0.028	0.069	0.015	0.007
Crop diseases	0.219	0.004	0.000	0.082	0.012	0.001	0.047	0.009	0.000
Livestock death	0.167	0.028	0.020	0.281	0.038	0.022	0.241	0.007	0.004
Livestock disease	0.123	0.058	0.039	0.096	0.051	0.022	0.088	0.010	0.004
Price shocks									
Food price increase	0.066	0.098	0.032	0.192	0.178	0.094	0.073	0.085	0.016
Input price increase	0.038	0.045	0.007	0.104	0.111	0.044	0.020	0.019	0.001
Fuel price increase	0.016	0.023	0.006	0.031	0.031	0.010	0.009	0.004	0.000
Economic Shocks									
Theft of goods/livestock	0.080	0.044	0.020	0.127	0.058	0.025	0.092	0.039	0.012
Forced contribution	0.001	0.000	0.000	0.039	0.003	0.001	0.041	0.000	0.000
Job loss	0.015	0.159	0.001	0.016	0.083	0.003	0.001	0.022	0.000
Money spent for ceremony	0.003	0.000	0.000	0.012	0.006	0.001	0.003	0.003	0.000
Demographic shocks									
Death of member	0.051	0.004	0.000	0.085	0.006	0.000	0.020	0.000	0.000
Illness of member	0.205	0.023	0.016	0.311	0.015	0.012	0.203	0.001	0.000
Divorce	0.007	0.102	0.000	0.003	0.105	0.001	0.001	0.045	0.000
Member left household	0.003	0.000	0.000	0.007	0.016	0.000	0.009	0.006	0.001
Person joined household	0.006	0.000	0.000	0.010	0.003	0.001	0.006	0.001	0.000
Observations	684			684			684		

Figure 1: Shock expectations and shock affectedness (percentage of households) for the five most common shocks

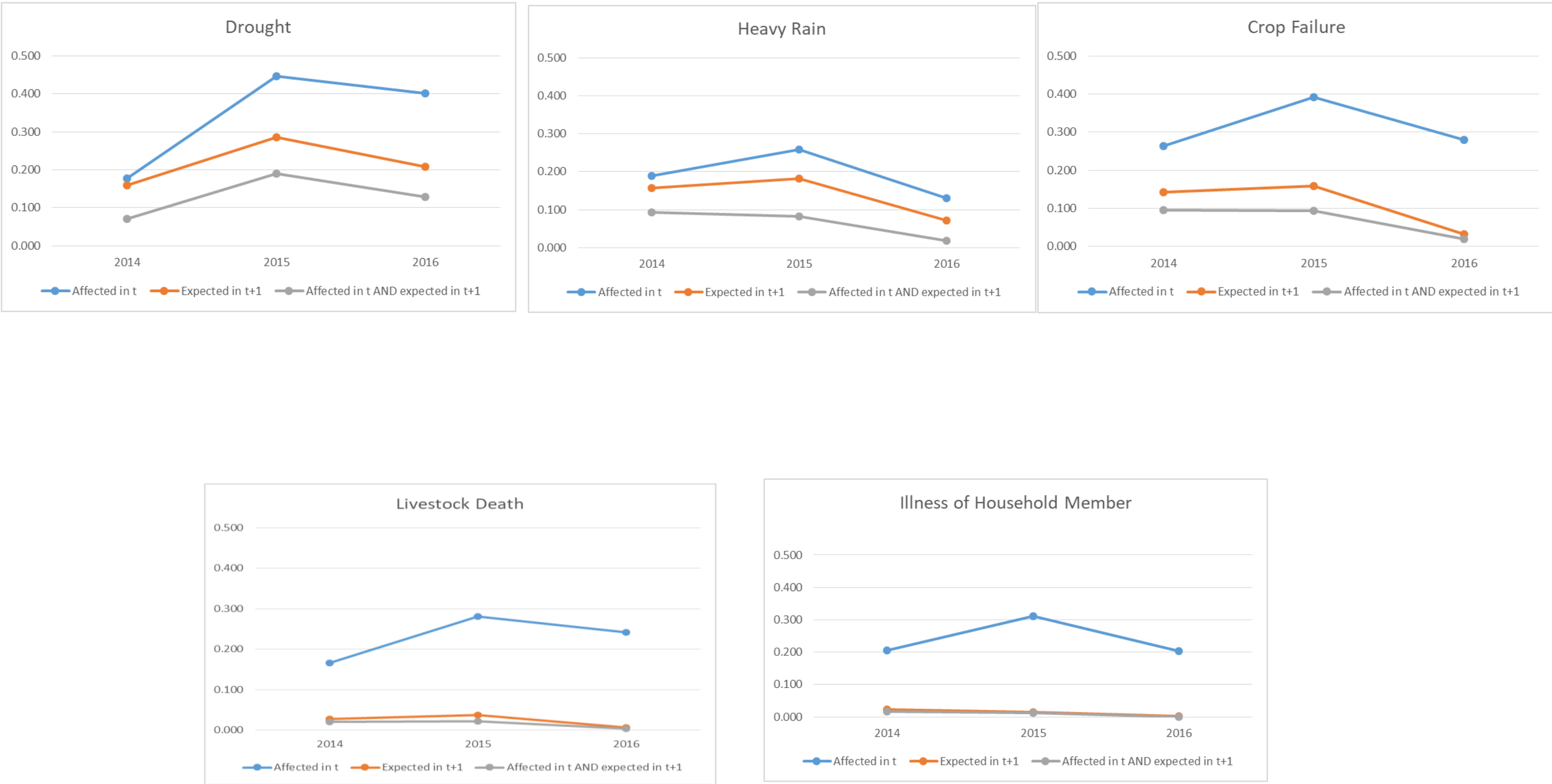

Table 3: Categorization of households by shock occurrence and expectation

	Percentage of households				
	Drought	Crop failure	Unusually heavy rain	Illness of hh member	Livestock death
"Optimistic"	26	38.88	35.8	53.25	51.54
"Pessimistic"	0.32	0.16	0.08	0	0
"Realistic"	10.08	15.18	23.78	25.57	25.16

Definition Optimistic: if respondent did not expect any shock to happen in neither 2014, 2015 nor 2016

Pessimistic: if respondent expected a specific shock to happen every year in both 2014, 2015 and 2016

Realistic: if respondent expected (did not expect) a specific shock to happen and was affected (was not affected) the following year.

Table 4: Determinants of shock expectations

	(1)	(2)	(3)	(4)	(5)	(6)
Affected=1	0.07***	0.15***	0.15***	0.10***	0.17***	0.17***
	(0.01)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)
Village affected; share	0.14***	0.14***	0.09***	0.13***	0.13***	0.08**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
No. of other shocks	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
L.expected=1	-0.56***	-0.56***	-0.56***	-0.56***	-0.56***	-0.56**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Affected=1×Agricultural shock=1				-0.06***	-0.06***	-0.06**
				(0.02)	(0.02)	(0.02)
Affected=1×Demographic shock=1				-0.09***	-0.09***	-0.10**
				(0.02)	(0.02)	(0.02)
Affected=1×Price shock=1				0.05*	0.05*	0.04*
				(0.03)	(0.03)	(0.03)
Affected=1× Economic shock=1				-0.05**	-0.05**	-0.06**
				(0.02)	(0.02)	(0.02)
Household size	-0.00	-0.00	0.00	-0.00	-0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Land size; ha	0.00	0.00	-0.00	0.00	0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Asser index	-0.01	-0.01	0.04*	-0.01	-0.01	0.04*
	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)
Shock severity		-0.03***	-0.03**		-0.03**	-0.03**
		(0.01)	(0.01)		(0.01)	(0.01)
year=2016			-0.02***			-0.02**
			(0.00)			(0.00)
Constant	0.06**	0.05**	0.04*	0.06**	0.06**	0.04*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Observations	32808	32806	32806	32808	32806	32806
R^2	0.439	0.440	0.441	0.442	0.443	0.444
sigma_u	0.23	0.23	0.23	0.23	0.23	0.23
sigma_e	0.16	0.16	0.16	0.16	0.16	0.16
rho	0.67	0.67	0.67	0.67	0.67	0.67
No. of clusters	684	684	684	684	684	684

Fixed effects linear models. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Expected=1 if farmer expects a shock to occur in t+1

Affected=1 if farmer was affected by a shock

Shock severity is self-assessed on a 4-point scale ranging from 0="no impact", 1="Low impact", 2="Medium impact", to 3="High impact".

L denotes lagged value (t-1)

Asset index is based on standardized principal component analysis scores for ownership of around 50 assets.

Weather shock (omitted category) refers to either crop drought, shortage of water, flood, unusually heavy rain, land slide, storm.

Table 5: Autocorrelation of forecast errors for whole sample and conditional on type of shock

	All		Weather		Price		Demo.		Agric.		Econ.	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
L.Forecast error	-0.54***	-0.06***	-0.82***	-0.13***	-1.64***	-0.21***	1.43***	0.12***	-0.46***	-0.07***	0.34	0.02
	(0.11)	(0.01)	(0.15)	(0.02)	(0.21)	(0.03)	(0.20)	(0.02)	(0.14)	(0.02)	(0.38)	(0.02)
No. of other shocks	0.00	0.00	-0.04	-0.01	0.17**	0.02**	-0.24***	-0.02***	-0.11*	-0.02*	-0.10	-0.01
	(0.00)	(0.00)	(0.05)	(0.01)	(0.08)	(0.01)	(0.06)	(0.00)	(0.06)	(0.01)	(0.07)	(0.00)
Household size	0.07*	0.01*	0.03	0.00	0.03	0.00	0.04	0.00	0.03	0.00	0.00	0.00
	(0.04)	(0.01)	(0.02)	(0.00)	(0.04)	(0.00)	(0.03)	(0.00)	(0.02)	(0.00)	(0.04)	(0.00)
Land size; ha	0.10	0.01	-0.05*	-0.01**	-0.01	-0.00	0.02	0.00	0.04	0.01	0.01	0.00
	(0.09)	(0.01)	(0.03)	(0.00)	(0.05)	(0.01)	(0.04)	(0.00)	(0.04)	(0.01)	(0.06)	(0.00)
Asset index	-0.07*	-0.01*	-0.50*	-0.08*	-0.87	-0.11	-0.27	-0.02	-0.03	-0.01	-0.28	-0.02
	(0.04)	(0.00)	(0.30)	(0.05)	(0.61)	(0.07)	(0.52)	(0.04)	(0.33)	(0.05)	(0.63)	(0.04)
Head is female; dummy	0.03*	0.00*	0.08	0.01	-0.21	-0.03	0.17	0.01	0.18	0.03	0.23	0.01
	(0.02)	(0.00)	(0.13)	(0.02)	(0.21)	(0.02)	(0.17)	(0.01)	(0.13)	(0.02)	(0.21)	(0.01)
Age; years	-0.00	-0.00	0.00	0.00	0.01	0.00	0.02***	0.00***	-0.01	-0.00	0.01	0.00
	(0.02)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
Education	-0.33	-0.04	0.08	0.01	0.14	0.01	0.16*	0.01*	-0.01	-0.00	0.13	0.01
	(0.24)	(0.03)	(0.06)	(0.01)	(0.12)	(0.01)	(0.09)	(0.01)	(0.07)	(0.01)	(0.11)	(0.01)
Constant		-0.04		-0.05		-0.18***		-0.08**		0.10*		-0.04
		(0.03)		(0.05)		(0.06)		(0.04)		(0.06)		(0.04)
County dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
cut1												
_cons	-2.46***	-2.40***	-2.06***		-1.38**		-2.33***		-3.14***		-2.72***	
	(0.24)	(0.25)	(0.33)		(0.57)		(0.49)		(0.38)		(0.58)	
cut2												
_cons	2.91***	2.98***	2.65***		4.85***		4.51***		1.81***		4.07***	
	(0.24)	(0.25)	(0.33)		(0.59)		(0.51)		(0.36)		(0.58)	
N	16032	16032	4008	4008	2004	2004	3340	3340	4008	4008	2672	2672
R^2		0.007		0.019		0.066		0.030		0.011		0.007
pseudo R^2	0.008		0.017		0.072		0.045		0.010		0.013	

Dependent variable: forecast error. Standard errors clustered at hh level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Models alternate between ordered logit and OLS regression. L denotes lagged value (t-1)
Asset index is based on standardized principal component analysis scores for ownership of around 50 assets.
Education is a categorical variable with referring to completion of 1="Preschool or lower"; 2="Primary"; 3="Secondary"; 4="Tertiary"; 5="University".
"Weather" refers to either crop drought, shortage of water, flood, unusually heavy rain, land slide, storm.
"Agri" refers to either crop failure, pests on livestock, pests on crops, crop disease, livestock death, livestock disease.
"Demo" shock refers to either death of household member, illness of household member, divorce, person joining or leaving the household.
"Price" refers to either food, fuel, or input price increase.
"Econ" refers to either theft of goods or livestock, job loss, forced contribution, money spent on ceremony.

Table 6: Autocorrelation of shock affectedness for whole sample and conditional on type of shock

	All	Weather	Price	Demo.	Agric.	Econ.
	(1)	(2)	(3)	(4)	(5)	(6)
L.Affected=1	0.12***	0.14***	0.09***	0.03**	0.11***	0.13***
	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)
No of other shocks	-0.01***	-0.02**	-0.02***	0.01	-0.01***	-0.02***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
Household size	0.00**	0.00*	0.00	0.00	-0.00	0.00*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Land size; ha	-0.00	-0.01*	0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Asset index	-0.01	-0.03	0.01	-0.02	0.01	0.01
	(0.02)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)
Respondent age; years	0.00	0.00	-0.00*	0.00	0.00	0.00**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Farmer is female=1	0.00	0.00	0.02	-0.02	0.00	0.00
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
Education	0.00	0.01	-0.00	0.01	0.01*	0.00
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	0.06***	0.07*	0.16***	0.00	0.01	-0.00
	(0.02)	(0.04)	(0.04)	(0.03)	(0.02)	(0.03)
County dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	16032	4008	4008	2004	2672	3340
R^2	0.028	0.040	0.017	0.009	0.025	0.038

Standard errors clustered at household level in parentheses. OLS Regressions. Dependent variable.=Shock affectedness (dummy)
L denotes lagged value (t-1). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Asset index is based on standardized principal component analysis scores for ownership of around 50 assets.
Education is a categorical variable with referring to completion of 1=”Preschool or lower”; 2=”Primary”; 3=”Secondary”; 4=”Tertiary”; 5=”University”.
“Weather” refers to either crop drought, shortage of water, flood, unusually heavy rain, land slide, storm.
“Agri” refers to either crop failure, pests on livestock, pests on crops, crop disease, livestock death, livestock disease.
“Demo” shock refers to either death of household member, illness of household member, divorce, person joining or leaving the household.
“Price” refers to either food, fuel, or input price increase.
“Econ” refers to either theft of goods or livestock, job loss, forced contribution, money spent on ceremony.

Table 7: Precautionary savings

	Prob. of saving for unexpected event			Savings amounts		
	(1)	(2)	(3)	(4)	(5)	(6)
Savings amount	0.06	0.08	0.06			
	(0.08)	(0.09)	(0.09)			
Total no. of shocks	0.11**	0.15***	0.17***	0.03	-0.03	-0.01
	(0.05)	(0.06)	(0.06)	(0.07)	(0.07)	(0.08)
Respondent age; years	0.00	0.00	0.00	0.01	0.02	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Farmer is female=1	0.04	0.01	-0.05	-0.76*	-0.72*	-0.85**
	(0.28)	(0.28)	(0.28)	(0.39)	(0.40)	(0.41)
Education	-0.05	-0.05	-0.05	0.09	0.06	0.06
	(0.13)	(0.14)	(0.14)	(0.19)	(0.19)	(0.19)
Household size	-0.02	-0.02	0.00	-0.15**	-0.11	-0.10
	(0.05)	(0.05)	(0.05)	(0.07)	(0.07)	(0.08)
Land size; ha	-0.08	-0.08	-0.07	0.01	-0.01	0.06
	(0.08)	(0.08)	(0.08)	(0.16)	(0.17)	(0.17)
Asset index	0.98	0.90	0.13	3.31***	3.61***	3.00***
	(0.63)	(0.65)	(0.74)	(0.94)	(0.96)	(1.11)
Constant	-2.21***	-2.11***	-2.28***			
	(0.73)	(0.74)	(0.77)			
lnsig2u						
_cons	-1.35	-1.32	-1.47			
	(1.42)	(1.40)	(1.59)			
cut1						
_cons				-1.31	-1.48	-1.78*
				(0.91)	(0.94)	(1.03)
cut2						
_cons				-0.39	-0.56	-0.85
				(0.89)	(0.92)	(1.01)
cut3						
_cons				0.63	0.48	0.21
				(0.89)	(0.92)	(1.01)
cut4						
_cons				2.35***	2.26**	2.01**
				(0.91)	(0.94)	(1.02)
cut5						
_cons				3.05***	2.99***	2.74***
				(0.93)	(0.96)	(1.04)
sigma2_u						
_cons				0.00	0.00	0.00
				(0.00)	(0.00)	(0.00)
County dummies	No	No	Yes	No	No	Yes
Year dummies	No	Yes	Yes	No	Yes	Yes
N	809	809	809	146	146	146

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Asset index is based on standardized principal component analysis scores for ownership of around 50 assets.
Education is a categorical variable with referring to completion of 1="Preschool or lower"; 2="Primary"; 3="Secondary"; 4="Tertiary"; 5="University".
Savings amounts is a categorical variable with 0=no savings; 1=0 to 5,000 KSH; 2=5,000-1,000 KSH; 3=10,000-50,000 KSH; 4= 50,000 to 100,000 KSH; 5=100,000 KSH and more.
Estimation model: random effects ordered logit model
Models (1)-(3) Random effects logit model. Dep. var=1 if reason for saving is unexpected events, 0 otherwise. Regressions conditional on hh currently having savings. Estimation model: random effects logit.
Models (4)-(6) Ordered random effects logit model. Dependent variable: Savings amount categories.

Table 8: Choice of harmful coping strategies

	All	Weather	Agric.	Price	Econ.	Dem.
	(1)	(2)	(3)	(4)	(5)	(6)
L.Expected=1	0.02	0.01	0.07	0.13*	0.27***	-0.15
	(0.03)	(0.04)	(0.06)	(0.07)	(0.06)	(0.17)
Shock severity	0.03	0.03	0.04	0.33**	-0.10	0.05
	(0.02)	(0.03)	(0.04)	(0.13)	(0.08)	(0.07)
Household size	0.04	0.00	0.02	0.25	0.07*	0.06
	(0.03)	(0.04)	(0.04)	(0.17)	(0.04)	(0.10)
Land size	0.00	0.03	-0.01	-1.50***	0.15***	0.03
	(0.01)	(0.02)	(0.02)	(0.53)	(0.05)	(0.10)
Asset index	-0.05	0.12	-0.27	-4.37***	-0.98**	0.46
	(0.23)	(0.34)	(0.25)	(1.25)	(0.42)	(1.07)
Respondent age; years	-0.00	-0.01	-0.01	-0.21***	0.03***	0.01
	(0.00)	(0.01)	(0.01)	(0.06)	(0.00)	(0.03)
Village affected; share	-0.03	0.03	-0.16	2.00**	-0.47	-0.01
	(0.12)	(0.14)	(0.22)	(0.79)	(0.46)	(0.82)
No. of other shocks	-0.01*	-0.02	-0.02	0.02	-0.12***	0.01
	(0.01)	(0.01)	(0.01)	(0.02)	(0.03)	(0.01)
Constant	-0.00	0.43	0.30	10.99***	-0.99***	-1.25
	(0.35)	(0.43)	(0.34)	(3.82)	(0.35)	(1.62)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	3351	1194	1191	291	227	448
R^2	0.023	0.066	0.031	0.849	0.866	0.042

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Linear fixed effects models. L denotes lagged value (t-1).
Estimation conditional on having been affected by the respective shock
Dependent variable=1 if any of these harmful coping strategies were chosen in response to a shock: buying less inputs, taking children out of school, making children work, selling of livestock, land, or storage, switching to lower valued food items, reducing number of meals, eating less diverse foods.
Expected=1 if farmer expects a shock to occur in t+1
Shock severity is self-assessed on a 4-point scale ranging from 0="no impact", 1="Low impact", 2="Medium impact", to 3="High impact".
Asset index is based on standardized principal component analysis scores for ownership of around 50 assets.

References

Assenza, T., Bao, T., Hommes, C., & Massaro, D. (2014). Experiments on expectations in macroeconomics and finance. In *Experiments in macroeconomics* (pp. 11–70). Emerald Group Publishing Limited.

Attanasio, O. P. (2009). Expectations and perceptions in developing countries: their measurement and their use. *American Economic Review*, *99*(2), 87–92.

Barberis, N. (2013). The psychology of tail events: Progress and challenges. *American Economic Review*, *103*(3), 611–616.

Baron, J., Hershey, J. C., & Kunreuther, H. (2000). Determinants of priority for risk reduction: the role of worry. *Risk Analysis*, *20*(4), 413–428.

Beatty, T. K. M., Shimshack, J. P., & Volpe, R. J. (2019). Disaster preparedness and disaster response: Evidence from sales of emergency supplies before and after hurricanes. *Journal of the Association of Environmental and Resource Economists*, *6*(4), 633–668.

Bellemare, M. F. (2009). When perception is reality: subjective expectations and contracting. *American journal of agricultural economics*, *91*(5), 1377–1381.

Besley, T. (1995). Savings, credit and insurance. *Handbook of development economics*, *3*, 2123–2207.

Blum, S. C., Silver, R. C., & Poulin, M. J. (2014). Perceiving risk in a dangerous world: Associations between life experiences and risk perceptions. *Social Cognition*, *32*(3), 297–314.

Bordalo, P., Gennaioli, N., & Shleifer, A. (2018). Diagnostic expectations and credit cycles. *The Journal of Finance*, *73*(1), 199–227.

Botzen, W. W., Kunreuther, H., & Michel-Kerjan, E. (2015). Divergence between individual perceptions and objective indicators of tail risks: Evidence from floodplain residents in New York City. *Judgment and Decision Making*, *10*(4), 365–385.

Brown, P., Daigneault, A. J., Tjernström, E., & Zou, W. (2018). Natural disasters, social protection, and risk perceptions. *World Development*, *104*, 310–325.

Brunnermeier, M. K., & Parker, J. A. (2005). Optimal expectations. *American Economic Review*, *95*(4), 1092–1118.

Bubeck, P., Botzen, W. J. W., & Aerts, J. C. (2012). A review of risk perceptions and other factors that influence flood mitigation behavior. *Risk Analysis: An International Journal*, *32*(9), 1481–1495.

Cassar, A., Healy, A., & Kessler, C. von. (2017). Trust, risk, and time preferences after a natural disaster: experimental evidence from Thailand. *World Development*, *94*, 90–105.

Coibion, O., & Gorodnichenko, Y. (2012). What can survey forecasts tell us about information rigidities? *Journal of Political Economy*, *120*(1), 116–159.

Coibion, O., & Gorodnichenko, Y. (2015). Information rigidity and the expectations formation process: A simple framework and new facts. *American Economic Review*, *105*(8), 2644–2678.

Coibion, O., Gorodnichenko, Y., & Kamdar, R. (2018). The formation of expectations, inflation, and the phillips curve. *Journal of Economic Literature*, *56*(4), 1447–1491.

Delavande, A. (2014). Probabilistic expectations in developing countries. *Annual Review of Economics*, *6*, 1–20.

Delavande, A., Giné, X., & McKenzie, D. (2011). Eliciting probabilistic expectations with visual aids in developing countries: how sensitive are answers to variations in elicitation design? *Journal of Applied Econometrics*, *3*(26), 479–497.

Dercon, S. (2002). Income risk, coping strategies, and safety nets. *The World Bank Research Observer*, *17*(2), 141–166.

Dercon, S. (2005). *Insurance against poverty*: Oxford University Press.

Dercon, S. (2008). Fate and fear: Risk and its consequences in Africa. *Journal of African Economies*, *17*(suppl_2), ii97-ii127.

Elbers, C., Gunning, J. W., & Kinsey, B. (2007). Growth and risk: methodology and micro evidence. *The World Bank Economic Review*, *21*(1), 1–20.

FAO (2014): *Country Programming Framework for Kenya 2014-2017*. Food and Agriculture Organization of the United Nations (FAO), Rome, Italy.

Fox, C. R., & Tversky, A. (1998). A belief-based account of decision under uncertainty. *Management science*, *44*(7), 879–895.

Gallagher, J. (2014). Learning about an infrequent event: evidence from flood insurance take-up in the United States. *American Economic Journal: Applied Economics*, 206–233.

Gilboa, I., Postlewaite, A. W., & Schmeidler, D. (2008). Probability and uncertainty in economic modeling. *Journal of Economic Perspectives*, *22*(3), 173–188.

Giné, X., Townsend, R., & Vickery, J. (2009). Forecasting when it matters: evidence from semi-arid India: Working Paper.

Gloede, O., Menkhoff, L., & Waibel, H. (2015). Shocks, individual risk attitude, and vulnerability to poverty among rural households in Thailand and Vietnam. *World Development*, *71*, 54–78. https://doi.org/10.1016/j.worlddev.2013.11.005

Hanaoka, C., Shigeoka, H., & Watanabe, Y. (2018). Do Risk Preferences Change? Evidence from the Great East Japan Earthquake. *American Economic Journal: Applied Economics*, *10*(2), 298–330.

Kahneman, D., & Tversky, A. (1972). Subjective probability: A judgment of representativeness. In *The concept of probability in psychological experiments* (pp. 25–48). Springer.

Karlan, D., Ratan, A. L., & Zinman, J. (2014). Savings by and for the Poor: A Research Review and Agenda. *Review of Income and Wealth*, *60*(1), 36–78.

Kebede, S. W., & Bokelmann, W. (2017). African Indigenous Vegetables and their Production Practices: Evidence from the HORTINLEA Survey in Kenya. *Agrotechnology*, *6*(170), 2.

Kinsey, B., Burger, K., & Gunning, J. W. (1998). Coping with drought in Zimbabwe: Survey evidence on responses of rural households to risk. *World Development*, *26*(1), 89–110.

Knuth, D., Kehl, D., Hulse, L., & Schmidt, S. (2014). Risk perception, experience, and objective risk: A cross-national study with European emergency survivors. *Risk Analysis*, *34*(7), 1286–1298. https://doi.org/10.1111/risa.12157

Kucinskas, S., & Peters, F. S. (2018). Measuring Biases in Expectation Formation: Working Paper.

Liebenehm, S. (2018). Temporal Stability of Risk Attitudes and the Impact of Adverse Shocks—A Panel Data Analysis from Thailand and Vietnam. *World Development*, *102*, 262–274.

Loewenstein, G. F., Weber, E. U., Hsee, C. K., & Welch, N. (2001). Risk as feelings. *Psychological bulletin*, *127*(2), 267.

Lucas, R. E., & Sargent, T. J. (1981). *Rational expectations and econometric practice*: U of Minnesota Press.

Luseno, W. K., McPeak, J. G., Barrett, C. B., Little, P. D., & Gebru, G. (2003). Assessing the value of climate forecast information for pastoralists: Evidence from Southern Ethiopia and Northern Kenya. *World Development*, *31*(9), 1477–1494.

Lybbert, T. J., Barrett, C. B., McPeak, J. G., & Luseno, W. K. (2007). Bayesian herders: Updating of rainfall beliefs in response to external forecasts. *World Development*, *35*(3), 480–497.

Mankiw, N. G., & Reis, R. (2002). Sticky information versus sticky prices: a proposal to replace the New Keynesian Phillips curve. *The Quarterly Journal of Economics*, *117*(4), 1295–1328.

Manski, C. F. (2004). Measuring expectations. *Econometrica*, *72*(5), 1329–1376.

Manski, C. F. (2018). Survey measurement of probabilistic macroeconomic expectations: progress and promise. *NBER Macroeconomics Annual*, *32*(1), 411–471.

Mathenge, M. K., & Tschirley, D. L. (2015). Off-farm labor market decisions and agricultural shocks among rural households in Kenya. *Agricultural economics*, *46*(5), 603–616.

Muth, J. F. (1961). Rational expectations and the theory of price movements. *Econometrica: Journal of the Econometric Society*, 315–335.

Rao, E. J. O., & Qaim, M. (2011). Supermarkets, farm household income, and poverty: insights from Kenya. *World Development*, *39*(5), 784–796.

Rheinberger, C. M., & Hammitt, J. K. (2018). Dinner with Bayes: On the revision of risk beliefs. *Journal of Risk and Uncertainty*, *57*(3), 253–280.

Rosenzweig, M. R., & Wolpin, K. I. (1993). Credit market constraints, consumption smoothing, and the accumulation of durable production assets in low-income countries: Investments in bullocks in India. *Journal of Political Economy*, *101*(2), 223–244.

Said, F., Afzal, U., & Turner, G. (2015). Risk taking and risk learning after a rare event: evidence from a field experiment in Pakistan. *Journal of Economic Behavior & Organization*, *118*, 167–183.

Sartore, G.-M., Kelly, B., Stain, H., Albrecht, G., & Higginbotham, N. (2008). Control, uncertainty, and expectations for the future: a qualitative study of the impact of drought on a rural Australian community. *Rural & Remote Health*, *8*(3).

Tversky, A., & Kahneman, D. (1973). Availability: A heuristic for judging frequency and probability. *Cognitive psychology*, *5*(2), 207–232.

Van der Pligt, J. (1996). Risk perception and self-protective behavior. *European Psychologist*, *1*(1), 34–43.

Viscusi, W. K. (1989). Prospective reference theory: Toward an explanation of the paradoxes. *Journal of Risk and Uncertainty*, *2*(3), 235–263.

Viscusi, W. K., & Zeckhauser, R. J. (2015). The relative weights of direct and indirect experiences in the formation of environmental risk beliefs. *Risk Analysis*, *35*(2), 318–331.

Voors, M. J., Nillesen, E. E. M., Verwimp, P., Bulte, E. H., Lensink, R., & van Soest, D. P. (2012). Violent conflict and behavior: a field experiment in Burundi. *American Economic Review*, *102*(2), 941–964.

Weinstein, N. D., Rothman, A. J., & Nicolich, M. (1998). Use of correlational data to examine the effects of risk perceptions on precautionary behavior. *Psychology and Health*, *13*(3), 479–501.

Wooldridge, J. M. (2002). *Econometric analysis of cross section and panel data*. Cambridge, Mass: MIT Press.

Annex

Figure A1: Location of the counties

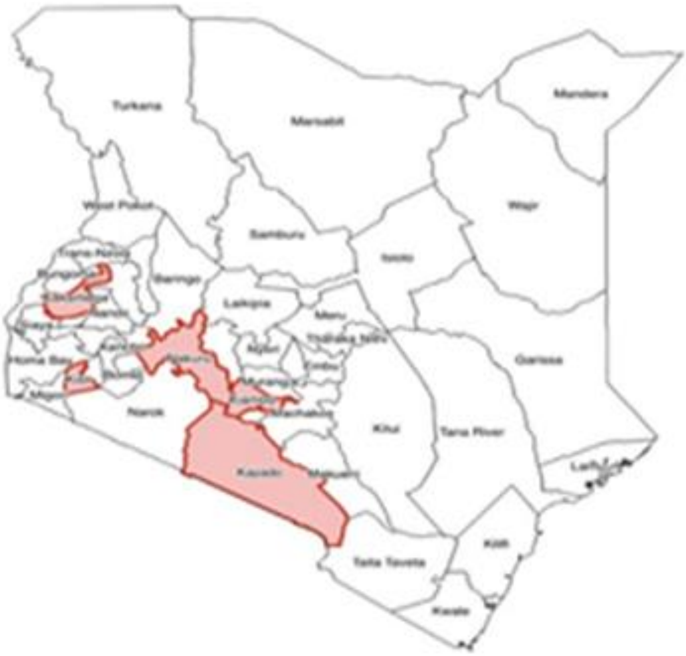

Table A1: Sample sizes per year and county

	2014	**2015**	**2016**
Kisii	401	201	199
Kakamega	407	202	197
Nakuru	221	151	145
Kiambu	183	152	144
Kajiado	20	dropped	dropped
Total	1232	706	685

Table A2: Test for randomness of attrition for base year 2014

	Dropped		Kept		
	mean	sd	mean	sd	*p*
Household size	4.450	1.638	5.631	2.344	.554
Highest level of education	2.600	0.883	2.746	0.773	.405
Respondent age; years	49.05	15.24	49.85	12.33	.305
Land size; ha	0.820	1.081	0.769	0.791	.689
Asset index	0.191	0.103	0.210	0.136	.050*
No. of shocks experienced	1.600	1.698	1.960	1.313	.397
No. of shocks expected	1.050	1.191	1.295	1.430	.008***
Avg. severity of shocks experienced	3.550	3.692	4.906	3.407	.301
Observations	548		684		

Source: HORTINLEA panel survey (2014), mean coefficients, Sd in parenthesis.
[1]*p*-values from two-sided t-test. . * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Asset index is based on standardized principal component analysis scores for ownership of around 50 assets.
Education is a categorical variable with referring to completion of 1=”Preschool or lower”; 2=”Primary”; 3=”Secondary”; 4=”Tertiary”; 5=”University”.
Shock severity is self-assessed on a 4-point scale ranging from 0=”no impact”, 1=”Low impact”, 2=”Medium impact”, to 3=“High impact”.