Received: 1 July 2021 | Revised: 31 October 2021 | Accepted: 3 April 2022

DOI: 10.1111/agec.12718

AGRICULTURAL ECONOMICS
The Journal of the International Association of Agricultural Economists
IAAE
WILEY

ORIGINAL ARTICLE

Experience of shocks, household wealth and expectation formation: Evidence from smallholder farmers in Kenya

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Data Appendix Available Online: A data appendix to replicate the main results is available in the online version of this article. Please note: Wiley-Blackwell is not responsible for the content or functionality of any supporting information supplied by the authors. Any queries (other than missing material) should be directed to the corresponding author for the article.

Abstract
When faced with uncertain events, decision-makers form expectations about the events' likelihood of occurrence. However, the drivers and moderators of such expectations are still poorly understood, especially for farm decision-makers in developing countries whose incomes are very risky by nature. This article analyses the dynamic shock expectation formation process of farmers in Kenya with regard to a range of shock events using a unique panel dataset. The results suggest that farmers are more likely to update their expectation regarding a specific adverse shock when they have recently been affected by that shock or by more shocks in general. In case of price shocks, farmers are also more likely to update expectations when a larger proportion of fellow village members was affected. However, household wealth moderates the relationship between shock expectation and experience, such that wealthier households are less likely to update their expectations following a shock. A better understanding of the drivers of expectation formation can help in the design of better risk management instruments that increase farmers' resilience.

KEYWORDS
farmers, risk, shocks, subjective expectations

JEL CLASSIFICATION
D81, D84, O12, Q12

1 | INTRODUCTION

When faced with uncertain adverse events or shocks[1], decision-makers form subjective expectations regarding the events' occurrence. Economists have long neglected the individual differences of this risk forecasting behaviour (Manski, 2004; Manski, 2018). While it has been assumed that usually individuals make statistically optimal forecasts following the rational expectations hypothesis (Muth, 1961) and Bayes' rule (Gallagher, 2014), this view has been challenged in recent empirical literature, mainly in macroeconomics and finance (e.g., Bordalo et al., 2018; Coibion et al., 2018). However, many aspects of the cognitive processes, decision heuristics and individual factors that determine the formation of expectations about uncertain events are still unknown (Barberis, 2013; Gilboa et al., 2008). Despite the critical importance of risk, risk

[1] In this paper references are made to the term shock as a "realization of the risky process" as in (2005), p. 10, which, in principle, is unpredictable.

perception and risk response in rural developing economies (Dercon, 2005, 2008; Elbers et al., 2007), there is little evidence on expectation formation with regard to risky events in these contexts (Attanasio, 2009; Delavande, 2014) as most research on the topic looks at professional forecasters (Bordalo et al., 2018; Coibion & Gorodnichenko, 2012, 2015; Kucinskas & Peters, 2018). Generally, most secondary datasets only include the observable outcomes of subjects' decisions, but not the subjective expectations that may have guided their decision-making process (Delavande et al., 2011). This makes them unsuitable for analysing expectation formation.

There is scarce empirical evidence from farm households addressing the heterogeneities of expectations about uncertain and adverse events. The existing studies suggest that such expectations are driven by household and farm-specific characteristics (Bellemare, 2009), as well as access to coping mechanisms (Giné et al., 2009). However, these studies are static and do not allow conclusions to be drawn regarding 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, *that is*, the objective probabilities of the random event over time, which is rarely observable outside a laboratory or without long term series (Assenza et al., 2014; Kucinskas & Peters, 2018). The extent to which the updating of expectations about adverse shocks depends on the specific type of shock is also unclear. Analysing how decision-makers in developing countries, and particularly farmers, form expectations about adverse shocks is highly relevant for at least three reasons. Firstly, agricultural production and incomes are very risky by their nature (e.g., Dercon, 2008). Secondly, observed behavior can be traced back to preferences and expectations and behavioral biases can be identified, offering a better understanding of farming behavior. And thirdly, because expectations about uncertain events play an important role in shaping farmers' response to technology adoption (Barham et al., 2015; Bonan et al., 2020; Tjernström et al., 2021; Trujillo-Barrera et al., 2016).

This article adds to the very limited literature analysing the dynamics of expectation formation in a developing country by looking at the binary expectations of Kenyan smallholder vegetable farmers with regard to a range of shock events over time. Detailed information is elicited over three consecutive years about farmers' experience and expectation of a range of adverse shocks.

Using that information, this article asks whether farmers are more likely to update their expectations of adverse shocks (1) if they recently experienced a particular shock, (2) if a larger proportion of village members recently experienced that particular shock, or (3) if they experienced more shocks overall. Furthermore, the study measures, (4) if the type of shock encountered determines whether farmers subsequently update their expectations. Finally, it tests (5) whether household wealth affects the updating of shock expectations. Knowing more about drivers of expectation formation is crucial for informing the design of better risk-management tools that could increase farmers' resilience.

The article is structured as follows. Section two presents the conceptual framework of this study, section three reviews the extant literature, and section four presents country information and data descriptions, while details of the estimation strategy are explained in section five. Both descriptive and econometric results are discussed in section six, and the last section discusses, concludes and gives an outlook for further research.

2 | CONCEPTUAL FRAMEWORK

Different theories on decision-making in uncertainty coincide in characterising 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 having two steps (Barberis, 2013; Fox & Tversky, 1998): First, individuals make a subjective assessment about the likelihood of a rare random event, and second, based on this probability assessment and taking into account their preferences, they make 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 has been found that the experience of shocks can alter individual risk preferences (Bourdeau-Brien & Kryzanowski, 2020; Gloede et al., 2015; Hanaoka et al., 2018; Liebenehm, 2018; Said et al., 2015; Voors et al., 2012).

Individual differences in decision-makers' subjective expectations in general; however, have long been neglected. This is because they 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 on average hold unbiased expectations. When analysing expectations about probabilities of uncertain events, the rational benchmark for updating such expectations in the light of new information is given by Bayes' rule. Following Gallagher (2014), a decision-maker's conditional expectation of the probability p of a random event under full information is given as:

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

where t is the number of observed time periods and $S_t = \sum_{s=1}^{t} \upsilon_s$ is the number of observed occurrences of the events. The fixed parameters α and β describe prior beliefs about the probability of the event, assuming that events are independent and the probability p follows a beta (α, β)-distribution. Hence, it would be consistent with Bayesian updating and hence rational if farmers were more likely to expect a particular adverse event to happen again after experiencing it more frequently in the past.

Bayesian learning is considered the benchmark for describing how individuals rationally incorporate new information into their beliefs. Even though empirically testing for Bayesianism is not straight forward and requires data with a large time dimension (Augenblick & Rabin, 2019), there is a range of studies documenting clear deviations in the formation of expectations about macroeconomic fundamentals (see Assenza et al., 2014; Coibion et al., 2018 for reviews) and probabilities (Barberis, 2013). It has been argued that the Bayesian updating process is cognitively too demanding to be realistically applied by humans. Another problem when analysing the determinants of expectations about personal risks is the fact that subjects can influence it and have unobservable, private risk information (Lloyd-Smith et al., 2018; Rheinberger & Hammitt, 2018). Strictly speaking, such risks are non-exogenous.

Other learning hypotheses that have been proposed include alarmist decisions, addressing the phenomenon that when receiving risk information from multiple sources, decision-makers will put higher weight on the source of information conveying a high risk (Cameron, 2005; Viscusi, 1997). There is also the "good news, bad news effect" (Eil & Rao, 2011) referring to the observed tendency of learners to weight the affective content of the new information differently, depending on whether it is "good news" or "bad news". Furthermore, there are social learning models such as De Groot learning (DeGroot, 1974), which assumes that agents in a social network update their expectations in line with the majority of their neighbours' prior expectations, a behaviour that has been confirmed empirically among vulnerable populations (Chandrasekhar et al., 2020). However, a single model is unable to incorporate all behavioural phenomena that are being observed in the field and will be reviewed in the following.

3 | LITERATURE REVIEW

3.1 | Expectation formation of farmers

Only recently has the importance of taking into account farmers' expectations when analysing their preferences regarding risk and uncertainty been recognized (Cerroni, 2020; Menapace et al., 2013; Ricome & Reynaud, 2022). Even though consequences of adverse risks are particularly severe in these settings, to date there is still little empirical evidence on the individual-specific determinants of expectations about uncertain events elicited specifically from decision-makers in developing countries and/or rural contexts (Attanasio, 2009; Delavande, 2014; Eisele et al., 2021). The scarce empirical evidence includes Bellemare (2009), who studies subjective perceptions of tenure insecurity of smallholder farmers under different contracting scenarios; Lybbert et al. (2007), who look at rainfall expectation formation of pastoralists in Ethiopia and Kenya; and Giné et al. (2009), who analyse Indian farmers' subjective beliefs about monsoon rains and their accuracy. In the following, we derive specific hypotheses about determinants of farmers' shock expectations from the literature.

3.2 | Drivers of shock expectations

It has been found that decision-makers tend to overestimate the probability of any event when past instances of the event are easier to recall from memory, such as recent and more salient events, due to 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 representativeness bias (Kahneman & Tversky, 1972). Emotions also play an important role in forming perceptions about risky events (Baron et al., 2000; Loewenstein et al., 2001). Experiencing adverse shocks may invoke negative emotions and lead to pessimism in the evaluation of the likelihood of future adverse events (Blum et al., 2014; Botzen et al., 2015; Brown et al., 2018; Sartore et al., 2008; Smith, 2008). These phenomena are supported by empirical evidence derived from research subjects other than farmers, suggesting that experiencing an emergency event increases the perceived likelihood of re-experiencing that same event (Brown et al., 2018) or other adverse events in general (Blum, Silver et al., 2014; Knuth et al., 2014). In line with this prior evidence, we hypothesize that farmers will be more likely to expect any adverse event to happen if they recently experienced that event. It is important to note, however, that we are unable to tell whether this behaviour is irrational from a theoretical point of view.

In line with social learning theories, decision-makers also derive new information about the likelihood of an adverse shock by observing the experience of others (Gallagher, 2014; Viscusi & Zeckhauser, 2015; Wachinger et al., 2013). However, decision-makers are likely to discount such indirect information, depending on how personally relevant it is to them (Viscusi & Zeckhauser, 2015), which in turn depends on individual specific factors

(Rheinberger & Hammitt, 2018; Viscusi, 1989). When we assume that information about the likelihood of incurring an adverse shock is private and imperfect, how farmers will react when they observe other farmers in their village experiencing shocks depends on how similar they believe they are in terms of exposure and behavioural factors that influence the likelihood of incurring shocks. If farmers perceive fellow village inhabitants to be similar to themselves in terms of shock exposure, which will be the case for covariate shocks, and self-protective behaviour, they should be more likely to expect a shock when they observe village members being affected, irrespective of whether or not they are affected themselves. Empirically, this idea is supported, for instance, by Sullivan-Wiley and Gianotti (2017) with a sample of Ugandan farmers. In line with these considerations, we expect that independently of whether they were personally affected, farmers will be more likely to expect an adverse event when its nature is covariate and more people in their social network were recently affected by that event.

Repeated experiences of negative events have also been shown to worsen people's general views of the world and about people being benevolent and alter the way in which the likelihood of future negative events is projected (Blum et al., 2014). Relatedly, it could be shown that the general risk taking behaviour of more emotionally stable decision-makers is less affected by negative life events (Kettlewell, 2019). In a farming context, this notion is also supported by Sullivan-Wiley and Gianotti (2017), who found that farmers who are more worried about a particular hazard tend to worry more about other hazards as well. In line with this evidence, we anticipate that farmers will be more likely to expect a particular adverse shock the more adverse events in general they have recently experienced.

3.3 | Differences by types of shocks

How decision-makers change their forecasts of shocks also depends on the type of shock. As argued by Rheinberger and Hammitt (2018), individual-specific factors affect decision-makers' confidence in new information when updating expectations about incurring an adverse event. In addition, whether experiencing a shock provides any information regarding the likelihood of future shock-affectedness varies by the type of shock. Furthermore, the tendency to revise expectations is contingent on how relevant the forecasted variable, in this case the probability of a shock, is to the decision-makers' livelihood (Brunnenmeier & Parker, 2005). Given these considerations, we assume that farmers are more likely to adjust their expectations in the case of agriculture-related shocks since these have direct consequences for their well-being as opposed to other types of shocks that are of less immediate concern.

3.4 | Wealth effects

Lybbert et al. (2007) argue in their state-contingent model that the value of updating expectations about future states of nature in light of new information consists not only in the information itself but in the variability of outcomes once the state of nature has materialized. In the case of adverse shocks, variability of outcomes in future states depends on the access to different coping strategies. Hence, if wealthier households have access to more coping strategies and their optimal livelihood strategy depends on the future state of nature, then the value of updating beliefs is increasing in wealth (Lybbert et al., 2007). However, the authors consider the possibility that the optimal livelihood strategy does not depend on the future state of nature, either because the farmer is very wealthy and can adopt coping strategies at no cost, or is very poor and has no coping strategies available at all. In either case, updating shock expectations has little value for the farmer. Results by Giné et al. (2009) are indicative of the latter hypothesis, showing that wealthier farmers made less accurate monsoon forecasts. In a setting where wealth is a good proxy for access to diverse productive options, it can be hypothesized that at least up to certain level the likelihood of updating of shock expectations is positively correlated with wealth.

4 | COUNTRY AND DATA DESCRIPTION

The stated research questions were answered using 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)[2] producers. Kenya's economy is based on agriculture (World Bank Group, 2019) and dominated by smallholder farmers who are prone to adverse shocks that lead to food insecurity and malnutrition, and the use of potentially harmful coping strategies (Mathenge & Tschirley, 2015).

The rural sites of the HORTINLEA study are located in two counties in Western Kenya, Kisii and Kakamega, while the peri-urban sites are in the counties of Kiambu, Nakuru

[2] According to Schippers (2000) , indigenous vegetables are those whose primary or secondary centre of origin is in the respective location, in this case Kenya. It is now widely recognized that AIVs are important sources of proteins and micronutrients, including vitamins, minerals, and antioxidants that are crucial for normal growth and health.

TABLE 1 Characteristics of respondents and their households (balanced sample)

	2014	2015	2016
“col1”>Age of respondent; years	46.39	47.23	48.24
	(11.85)	(11.74)	(11.76)
Respondent is female; dummy	.302	.302	.302
	(.460)	(.460)	(.460)
Household size	5.421	5.705	5.866
	(2.275)	(2.250)	(2.241)
Age of household head; years	49.30	50.73	51.63
	(12.02)	(12.00)	(11.91)
Head has secondary educ., dummy	.569	.562	.564
	(.496)	(.497)	(.496)
Household head is female; dummy	.282	.264	.259
	(.451)	(.442)	(.439)
Land size; ha	.734	.898	.914
	(.743)	(1.342)	(1.188)
No. of assets [min = 0; max = 48]	13.92	15.64	15.95
	(5.389)	(5.125)	(5.200)
No. of shocks experienced in current year	1.887	2.977	1.877
	(1.275)	(1.964)	(1.145)
No. of shocks expected in next year	1.204	1.695	.683
	(1.398)	(2.087)	(1.108)
Share of respondents that expected no shock in next year	.426	.315	.615
	(.495)	(.465)	(.487)
Observations	397	397	397

Coefficients = means, standard errors in parenthesis.

and Kajiado (Figure A1 in the Appendix). Households were selected using a multi-stage sampling approach. First, the four counties were purposefully selected based on the 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 Appendix for details). The survey was conducted using face-to-face interviews with one household representative. Even though the sample is not nationally representative, given the randomised sampling within the most prominent AIV production regions, the results of the analysis of survey data could be generalised to AIV producers in rural and peri-urban areas in Kenya.

In 2014, the number of households interviewed was 1232, but this was reduced to 700 households in the subsequent surveys in 2015 and 2016 for budgetary reasons. However, households were randomly dropped, keeping the proportion of respondents constant within the counties. As Table A2 in the Appendix shows, households dropped from the survey after 2014 had similar socioeconomic characteristics and were affected by a similar number of shocks, except that they are more likely to be female headed and were slightly smaller. In addition, households that were kept expected on average significantly more shocks than those that were dropped. Overall, irrespective of the planned reduction in sample size from 2014 to 2015, the attrition rate was 2.8 %. However, respondents within the households varied in some cases over the years; hence, for the analyses only a balanced sample of the same 397 respondents across years is kept. This step shrinks our sample considerably, but it is crucial for our research questions to use an individual-level panel. Since the original sample is not nationally representative, we do not lose external validity by dropping these households. Rather, we argue that shedding light on the general behavioural phenomenon of expectation formation hinges on the availability of panel data, uniquely encompassed in this dataset.

The survey has an extensive module on shocks that elicits binary data on the experience of 24 different shocks every year. Experiences of shock occurrences were elicited using the following question during the survey: “We want to ask you about occurrence of any unexpected events

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in the past 12 months that caused reduction in income, consumption, or led to a loss in household assets. Was your household affected by [event] in the past 12 months?" where [event] refers to each of the 24 shocks. Expectations were prompted using the following similar survey question: "We want to ask you about any possible future events in the next 12 months that will cause reduction in income, consumption, or lead to a loss in household assets. Do you think [event] will occur in the next 12 months?". While a frequentist measure would be preferred, binary measures have also been used when assessing subjective mortality expectations in relation to occupational health (Viscusi, 1979). Shock events can be roughly categorised as weather shocks (such as drought and flood), agricultural production shocks (such as pests), economic shocks (such as job losses of a household member and expenditure on festivities), price shocks (such as food and input price increases) and demographic shocks (such as illness or death of a household member). In addition, the survey questionnaire comprises demographic, socio-economic and asset modules which enables inclusion of relevant explanatory variables in the analysis.

Even though AIVs have been produced in Kenya for many years, their promotion in terms of marketing and urban consumption is a recent phenomenon. Especially, marketing of AIVs with value addition and income generation for farmers (Rao & Qaim, 2011) is given due focus just recently, with the promotion of sustainable supply of these nutritious products in high value markets such as supermarkets in urban areas. As is common with other agricultural products, these vegetables are grown in rainfed conditions, which makes them prone to various shocks, such as weather-related shocks of drought and water shortages as well as pests and diseases. However, we go beyond agricultural shocks by looking at other demographic and economic shocks that might affect the livelihoods of the farmers. This sample of indigenous vegetable producers provides an ideal setting for an assessment of smallholders' exposure to various shocks and their expectation formation. In addition, it offers an opportunity to recommend policies that reduce farmers' vulnerability by understanding determinants of expectation formation and interrelations with mitigation behaviours.

5 | ESTIMATION STRATEGY

In order to test for the factors that affect the updating of expectations, the data were pooled across shocks. The determinants of shock expectations were estimated controlling for a range of time-variant covariates with linear fixed-effects panel models. The outcome variable is an indicator whether a respondent expects a particular shock to happen in the next 12 months. Since the outcome is binary, a non-linear estimator would be the first choice, however, the incidental parameters problem in non-linear fixed-effects panel models with large cross-sections and short fixed time-series would introduce bias (Greene, 2004; Wooldridge, 2002). For this reason, a linear probability model (LPM) was used. Bellemare et al. (2015) argue that the advantage of using a LPM with fixed effects outweighs the disadvantage of potential bias relative to using a non-linear model. LPM coefficients can also be directly interpreted in terms of marginal effects, that is, changes in probabilities. Obtaining meaningful results using fixed-effects models requires that a major share of the variation in the data is within-variation, which is confirmed in Table A3 in the Appendix.

The use of fixed effects controls for unobserved time-invariant heterogeneity, such as a farmer's general exposure to environmental risks due to, for instance, the location of his or her plot as well as time-invariant shock-specific factors. Fixed effects also allow to capture within-variation, meaning what drives the same farmers to change their expectations over time, and not differences between farmers. By using fixed effects, the problem of shock experience being a subjective variable is also addressed, assuming that the definition of what constitutes a shock does not change within the farmer over time in a non-random way. The estimation model was:

$$y_{sijt} = c + \alpha X'_{sijt} + \beta Z'_{ijt} + u_{sij} + e_{sijt}$$
$$\text{with } X'_{sijt} = \left(v_{sijt};\ \overline{v}_{sjt};\ \sum_{s=1}^{24} v_{sijt} \right) \tag{4}$$

where y_{sijt} is a binary indicator variable taking the value 1 if farmer i of village j expects at time t that a specific shock s will occur in the next 12 months. X'_{sijt} is a vector of time-variant, shock-specific regressors. It includes a binary variable v_{sijt} indicating whether farmer i experienced shock s in the 12 months prior to t, 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 farmer i could have experienced in t. Z'_{ijt} is a vector of household-specific, time-variant characteristics varying by estimated model, including household size, dependency ratio, land size, and asset index. The survey asks whether households own any of a list of 48 assets (full list in Table A5 in the Appendix). Based on this information, an asset index is developed using standardized principal component analysis (PCA) scores of the first principal component as suggested in Filmer and Pritchett (2001). As noted by the authors, the asset index proxies long-run economic status and does not capture short-term economic shocks. The Kaiser-Maier-Ohlin statistic (Kaiser, 1974) for sampling adequacy is greater than .85 across years, indicating that the asset ownership variables have enough in common to be suitable for PCA. The dependency ratio is the ratio between the number of inactive household members (aged below 14 and above 65) divided by number of working age household members (aged 15–64). The terms u_{sij} and e_{sijt} denote the time-invariant individual- and shock-specific fixed effects and the error term, respectively. In the estimations, standard errors were clustered at respondent level to correct for serial correlation within respondents. In further specifications, the sample is conditioned on shock type in order to test for differences in the effects of weather, agriculture, demographic, economic, and price shocks.

As a robustness test, we run a conditional fixed effects logit model (Chamberlain, 1980) of the following specification:

$$\Pr(y_{it} = 1|x_{it}) = \mathrm{F}(\alpha_i + x_{it}\beta) \tag{5}$$

Here, F is the cumulative logistic distribution $F(z) = \frac{\exp(z)}{1+\exp(z)}$, i refers to the independent groups of observations by individual and shock type, x_{it} refers to the time-variant covariates (at individual, shock, or village level), and $T_i = 3$ refers to the survey years. The difficulty of estimating the incidental parameters α_i can be overcome by estimating the structural parameters of the non-linear logit model conditioning the likelihood function on minimal sufficient statistics for the incidental parameters (Cameron & Trivedi, 2005). Specifically, the probability of $y_{it} = (y_{i1}, \ldots, y_{iT_i})$ is estimated conditional on $\sum_t^{T_i} y_{it}$.

In order to address the hypothesized heterogeneities in the effect of shock experience on expectations by wealth level, we interact the asset index variable with the shock experience variable when estimating Equation (4) and compute contrasts of marginal linear effects for different levels of the asset index.

6 | RESULTS

6.1 | Descriptive results

Table 1 presents some sociodemographic characteristics of the balanced sample by year. In 2014, the average respondent was 46 years old, owned around .73 ha of land, lived in a household with around six persons, and had completed at least secondary education. Around 70% of respondents were male. On average, they experienced between two and three shocks a year between 2014 and 2016 and expected on average 1.2, 1.6 and .6 shocks to occur in 2015, 2016 and 2017, respectively. Between 31.5% and 61.5% of respondents expected no shock to occur during the next 12 months in a given year.

Table 2 describes the respondent households' shock experience in the 12 months prior to the survey as well as their respective shock expectations for the following 12 months, separately by shock and survey year for the balanced sample. Drought is the most widespread shock reported by 18%, 46%, and 39% of the balanced sample in 2014, 2015 and 2016, respectively, followed by crop failure. Illness of a household member was reported by about 19%, 31%, and 20%, while livestock death was reported by about 16%, 30%, and 25% of the respondents in years 2014, 2015, and 2016, respectively. It becomes evident from these numbers that there is substantial variation across years. In general, weather and agricultural production shocks were found to be most dominant among the surveyed households, reflecting their livelihood being based on rain-fed agriculture. Demographic shocks other than 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 6-7% of households in 2014 and 2016 but 19% in 2015. Comparing shock expectations, this sample of households seemed to be optimistic in a sense that on average the proportion of farmers having experienced shocks in the prior 12 months was substantially higher than those expecting them in the coming 12 months in any given year.

Figure 1 depicts the time trends of three variables for the five most common shocks: the proportion of farmers that (1) was affected by a particular shock during the last 12 months, (2) expected this shock to occur in the coming 12 months, and (3) expected this shock to occur in the coming 12 months conditional on having been affected during the last 12 months. The graphs are indicative of a positive correlation between experiencing and expecting shocks and show that farmers tend to update their expectations based on their experience. The proportion of farmers that was both affected by a shock and expected this shock to reoccur is substantially lower, suggesting that also unaffected respondents updated expectations. This was clearly observed, in particular 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, few farmers expected health-related shocks as compared to weather-related production shocks. The reasons for this are most likely cultural in nature, as explicitly expecting health shocks might connote an omen of bad luck.

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

	2014			2015			2016		
	Affected	Expecting	Affected & expecting	Affected	Expecting	Affected & expecting	Affected	Expecting	Affected & expecting
Weather shocks:									
Drought	.184	.144	.065	.458	.280	.199	.385	.191	.121
Shortage of water	.078	.060	.033	.209	.103	.048	.078	.038	.015
Flood	.018	.033	.013	.058	.048	.013	.010	.020	.005
Unusually heavy rain	.154	.136	.081	.252	.164	.076	.128	.081	.023
Land Slide/erosion	.013	.013	.008	.050	.048	.025	.008	.003	.000
Storm	.040	.030	.010	.045	.025	.010	.045	.020	.003
Agricultural shocks:									
Crop failure	.287	.144	.096	.388	.164	.088	.264	.030	.023
Pests on livestock	.020	.028	.015	.050	.048	.008	.020	.015	.000
Pests on crops	.118	.055	.028	.101	.086	.033	.081	.020	.013
Livestock death	.156	.020	.013	.302	.040	.025	.249	.010	.008
Livestock disease	.123	.050	.028	.088	.040	.013	.101	.013	.008
Crop diseases	.224	.005	.000	.086	.013	.000	.053	.013	.000
Price shocks:									
Food price increase	.065	.091	.030	.186	.199	.111	.058	.093	.018
Input price increase	.033	.050	.010	.076	.111	.035	.013	.023	.000
Fuel price increase	.013	.023	.000	.025	.025	.005	.003	.005	.000
Economic shocks:									
Theft of goods/livestock	.103	.045	.028	.123	.055	.023	.108	.035	.010
Job loss	.008	.151	.000	.010	.071	.003	.003	.015	.000
Forced contribution	.000	.000	.000	.035	.003	.003	.040	.000	.000
Money spent for ceremony	.003	.000	.000	.008	.005	.003	.003	.005	.000
Demographic shocks:									
Death of member	.045	.005	.000	.093	.008	.000	.018	.000	.000
Illness of member	.186	.023	.018	.310	.018	.015	.199	.000	.000
Divorce	.010	.098	.000	.003	.128	.003	.000	.048	.000
Member left household	.003	.000	.000	.008	.010	.000	.005	.005	.000
Person joined household	.003	.000	.000	.013	.005	.003	.005	.000	.000
Total	.079	.050	.020	.124	.071	.031	.078	.028	.010
Observations	397			397			397		

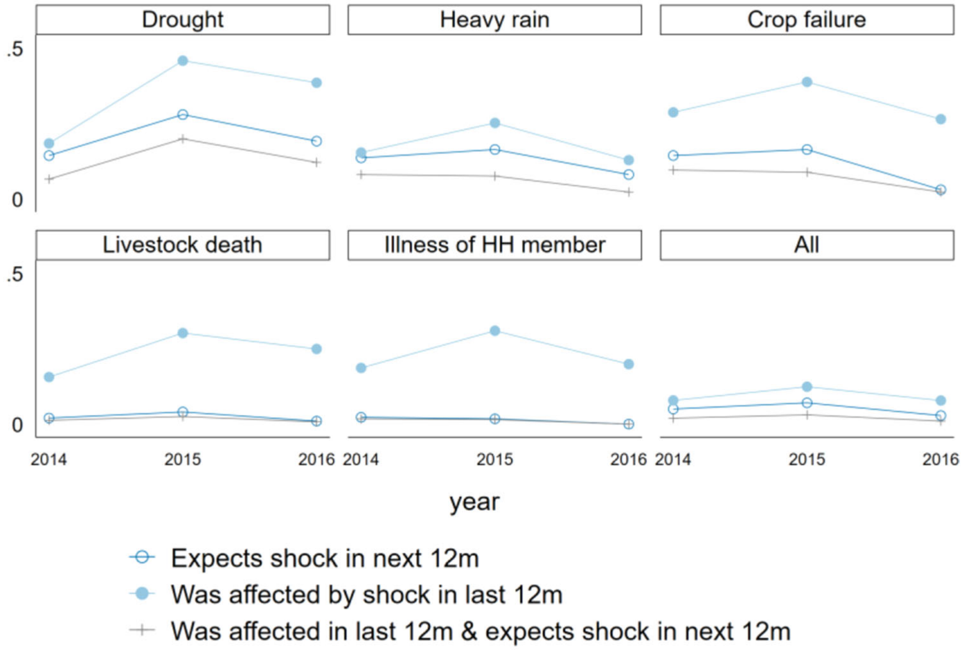

FIGURE 1 Shock expectations and affectedness for five most frequent shocks and total

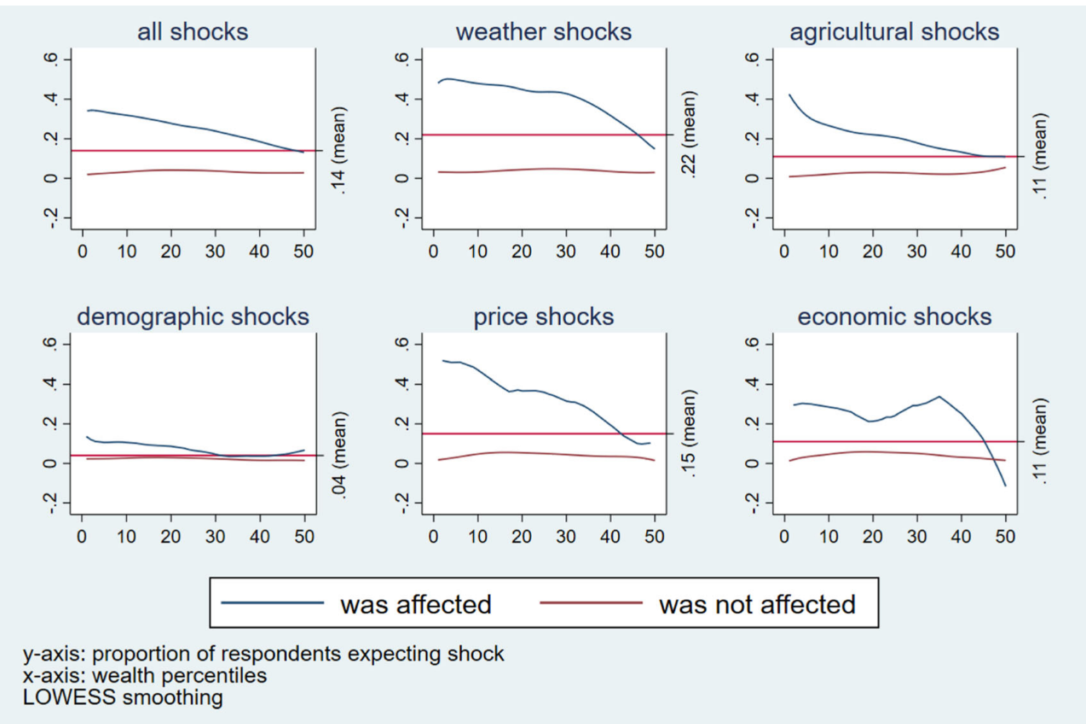

FIGURE 2 Shock expectations by wealth level and shock affectedness (2014)

Figure 2 shows how shock expectations vary by wealth level in the base year 2014. The data were averaged by 50 wealth quantiles and a smooth line was interpolated using locally weighted regression smoothing (LOWESS). The share of respondents that expect a particular shock after experiencing it is declining with wealth across shock types. The share of respondents that expect a shock they did not experience is close to zero and is unrelated to wealth. The wealth interaction is explored in more detail in the estimation results.

TABLE 3 Determinants of shock expectations

	All (1)	(2)	Weather (3)	Agri. (4)	Demogr. (5)	Price (6)	Econ (7)
Affected by shock in last 12 months; dummy	.158***	.150***	.212***	.107***	.039***	.347***	.103***
	(.010)	(.010)	(.022)	(.014)	(.013)	(.039)	(.029)
Village members affected in last 12 months; share		.075**	.064	−.030	−.037	.485***	.063
		(.031)	(.060)	(.033)	(.044)	(.105)	(.099)
No. of other shocks experienced in last 12 months		.016***	.018***	.017***	.009***	.017***	.014***
		(.002)	(.004)	(.004)	(.002)	(.004)	(.003)
Household size	−.002	−.004	−.011**	−.001	.000	−.002	−.004
	(.003)	(.003)	(.005)	(.005)	(.004)	(.007)	(.005)
Dependency ratio	−.001	−.002	.002	.001	−.010**	.007	−.002
	(.004)	(.004)	(.009)	(.008)	(.005)	(.008)	(.006)
Log(land size)	.004	.001	.000	.003	.000	.004	.002
	(.003)	(.002)	(.005)	(.004)	(.003)	(.007)	(.004)
Asset index[a]	.075***	.047*	.032	.020	.018	.181**	.088***
	(.026)	(.024)	(.047)	(.039)	(.024)	(.085)	(.034)
Constant	.037**	.019	.066**	.009	.011	−.036	.025
	(.018)	(.015)	(.030)	(.026)	(.023)	(.043)	(.025)
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Respondent × shock fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	28584	28584	7146	7146	5955	3573	4764
No. of clusters	397	397	397	397	397	397	397
R2	.052	.064	.088	.062	.019	.157	.038

Standard errors in parentheses. Linear fixed effects estimator.

*$P < .1$. **$P < .05$. ***$P < .01$.

[a]Asset index: standardized principal component analysis (PCA) score based on households' ownership of a maximum of 48 household and productive assets.

6.2 | Estimation results

The coefficients from estimating Equation (4) are reported in Table 3, both across all types of shocks and for each type of shock separately. All models controlled for time-variant socio-demographic variables as well as year × shock fixed effects. First, it was found that being affected by a particular shock in the current year significantly increased farmers' likelihood of expecting the same shock to occur again in the coming year by around 15% on average in the preferred specification in Model (2) which includes time-variant covariates. Disaggregated by shock type, the effect of shock experience on expectation is highest for price shocks with 35% (Model 6) and lowest for demographic shocks with 4% (Model 5). This result is as hypothesized; stating that farmers' expectations react to the experience of shocks, and it is in line with the descriptive findings from Figure 1. Second, after controlling for farmers' own experience of the shock, a larger proportion of other village inhabitants being affected (excluding the farmer him/herself) was found to increase the expectation of a price shock in the coming year by a magnitude of 4.9% for each additional 10% of one's village affected. This is partly in line with the hypothesis that farmers update their expectations about a shock based on relevant others' experience of that shock. However, this relationship is shock-specific and does not hold for other shock types. This could be due to the covariate nature of price shock, but then this relationship should also hold for weather shocks.

Lastly, the greater the total number of shocks experienced in a given year, the greater the perceived likelihood of being affected by any shock in the coming year. The likelihood increases by 1.6% for each additional shock. This is in line with the literature documenting cross-over effects between different shocks and respective expectations, and arguing that the more adverse life events one has experienced, the greater likelihood there is of expecting other adverse events to occur in future (Blum, Silver et al., 2014; Knuth et al., 2014). However, the effect size was rather small.

Models (3) to (7) estimated the effect of shock affectedness by shock type. The composition of the shock categories can be found in Table 2. It was hypothesised that farmers would update their expectations more strongly in

TABLE 4 Heterogeneous wealth effects in the determinants of shock expectations

	All (1)	(2)	Weather (3)	Agriculture (4)	Demography (5)	Price (6)	Economic (7)
Affected by shock in last 12 months; dummy	.209***	.200***	.250***	.170***	.057***	.367***	.162***
	(.020)	(.020)	(.040)	(.024)	(.022)	(.074)	(.048)
Asset index[a]	.089***	.062***	.046	.052	.022	.182**	.096***
	(.026)	(.024)	(.044)	(.039)	(.025)	(.085)	(.034)
Affected by shock in last 12 months × Asset index	−.224***	−.220***	−.171	−.264***	−.088	−.096	−.220*
	(.067)	(.066)	(.149)	(.068)	(.069)	(.307)	(.115)
Household size	−.002	−.004	−.011**	−.001	.000	−.002	−.004
	(.003)	(.003)	(.005)	(.005)	(.004)	(.007)	(.005)
Dependency ratio	−.001	−.002	.002	.001	−.010**	.007	−.003
	(.004)	(.004)	(.009)	(.009)	(.005)	(.008)	(.006)
Log(land size; ha)	.004	.001	.000	.003	.000	.004	.001
	(.003)	(.002)	(.005)	(.004)	(.003)	(.007)	(.004)
No. of other shocks experienced in last 12 months		.016***	.018***	.017***	.009***	.017***	.014***
		(.002)	(.004)	(.004)	(.002)	(.004)	(.003)
Village members affected in last 12 months; share		.073**	.063	−.033	−.041	.483***	.055
		(.031)	(.059)	(.034)	(.044)	(.105)	(.099)
Constant	.034*	.016	.063**	.002	.010	−.036	.023
	(.018)	(.015)	(.029)	(.026)	(.023)	(.043)	(.025)
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Respondent × shock fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	28584	28584	7146	7146	5955	3573	4764
No. of clusters	397	397	397	397	397	397	397
R2	.054	.066	.089	.068	.019	.157	.039

Standard errors in parentheses. Linear fixed effects estimation.

*$P < .1$. **$P < .05$. ***$P < .01$.

[a]Asset index: standardized principal component analysis (PCA) score based on households' ownership of a maximum of 48 household and productive assets.

response to experiencing shocks that relate to their agricultural production, as these have direct impact on their livelihood. While it was found that farmers react more strongly to agricultural shocks than to demographic or general weather shocks ($P < .01$), they react by the same magnitude to economic shocks and significantly more strongly to price shocks ($P < .01$). This only partly reflects our assumption that expectations move more strongly with experience of shocks that are of direct significance to agricultural production. However, price and other economic shocks also have direct relevance to the farmers' livelihood, which could explain the strong effects. The wealth level, proxied by the asset index, is positively correlated with shock expectations. This relationship follows naturally as some shocks in the analysis are conditional on ownership of certain assets, such as livestock death or theft. Nevertheless, this relationship does not explain potential differences in the effect of shock experience on updating of expectations, which is discussed in the next section.

The results of the conditional fixed-effects model (Equation 5) as a robustness test are shown in Table A4 in the Appendix. The drawback of this estimation approach is that the individual fixed effects cannot be estimated and that the conditional probability is difficult to interpret. One cannot infer predicted probabilities and the most straight forward interpretation is in terms of odds ratios. The significance levels and relative sizes of the coefficients, however, do confirm the results of the LPM.

The heterogeneous effects of own shock experience on updating of expectations by household wealth proxied by the asset index are shown in Table 4. While wealth is expected to be positively correlated with shock expectations, there is no clear prior expectation on the relationship between wealth and *updating* of expectations. We find a statistically significant and negative interaction effect, considering the average across shock types (models 1 and 2), indicating that the coefficient for the positive relationship between own experience of a shock and future expectations is decreasing with wealth. The positive effect of shock experience on expectation is, therefore, driven by respondents from households with wealth levels below the mean. This becomes evident in the plotted contrast graphs in

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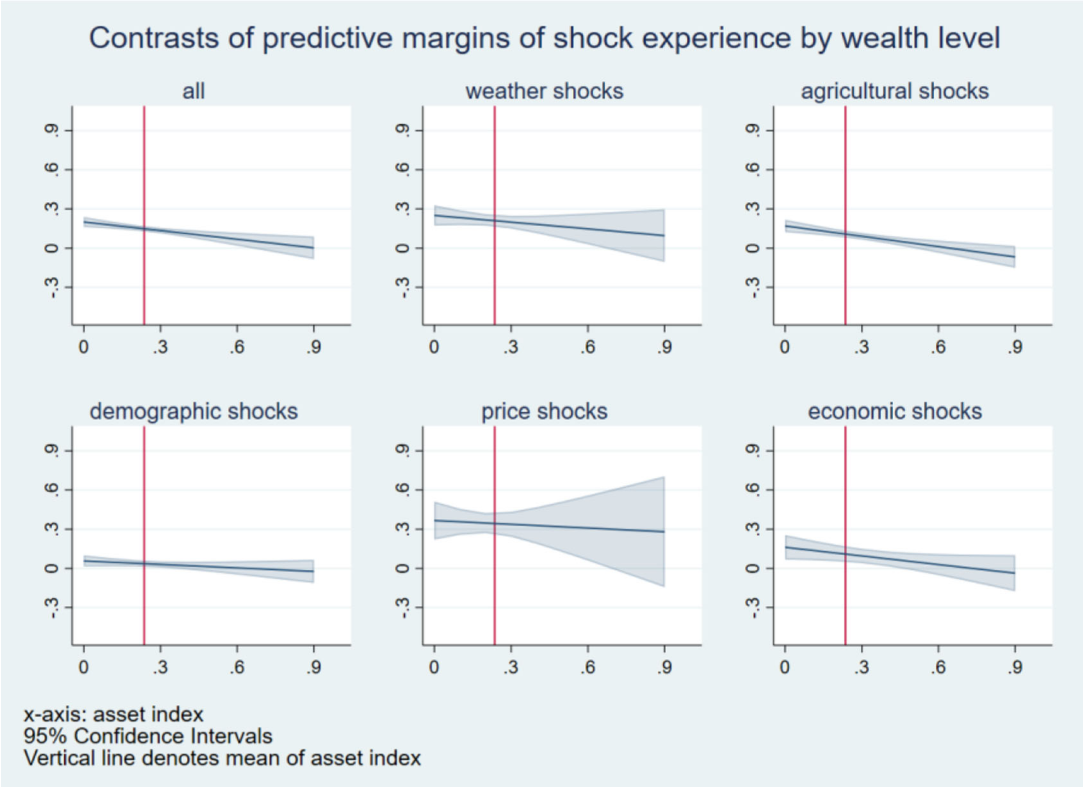

FIGURE 3 Contrasts of predictive margins of shock experience by shock type and wealth

Figure 3, which show consistently across shock types that the effect of shock experience on updating of expectations decreases with wealth.

7 | CONCLUSIONS

Rural households in developing countries face multiple adverse events. In this article, a large three-wave panel survey of Kenyan vegetable farmers was used with detailed information on a wide range of self-reported adverse shock events and shock expectations to explore the question of how farmers form expectations about such events. In general, few farmers in the sample expected any shocks to occur in the coming year, and on average they expected a lower number of shocks to occur than they were affected by during the previous year. However, farmers were found to update their expectation of a shock occurring in the following year when they had experienced that shock in the past year or, for price shocks, more other villagers had experienced it. In addition, the more shocks farmers experienced overall, the more likely they were to expect any shock to affect them in the future, even shocks that they had not been affected by in the past year. Potentially, this is due to an increased perceived vulnerability and greater pessimism about the future when experiencing multiple adverse events simultaneously.

Furthermore, this article finds that the effect of shock experience on expectations is moderated by wealth, and the relatively poorer farmers in terms of assets are more likely to update their expectations about future shocks following their own experience. This result is in contrast to the theoretical considerations by Lybbert et al. (2007), who argue that when wealthier households have access to more livelihood strategies and their choice of strategies depends on the future state of nature, then the value of updating beliefs is increasing with wealth. However, it is also possible that for wealthier households the choice of livelihood strategy does not depend on the adverse event, in line with the empirical findings by Giné et al. (2009). Adapting their own expectations in the light of past experiences, no matter if rational or not, is a behaviour that is not shown by the more wealthy farmers. Since wealthier farmers may have more coping strategies and livelihood options available that are independent of whether they experience any of the stated shocks, they have no need in adapting their expectations about the future in light of new information. However, more research is needed on the relationship between livelihood strategies, shock experience and expectations to identify the indicated pathway.

Some notes on the shortcomings of this article are pertinent. The panel covers only three years, which might be a relatively short time span to analyse behaviour over time, and longer panels could deliver more insights on the dynamics of expectation formation. Furthermore, the expectations about the likelihood of adverse shocks are elicited as binary variables, and cannot be interpreted as subjective probabilities without strong assumptions about the subjective probability distribution. A more nuanced analysis of the updating of subjective probabilities would be desirable, but would require data that elicit the whole distribution. Despite these points, to the best of our knowledge to date this is the only article that uses a large multi-year panel dataset eliciting multiple subjective shock expectations and self-reported experiences.

If, as suggested by previous research, expectations of adverse events affect farmers' willingness to adopt new technologies (Barham et al., 2015; Bonan et al., 2020; Tjernström et al., 2021; Trujillo-Barrera et al., 2016) or buy insurance as a risk mitigation strategy (Gallagher, 2014; Royal & Walls, 2019), then it is important for policy makers to factor in farmers' recent experiences when designing programs and interventions, as they may affect their outcomes. The causal relationship between shock expectations and adaptation and mitigation behaviours, however, remains to be investigated.

REFERENCES

Assenza, T., Bao, T., Hommes, C., & Massaro, D. (2014). Experiments on expectations in macroeconomics and finance. *Research in Experimental Economics*, *17*, 11–70. https://doi.org/10.1108/S0193-230620140000017002

Attanasio, O. P. (2009). Expectations and perceptions in developing countries: Their measurement and their use. *American Economic Review*, *99*(2), 87–92. https://doi.org/10.1257/aer.99.2.87

Augenblick, N., & Rabin, M. (2019). Belief movement, uncertainty reduction, and rational updating. Retrieved from: http://faculty.haas.berkeley.edu/ned/AugenblickRabin_MovementUncertainty.pdf

Barberis, N. (2013). The psychology of tail events: Progress and challenges. *American Economic Review*, *103*(3), 611–616. https://doi.org/10.1257/aer.103.3.611

Barham, B. L., Chavas, J.-P., Fitz, D., Ríos-Salas, V., & Schechter, L. (2015). Risk, learning, and technology adoption. *Agricultural Economics*, *46*(1), 11–24.

Baron, J., Hershey, J. C., & Kunreuther, H. (2000). Determinants of priority for risk reduction: The role of worry. *Risk Analysis*, *20*(4), 413–427. https://doi.org/10.1111/0272-4332.204041

Bellemare, M. F., Novak, L., & Steinmetz, T. L. (2015). All in the family: Explaining the persistence of female genital cutting in West Africa. *Journal of Development Economics*, *116*, 252–265.

Bellemare, M. F. (2009). When perception is reality: Subjective expectations and contracting. *American Journal of Agricultural Economics*, *91*(5), 1377–1381. https://doi.org/10.1111/j.1467-8276.2009.01351.x

Blum, S. C., Silver, R. C., & Poulin, M. J. (2014a). Perceiving risk in a dangerous world: Associations between life experiences and risk perceptions. *Social Cognition*, *32*(3), 297–314. https://doi.org/10.1521/soco.2014.32.3.297

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

Bonan, J., Kazianga, H., & Mendola, M. (2020). *Agricultural Transformation and Farmers' Expectations: Experimental Evidence from Uganda* (GLO Discussion Paper No. 456).

Bordalo, P., Gennaioli, N., & Shleifer, A. (2018). Diagnostic expectations and credit cycles. *The Journal of Finance*, *73*(1), 199–227. https://doi.org/10.1111/jofi.12586

Botzen, 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.

Bourdeau-Brien, M., & Kryzanowski, L. (2020). Natural disasters and risk aversion. *Journal of Economic Behavior & Organization*, *177*, 818–835.

Brown, P., Daigneault, A. J., Tjernström, E., & Zou, W. (2018). Natural disasters, social protection, and risk perceptions. *World Development*, *104*, 310–325. https://doi.org/10.1016/j.worlddev.2017.12.002

Brunnermeier, M. K., & Parker, J. A. (2005). Optimal expectations. *American Economic Review*, *95*(4), 1092–1118. https://doi.org/10.1257/0002828054825493

Cameron, A. C., & Trivedi, P. K. (2005). *Microeconometrics: Methods and applications*. Cambridge University Press.

Cameron, T. A. (2005). Updating subjective risks in the presence of conflicting information: An application to climate change. *Journal of Risk and Uncertainty*, *30*(1), 63–97.

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

Cerroni, S. (2020). Eliciting farmers' subjective probabilities, risk, and uncertainty preferences using contextualized field experiments. *Agricultural Economics*, *51*(5), 707–724.

Chamberlain, G. (1980). Analysis of covariance with qualitative data. *The Review of Economic Studies*, *47*(1), 225–238.

Chandrasekhar, A. G., Larreguy, H., & Xandri, J. P. (2020). Testing models of social learning on networks: Evidence from two experiments. *Econometrica*, *88*(1), 1–32.

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. https://doi.org/10.1257/aer.20110306

Coibion, O., Gorodnichenko, Y., & Kamdar, R. (2018). The formation of expectations, inflation, and the phillips curve. *Journal of Economic Literature*, *56*(4), 1447–1491. https://doi.org/10.1257/jel.20171300

Degroot, M. H. (1974). Reaching a consensus. *Journal of the American Statistical Association*, *69*(345), 118–121.

Delavande, A. (2014). Probabilistic expectations in developing countries. *Annual Review of Economics*, *6*(1), 1–20. https://doi.org/10.1146/annurev-economics-072413-105148

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. https://doi.org/10.1596/prwp

Dercon, S. (2005). Insurance against poverty. UNU-Wider studies in development economics. Oxford: Oxford University Press.

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

Eil, D., & Rao, J. M. (2011). The good news-bad news effect: Asymmetric processing of objective information about yourself. *American Economic Journal: Microeconomics*, *3*(2), 114–138.

Eisele, M., Troost, C., & Berger, T. (2021). How bayesian are farmers when making climate adaptation decisions? A computer laboratory experiment for parameterising models of expectation formation. *Journal of Agricultural Economics*, *72*, 805–828.

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

Filmer, D., & Pritchett, L. H. (2001). Estimating wealth effects without expenditure data–or tears: An application to educational enrollments in states of India. *Demography*, *38*(1), 115–132. https://doi.org/10.1353/dem.2001.0003

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*, *6*(3), 206–233. https://doi.org/10.1257/app.6.3.206

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*. Mimeo. Retrieved from http://www.robertmtownsend.net/sites/default/files/files/papers/working_papers/dist_art_all_10122015.pdf

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

Greene, W. (2004). The behaviour of the maximum likelihood estimator of limited dependent variable models in the presence of fixed effects. *The Econometrics Journal*, *7*(1), 98–119.

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. *Cognitive Psychology*, *3*(3), 430–454.

Kaiser, H. F. (1974). An index of factorial simplicity. *Psychometrika*, *39*(1), 31–36.

Kebede, S. W., & Bokelmann, W. (2017). African indigenous vegetables and their production practices: Evidence from the HORTINLEA Survey in Kenya. *Agrotechnology*, *6*(170), 2. https://doi.org/10.4172/2168-9881.1000170

Kettlewell, N. (2019). Risk preference dynamics around life events. *Journal of Economic Behavior & Organization*, *162*, 66–84.

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*. Mimeo. Retrieved from: https://ssrn.com/abstract=3188065

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. https://doi.org/10.1016/j.worlddev.2017.07.020

Lloyd-Smith, P., Schram, C., Adamowicz, W., & Dupont, D. (2018). Endogeneity of risk perceptions in averting behavior models. *Environmental and Resource Economics*, *69*(2), 217–246.

Loewenstein, G. F., Weber, E. U., Hsee, C. K., & Welch, N. (2001). Risk as feelings. *Psychological Bulletin*, *127*(2), 267–286. https://doi.org/10.1037/0033-2909.127.2.267

Lucas, R. E., & Sargent, T. J. (1981). *Rational expectations and econometric practice: Vol. 1*. University of Minnesota Press.

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. https://doi.org/10.1016/j.worlddev.2006.04.004

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

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

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. https://doi.org/10.1111/agec.12157

Menapace, L., Colson, G., & Raffaelli, R. (2013). Risk aversion, subjective beliefs, and farmer risk management strategies. *American Journal of Agricultural Economics*, *95*(2), 384–389.

Muth, J. F. (1961). Rational expectations and the theory of price movements. *Econometrica*, *29*(3), 315–335. https://doi.org/10.2307/1909635

Rao, E. J. O., & Qaim, M. (2011). Supermarkets, farm household income, and poverty: Insights from Kenya. *World Development*, *39*(5), 784–796. https://doi.org/10.1016/j.worlddev.2010.09.005

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.

Ricome, A., & Reynaud, A. (2022). Marketing contract choices in agriculture: The role of price expectation and price risk management. *Agricultural Economics*, *53*(1), 170–186.

Royal, A., & Walls, M. (2019). Flood risk perceptions and insurance choice: Do decisions in the floodplain reflect overoptimism? *Risk Analysis*, *39*(5), 1088–1104. https://doi.org/10.1111/risa.13240

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. https://doi.org/10.1016/j.jebo.2015.03.001

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 and Remote Health*, *8*(3), 950.

Schippers, R. R. (2000). *African indigenous vegetables: An overview of the cultivated species*. Chatham, UK: Natural Resources

Institute/ACP-EU Technical Centre for Agricultural and Rural Cooperation.

Smith, V. K. (2008). Risk perceptions, optimism, and natural hazards. *Risk Analysis*, *28*(6), 1763–1767.

Sullivan-Wiley, K. A., & Short Gianotti, A. G. (2017). Risk perception in a multi-hazard environment. *World Development*, *97*, 138–152. https://doi.org/10.1016/j.worlddev.2017.04.002

Tjernström, E., Lybbert, T. J., Hernández, R. F., & Correa, J. S. (2021). Learning by (virtually) doing: Experimentation and belief updating in smallholder agriculture. *Journal of Economic Behavior & Organization*, *189*, 28–50.

Trujillo-Barrera, A., Pennings, J. M. E., & Hofenk, D. (2016). Understanding producers' motives for adopting sustainable practices: The role of expected rewards, risk perception and risk tolerance. *European Review of Agricultural Economics*, *43*(3), 359–382.

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

Viscusi, W. (1989). Prospective reference theory: Toward an explanation of the paradoxes. *Journal of Risk and Uncertainty*, *2*(3), 235–263. https://doi.org/10.1007/BF00209389

Viscusi, W. K. (1997). Alarmist decisions with divergent risk information. *The Economic Journal*, *107*(445), 1657–1670.

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. https://doi.org/10.1111/risa.12271

Voors, M. J., Nillesen, E. E. M., Verwimp, P., Bulte, E. H., Lensink, R., & Soest, D. P. V. (2012). Violent conflict and behavior: A field experiment in Burundi. *American Economic Review*, *102*(2), 941–964. https://doi.org/10.1257/aer.102.2.941

Wachinger, G., Renn, O., Begg, C., & Kuhlicke, C. (2013). The risk perception paradox–implications for governance and communication of natural hazards. *Risk Analysis*, *33*(6), 1049–1065. https://doi.org/10.1111/j.1539-6924.2012.01942.x

Wooldridge, J. M. (2002). *Econometric Analysis of Cross Section and Panel Data*. Cambridge, MA: MIT Press.

World Bank Group (2019). *Kenya Economic Update, April 2019, No. 19: Unbundling the Slack in Private Sector Investment – Transforming Agriculture Sector Productivity and Linkages to Poverty Reduction*. Retrieved from World Bank. https://openknowledge.worldbank.org/handle/10986/31515 License: CC BY 3.0 IGO

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Freudenreich, H., & Kebede, S. W. (2022). Experience of shocks, household wealth and expectation formation: Evidence from smallholder farmers in Kenya. *Agricultural Economics*, *53,* 756–774. https://doi.org/10.1111/agec.12718

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APPENDIX

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 Differences in initial and balanced sample for base year 2014

.	Original sample		Dropped sample		Kept sample		
	Mean	sd	Mean	sd	Mean	sd	*P*
Household size	5.633	2.267	5.838	2.248	5.701	2.233	.026
Head is female; dummy	.193	.395	.157	.364	.269	.444	.000
Land size; ha	.793	.867	.831	.892	.783	.779	.097
No of assets	13.95	5.358	13.80	5.180	13.93	5.092	.865
No. of shocks experienced in last 12 months	1.974	1.338	2.292	1.221	2.216	1.086	.111
No. of shocks expected in next 12 months	1.369	1.468	1.589	1.510	1.405	1.420	.007
Avg. severity of shocks experienced	1.482	.595	.183	1.530	.230	.123	.574
Observations	1232		835		397		

[†] *p*-values from two-sided *t*-test. $^{*}P < .1$, $^{**}P < .05$, $^{***}P < .01$, sd: standard deviation. *p*-value is reported for *t*-test between dropped sample ($N = 835$) and kept sample ($N = 397$).
Asset index is based on standardised principal component analysis scores for ownership of 48 assets.
Shock severity is conditional on experiencing at least one shock. It is self-assessed on a 4-point scale ranging from 0 = "no impact".
1 = "Low impact", 2 = "Medium impact", to 3 = "High impact".

TABLE A3 Variance decomposition of shock variables between and within respondents

		Within			Between		
	Within-variance share	Max	Min	sd	Max	Min	sd
Dependent variable							
Expects shock in coming 12 months; dummy	98%	1.04	−.16	.21	.21	.00	.04
Independent variables							
Affected by shock in last 12 months; dummy	99%	1.08	−.14	.29	.24	.01	.04
Village members affected in last 12 months; share	99%	.80	−.02	.12	.11	.07	.01
No. of other shocks experienced in last 12 months	82%	10.72	−3.28	1.27	5.43	.32	.88

Time periods = 3, $n = 9528$.
[†] Asset index: standardized principal component analysis (PCA) score based on households' ownership of a maximum of 48 household and productive assets.

TABLE A4 Conditional fixed effects logit model for shock expectations (odds ratios)

	All		Weather	Agri.	Demogr.	Price	Econ
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Affected by shock in last 12 months; dummy	4.884***	4.926***	3.676***	5.716***	13.989***	16.524***	10.445***
	(.538)	(.545)	(.520)	(1.305)	(12.977)	(8.073)	(7.933)
Village members affected in last 12 months; share	2.801**	2.693**	1.581	2.412	2.760	294.381***	.079
	(1.199)	(1.166)	(.829)	(2.172)	(10.344)	(611.544)	(.332)
No. of other shocks experienced in last 12 months	1.341***	1.338***	1.240***	1.436***	1.587***	1.328***	1.404***
	(.037)	(.038)	(.053)	(.096)	(.148)	(.118)	(.118)
Household size		.989	.879*	1.266	1.174	.975	.927
		(.055)	(.062)	(.206)	(.328)	(.200)	(.131)
Dependency ratio		.867	.934	.875	.590*	1.066	.700
		(.101)	(.194)	(.228)	(.172)	(.391)	(.225)
Log(land size)		1.112*	1.050	1.328*	1.010	1.074	1.142
		(.067)	(.100)	(.195)	(.231)	(.148)	(.209)
Asset index†		8.360***	3.292	3.035	1.354	154.302***	28.277**
		(4.680)	(3.000)	(3.843)	(2.973)	(237.713)	(41.487)
Respondent age		.996	1.011	.855	1.043	.987	.726
		(.018)	(.025)	(.139)	(.065)	(.034)	(.351)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3780	3780	1467	876	375	642	420

Standard errors in parentheses.
Conditional fixed effects logit model (odds ratios).
$^{*}P < .1$, $^{**}P < .05$, $^{***}P < .01$.
†Asset index: standardized principal component analysis (PCA) score based on households' ownership of a maximum of 48 household and productive assets.

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TABLE A5 Household items for asset index

Home appliances	Furniture	Electronic goods	Transportation
Refrigerator	Bed	Mobile phone	Bicycle
Ox-plough	Sofa	Landline phone	Motorcycle/Bodaboda
Panga	Chair/stool	Photo camera	Car/Vehicle
Jembe	Wardrobe closet	Video camera	Truck (including pickup)
Slasher	Table	Radio	Tractor
Axe	Wooden trunk/Benches	CD or tape player	Animal cart/Wagon
Hammer	Cupboard/TV cabinet	TV	Other, specify
Fork jembe	Basket	Computer or laptop	
Wheel barrow	Carpet	Satellite dish	
Spade/ shovel		Home theater/speakers	
Sewing machine			
Electric/gas (LPG) cooker			
Charcoal stove			
Fuel/Kerosene stove			
Traditional firewood/coal/dung stove			
Electric heater			
Electric iron			
Micro-wave oven			
Fans			
Electric blender			
Electric toaster			
Food mixer, deep fryers			

Survey question asked: "Does your household own a [item]?" Answer scale: 1 (yes), 0 (no).

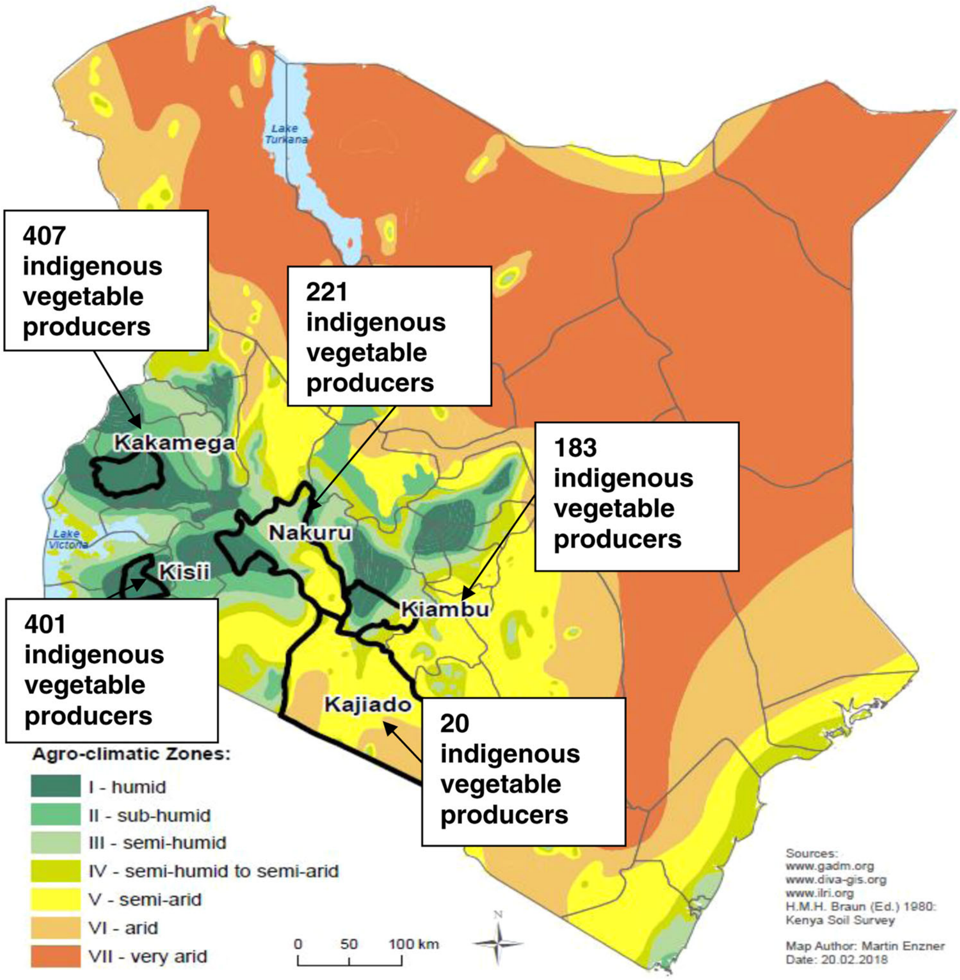

FIGURE A1 Location of the counties