Locus of Control as a Moderator of the Relationship Between Experience, Learning, and Investment

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1 Introduction

What happens in life results from a combination of individual actions and forces outside of one's own control. Natural disasters and human-made tragedies are a fact of life. Between 2000 and 2019, over 7,000 major disaster events were recorded by Centre for Research on the Epidemiology of Disasters[1], 90% of which were climate-related. These events are estimated to have affected over 4 billion people and caused nearly USD 3 trillion in economic losses (United Nations, 2020).

The human toll of these disasters – losses of life, livelihoods, dignity, and aspiration to use the words of USAID (2019) – is largely born by the poor. While many of the events themselves may not be preventable, their impact on local economies and human suffering may be mitigated through investment in early warning systems and well-functioning markets for financial services. Others events, like food shortages and income loss due to drought or flood may be partially prevented. Malacarne and Paul (2022) show that, in the same rainfed agricultural context used in the second half of this paper, investment in improved management practices partially mitigates the large negative effects of drought on household nutritional outcomes. Reducing the impact of these shocks even marginally could result in large gains, given the millions of vulnerable individuals who rely on rainfed agriculture for their livelihoods.

To fulfill the potential of these investments, however, they not only need to achieve broad uptake but also high levels of use among the most vulnerable households. It is these households, after all, that stand to gain the most from adoption. If, however, the same risks that motivate the development of resilience-enhancing technologies also leave decision-makers with the belief that their actions are inconsequential relative to external forces, then achieving targeted adoption becomes even more challenging.

[1] The Centre for Research on the Epidemiology of Disasters maintains the Emergency Events Database (EM-DAT). Disasters are defined as events in which at least one of the following criteria are met: 1) ten or more people dead 2) 100 or more people affected, 3) a state of emergency is declared, 4) a call for international assistance is made (EM-DAT, 2022).

Since the 1950s, research in psychology has noted that locus of control, the extent to which a decision-maker believes that outcomes are determined by her actions relative to forces outside of her control, is an important component of behavior and learning (Lefcourt, 1982). Repeated exposure to negative shocks may create in decision-makers the sense that their investment is dwarfed by the influence of external forces. In addition to deriving their livelihoods from a risky production process, households engaged in rainfed maize production are often poor and live in remote areas. Both of these characteristics increase exposure to the type of shocks believed to affect locus of control.

Economic research has also documented associations between cognitive skills, including locus of control, and decision-making. This paper seeks to more fully integrate the rich history of locus of control into models of economic decision-making. Section 2 discusses the conceptual link between locus of control and neoclassical choice. Neoclassical choice theory sets out clear conditions for optimal behavior. In order to be incorporated into this theory, locus of control must influence at least one element present in these conditions. In the present context of this paper, which will focus on risk-exposed, smallholding farmers, that means affecting prices, preferences, probabilities, or production functions. As a belief about the input-output relationship, the intuitive pathway is for locus of control to influence beliefs about the production function.

From there, Section 4 uses primary data from a large sample of maize-producing households in Eastern Africa to empirically study the influence of locus of control on investment. Specifically, I focus on the use of improved maize seed varieties in a large sample of maize-producing households from Mozambique and Tanzania. This population is ideal for studying the relationship between locus of control and investment in risky environments owing to the need to make reoccurring choices of technology and frequent exposure to the type of shocks likely to induce differences in locus of control.

To best reflect the influence suggested in the psychology literature, I develop a survey instrument for locus of control specific to maize production. I use this measure alongside a standard, more general locus of control instrument commonly found in the economic literature. I show that farmers exhibiting a more external locus of control in maize production – those who believe that the variability in harvest due to input choice is small relative to the variability in harvest due to weather outcomes – are significantly less likely to use improved maize varieties. The size of this effect is non-trivial: up to eleven percentage points.

In support of the hypothesized pathway, I show that there is a strong relationship between locus of control and the expected return to adopting improved seed varieties. I demonstrate that this relationship is not a mechanical function of the newly developed survey instrument, but rather a manifestation of a deeper connection between the locus of control construct and the subjective production function. I also show that in the current sample, locus of control is not strongly related to either subjective expectations about weather patterns or risk attitudes.

2 Background

Locus of control – where or with whom control of outcomes lies – denotes the location of an individual's beliefs along a spectrum from internal to external (Rotter, 1966). An internal locus of control reflects the belief that one's own actions are a primary force in determining outcomes. External locus of control, on the other hand, is the belief that outcomes are principally determined by external forces.

In the 1940s and 1950s, psychology in North America was working to be accepted as an objective science. The behaviorism movement, most associated with Ivan Pavlov and John B. Watson, promoted the idea that for this to happen, psychology must be based on the observed behavior of test subjects. In pursuing this ideal, many experiments were conducted in which both human and non-human subjects were repeatedly exposed to different stimuli and the patterns in their behavior observed. The behaviorism movement would eventually give rise to a reactionary movement known as the cognitive revolution, which focused more explicitly on the mental processes underlying behavior previously considered to be a mechanical response to stimuli. A driving force in this revolution was the observation that perceived control seemed to play a central role in how subjects responded to stimuli within experiments (Miller, 2003).

Perceived control is the belief that subjects can (or cannot) affect what is happening to them. In the context of the experiments of the time, this was commonly measured by recording avoidance behavior: the effort exerted by test subjects to avoid or escape negative stimuli (Lefcourt, 1982). Two sets of early experiments with non-humans showed that exposure to inescapable negative stimuli resulted in lower levels of avoidance behavior that persisted even after the stimuli were made escapable (Dickinson and Pearce, 1977; Overmier and Seligman, 1967; Hiroto, 1974). These experiments resulted in the popularization of the term learned helplessness to describe a subject's induced belief in the independence of actions and outcomes (Lefcourt, 1982).

The movement in psychology away from instinctual response was heavily influenced by the idea of learned helplessness. The 1950's began a period of focused attention on the degree to which outcomes are believed to result from a decision-maker's actions as opposed to forces outside of her control. The formalization of this belief, which would come to be known as locus of control, grew out of the the social learning theories published in Julian Rotter's *Social Learning and Clinical Psychology* (1954).

Social learning theory recognizes four principle classes of variables: behaviors, reinforcements, psychological situations, and expectancies (Rotter, 1975). Which behaviors are chosen is a function of an individual's beliefs about the reinforcements that are possible, or likely, in a particular psychological situation. Expectancies link behaviors to reinforcements, capturing a decision-maker's beliefs about the likelihood that a certain reinforcement will result from a particular action in a given circumstance (Patenzuela, 1987). This belief is informed both by a decision-maker's experience with that exact action and circumstance in the past, as well as her experience with actions and circumstances that she considers similar (Rotter, 1954, 1966; Patenzuela, 1987).

The theory in Rotter's 1954 work centers on an agent who chooses the action or set of actions with the greatest likelihood of satisfying her needs. Rotter terms this property of an action set "need potential". Need potential is a function of two components: freedom of movement and need value. In the language of social learning theory, need value – referring to how large or salient the need being satisfied is to the agent – is a reinforcement. Freedom of movement, on the other hand, is an expectancy, capturing an agent's experiences with the various possible actions and their likely reinforcements. It is this final component that would evolve into locus of control.

Like the behavioralist movement proceeding it, locus of control is rooted in the relationship between actions and responses. Now, however, the link between action and response is mediated by a mental process. Lived experiences are codified into beliefs according to a decision-maker's perception of whether the outcome resulted from her own actions or was a product of external forces. This belief can be said to exist on a spectrum between the poles of external and internal. Decision-makers who come to believe that outcomes are largely independent of their actions are said to have an external locus of control. At the other end of the spectrum are those decision-makers who come to believe that there is strong causal link between their actions and outcomes. These individuals are said to have an internal locus of control.

Once named, locus of control became a commonly studied construct. The laboratory experiments that helped launch the cognitive revolution had demonstrated that locus of control could be manipulated in test subjects (Miller, 2003).[2] Outside of the laboratory, researchers soon showed that life itself provided the conditioning necessary to create differences in locus of control. Studies often focused on populations subject to discrimination or exposed to high levels of risk, especially at early ages. Racial groups and socioeconomic class (Lefcourt and Ladwig, 1965; Battle and Rotter, 1963), urban and rural dwellers (Nelsen and Frost,

[2]Still referred to as perceived control in the earliest experiments

1971), and inmates (Lefcourt and Ladwig, 1965) were common populations of interest and consistently demonstrated different attitudes about their ability to control outcomes.

Psychologists also linked locus of control to many behavioral outcomes, including decision-time, stress coping, and academic performance (Franklin, 1963; Mc Ghee and Crandall, 1968; Bar-Tal and Bar-Zohar, 1977). Early evidence for locus of control as a predictor of behavior comes from Phares (1957) and James and Rotter (1958), who study effort exerted in tasks framed as either skill or luck driven. The academic performance literature also found consistent results linking locus of control to achievement and effort (Franklin, 1963; Mc Ghee and Crandall, 1968). In one of the most significant results, beliefs akin to internal locus of control were found to be the best predictor of achievement in underprivileged child populations (Pettigrew, 1967; Coleman, 1971).

Locus of control is not entirely new to economics, though it is far from prominent. Given the domains and behaviors to which psychologists have applied the locus of control construct, it is not surprising that it should catch the eye of economists. Much of the inquiry into the behavior of microeconomic agents focuses on a choice of actions that combine with external forces to satisfy needs. The particular context treated here – the production of food and economic security through investment in risky agricultural production – certainly constitutes an example of this.

A small body of empirical literature has emerged linking economic behavior to locus of control. The findings in economics largely parallel the psychological literature that proceeded them. A more internal locus of control is associated with a greater likelihood of participating in job training programs (Caliendo et al., 2016), labor market success (Cobb-Clark, 2015), and agricultural productivity and investment (Laajaj and Macours, 2021; Abay, Blalock and Berhane, 2017). Efforts to link locus of control to neoclassical choice theory more formally, however, have lagged far behind the promising empirical results.

3 Incorporating Locus of Control in Economic Choice

The expected utility maximization problem is the workhorse of neoclassical choice theory for describing individual behavior. In order to be incorporated into this framework, locus of control must influence an element present in the expected utility maximization problem. Locus of control will be most relevant for activities in which outcomes are influenced by both the decision-maker and external forces. There is no shortage of such activities. Decisions facing economic agents related to business, health, education, and, of course, agriculture, all satisfy this criterion.

Consider a production technology that generates output from two inputs (x,e). Let x be an input under the decision-maker's control and let e be an input that is not. To put this in the context of rainfed agriculture for consistency with the later application, x can be thought of as investment in improved inputs and e as the quality of the growing season – a complicated interaction of rainfall, temperature, and timing. Assume that the decision-maker can describe her beliefs about the possible realizations of e using the probability density function $\phi_i(e)$ and that x can be precisely chosen.[3] Given an input cost (c), output price (p) and wealth endowment (A_i), the expected utility maximization problem can be written as:

$$\max_x E[U_i] = E\left[U_i\left(pf_i(x,e) + A_i - cx\right)\right] \quad s.t. \quad x \geq 0,\ cx \leq A_i \tag{1}$$

Assume a concave utility function and positive but diminishing marginal returns to each input in $f_i(x, e)$. The subscript i identifies elements of the optimization problem that might differ across individuals. These differences can be objective reflections of circumstance – such as soil quality, wealth, or decision-maker ability – or they can reflect differences in beliefs. As

[3] By allowing x to be precisely chosen, I assume away any influence of perceived self-efficacy. Perceived self-efficacy is colloquially similar to locus of control but concerns a decision-maker's belief that she can successfully execute a course of action rather than her beliefs about how outcomes are determined. Wuepper and Lybbert (2017) provide more detail on perceived self-efficacy and its application to economics.

Figure 1 depicts, in order to affect decision-making within the expected utility maximization framework, locus of control will need to influence at least one of these elements: production functions, probabilities, preferences, or prices (and endowments). The principle hypothesis for the remainder of this paper will be that locus of control affects behavior by influencing beliefs about the production function.

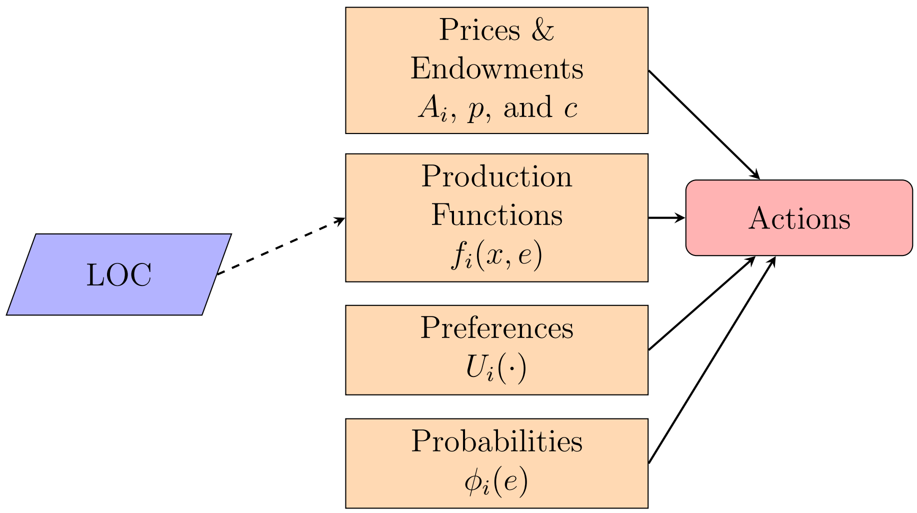


Figure 1: Locus of control and the Expected Utility Maximization Problem.

3.1 Locus of Control and the Production Function

If locus of control is to affect behavior through the production function, individuals with an internal locus of control will need to believe that the production function is systematically different than individuals with an external locus of control[4]. Put another way, an individual who believes that her own actions are the primary force in determining outcomes believes that choosing effort level $x^\star$ likely results in a different output than an individual who believes that forces outside of her control play a dominant role in determining outcomes.

Formally, let locus of control for individual i be denoted by LOC_i. Keeping with convention in psychology, larger values of LOC_i are associated with a more external locus of

[4]The Supplemental Appendix Section **??** includes a discussion of the choice to focus on the production function rather than subjective probabilities, preferences, or prices, endowments and other constraints.

control. Let Z_i be a vector of other individual characteristics that might affect beliefs about the production function – such as location or ability. The production function can then be written as:

$$f_i(x, e; Z_i, LOC_i) \tag{2}$$

Assume that marginal products are positive for both inputs and exhibit diminishing marginal returns.

$$\frac{\partial f_i(x, e; Z_i, LOC_i)}{\partial x} > 0 \qquad \frac{\partial^2 f_i(x, e; Z_i, LOC_i)}{\partial x^2} < 0$$
$$\frac{\partial f_i(x, e; Z_i, LOC_i)}{\partial e} > 0 \qquad \frac{\partial^2 f_i(x, e; Z_i, LOC_i)}{\partial e^2} < 0$$

Also assume that the two inputs are complements in production.

$$\frac{\partial^2 f_i(x, e; Z_i, LOC_i)}{\partial x \partial e} > 0 \qquad \frac{\partial^2 f_i(x, e; Z_i, LOC_i)}{\partial e \partial x} > 0 \tag{3}$$

In a 1982 review of research into the locus of control construct, the psychology scholar Herbert Lefcourt characterized individuals with an internal locus saying:

> *"Those who report (on a given scale) that they perceive events as being largely contingent upon their personal efforts at the present time, as opposed to those who feel more fatalistic about the manner in which outcomes occur."*
> (Lefcourt, 1982)

Drawing on this characterizations of locus of control, assume that the influence of locus of control on beliefs about the production function are fully captured by noting its effect on the marginal products of x and e.

Hypothesis 1 (H1)**.** *A more external locus of control will reduce the decision-maker's perception of the return to her own investment and increase her perception of the return to the input she does not control*

$$\frac{\partial^2 f_i(x, e; Z_i, LOC_i)}{\partial LOC_i \, \partial x} < 0 \qquad \forall x \tag{4}$$

$$\frac{\partial^2 f_i(x, e; Z_i, LOC_i)}{\partial LOC_i \, \partial e} > 0 \qquad \forall e \tag{5}$$

Equations 4 and 5 capture the assumption posed in H1. Incorporating locus of control into neoclassical choice as an influence on beliefs about the production function fits into a line of behavioral economic research that acknowledges that economic parameters are informed by situational and environmental factors. Famously, Appadurai (2004) and Genicot and Ray (2020) model aspirations as introducing non-convexities into decision-maker's utility functions. Other work in the space includes Moya (2018), which considers the effects on risk attitudes of exposure to violence in Colombia and Laajaj (2017) studies the effect of economic distress on the choice of planning horizon.[5]

The decision to include locus of control as an influence on $f(\cdot)$ rather than define it using $f(\cdot)$ – in the way that the Arrow-Pratt measures of risk aversion are defined using the utility function – is also grounded in psychology theory. Specifically, Rotter (1966) notes that the class of social learning theory variables known as expectancies from which locus of control originates, "generalize from a specific situation to a series of situations which are perceived as related or similar (Rotter, 1966)". In other words, locus of control is not a belief about one production function but a belief about causality that influences how a decision-maker sees her role in many different production processes. Accodringly:

Hypothesis 2 (H2)**.** *Locus of control will relate more strongly to beliefs about production functions than to preferences (reflected by risk attitudes) or probabilities.*

To see how locus of control affects investment decisions under the above hypotheses, I return to the maximization program in Equation 1. Given the earlier assumptions, the

[5] As Figure **??** depicts in the Supplementary Appendix, all of these examples amount to allowing a decision-maker's experiences to influence an element of the expected utility maximization problem.

second order condition is satisfied everywhere and the interior solution[6] is characterized by

$$E\left[U_i'(\cdot)(pf_{ix})\right] - E\left[U_i'(\cdot)(c)\right] = 0$$

Rearranging terms and expanding the expectation

$$p\int_e \left(U_i'(pf_i(x,e) + A_i - cx)\frac{\partial f_i(x,e)}{\partial x}\right)\phi_i(e)de = c\int_e \left(U_i'(pf_i(x,e) + A_i - cx)\right)\phi_i(e)de \quad (6)$$

Note that the marginal product of the externally controlled input does not appear in Equation 6. The influence of locus of control on investment will thus be driven by the changes it induces on the perceived marginal product of x. Rearranging equation 6:

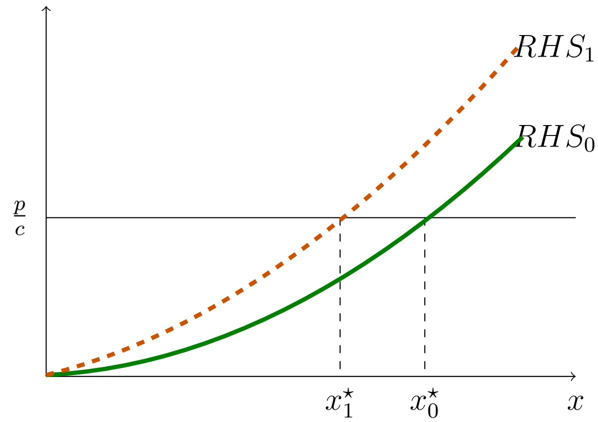
$$\frac{p}{c} = \frac{\int_e U_i'(pf_i(x,e) + A_i - cx)\phi_i(e)de}{\int_e U_i'(pf_i(x,e) + A_i - cx)\frac{\partial f_i(x,e)}{\partial x}\phi_i(e)de} \quad (7)$$

Given diminishing marginal returns in x, the right-hand side of Equation 7 approaches p/c from below. A more external locus of control implies a reduction in $\frac{\partial f(x,e)}{\partial x}$ at every value of x and thus an increase in the right-hand side of Equation 7. Equation 7 will thus be satisfied at a lower level of investment. This leads to to H3:

Hypothesis 3 (H3)**.** *A more external locus of control will be associated with lower investment.*

The hypothesis in H3 is consistent with previous empirical work in both economics and psychology discussed in the previous section. That hypothesis, along with the previous two, can be tested empirically. The challenge of demonstrating a convincing causal story will come from disentangling locus of control from unobservable characteristics present in Z_i with which it might be correlated. The next section begins both of these tasks.

[6]The corner solutions to the program in Equation 1 are considered in the Supplemental Appendix Section **??**. Under the current assumptions, the zero investment corner is not feasible. The endowment necessary to avoid the liquidity constrained corner moves opposite the optimal investment level described in the interior solution.



Note: A more external locus of control decreases $\partial f_i/\partial x$ and shifts the RHS of Equation 7 upward at any value of x.

Figure 2: Locus of Control and Optimal Investment

4 Eliciting Locus of Control Among Small Farm Households in Mozambique and Tanzania

The psychology literature provides some guidance in moving from theoretical to real-world studies of locus of control to decision-making. Some of this guidance is practical – for example, highlighting problems of acquiescence bias (Rammstedt, Kemper and Borg, 2013) and measurement challenges in populations with low education levels (Soto et al., 2008). Other points are conceptual.

The most relevant of the conceptual point concerns the breadth of the activity domain over which locus of control is defined. Rotter (1975) notes that locus of control can be defined very broadly or very narrowly. For example, an individual may hold beliefs about her ability to affect outcomes in life broadly, in educational settings, in economics courses, or in microeconomic theory courses in particular. These beliefs may be related, as I will show in section 4.3, but they are also separable. I will call an individual's belief about her ability to affect outcomes in life broadly her general locus of control. The successive refinements I will call activity specific locus of control.

A primary contribution of this Section is the creation of an activity specific measure of locus of control for rainfed maize production. The current literature in economics exclusively uses general measures of locus of control, which are often easier to elicit and may inform understanding of a broad set of activities. Rotter (1975) notes, however, that general locus of control may only provide weak predictions of behavior in specific activities. When researchers are interested in a particular activity domain, such as rainfed maize production, it is possible to create a more focused measure of locus of control.

4.1 Data

To study the relationship between locus of control and decision-making empirically, I make use of primary data on a sample of just over 3,000 maize-growing households across 153 communities in Tanzania and Mozambique collected. The data constitute a three wave panel collected between the years of 2016 and 2018. In each round, farmers reported their input decisions, planting practices, and harvest from the previous year. Farmers also completed the survey modules designed to elicit current attitudes toward risk, beliefs about weather patterns, and locus of control.

The average household in the sample cultivates about two hectares of maize and plants predominantly local, non-certified seed varieties. While all households in the study grow maize, many also engage in a diverse portfolio of income generating activities (Table 1). By diversifying their income sources, households protect themselves from the relying too heavily on a risky activity such as rainfed agriculture for their economic and nutritional needs. Many households in both countries operate small businesses, sell labor for wages, and receive remittances to supplement their income from agriculture. A significant fraction of households however, thirty-seven percent in Tanzania and thirty-four percent in Mozambique, report having no source of income other than maize production.

Table 1: Household Characteristics and Asset Ownership (2016)

	Tanzania	Mozambique	Total
Average HH Members	6	6.9	6.4
Highest Level of Education (HH Head)			
None or Below Lower Primary	.18	.39	.27
Lower Primary	.08	.36	.20
Upper Primary	.67	.15	.45
Secondary or Above	.07	.10	.08
Income Generating Activities			
Maize Only	.37	.34	.35
Salaried Job	.04	.16	.09
Operate A Business	.39	.34	.37
Daily Wage Labor	.29	.32	.30
Receive Pension	.02	.05	.03
Receive Remittances	.11	.17	.14
Asset Ownership			
Mobile Phone	.80	.56	.69
Bicycle	.53	.76	.63
Radio	.60	.57	.59
Solar Panel	.37	.45	.41
Average Simple Poverty Score^{+}	37.4	25.7	32.4
Probability Below National Poverty Line	20.2	72	42.4
Probability Below International $1.25/Day Line	35.2	78.3	53.7
N	1,788	1,345	3,133

Notes: This table contains descriptive statistics for the sample of farm households in this section. For more information on the households represented in the data, see Boucher et al. (2021)

4.2 General Locus of Control

Many instruments exist to elicit locus of control. Instruments generally rely on a series of questions asking respondents to identify with either a framing consistent with own-control of outcomes or a framing consistent with external-control of outcomes. This can be achieved either with Likert scales or forced choice pairs – in which two statements are presented and the respondent chooses the statement that most accurately reflects her beliefs. Both elicitation methods result in ordinal scores and are thus best used to situate respondents with respect to one another in a comparable population. The scores have little meaning by themselves, unlike, for example, the CESD-R depression scales where scoring above a certain threshold indicates a high probability of clinical depression (Alloush, 2019). This point was cited as the cause of one most frequent misuses of locus of control in the psychology literature (Rotter, 1975). Instead, a decision-maker's position in the distribution of survey responses identifies her as holding more external or more internal beliefs than her peers.

The general locus of control measure administered as part of this study is a version of the Levenson IPC scales (Levenson, 1981), adapted for local appropriateness and language needs. The Levenson scales seek to capture attribution of control to each of three sources. The internal dimension (I) reflects control by one's own actions. Control of outcomes can also reside with chance influences (C) or powerful other agents (P) such as community leaders, politicians, or spouses. The latter two dimensions are both external in the classical Rotter sense.

Of twenty-one total statements, seven belong to each of the three scale dimensions.[7] To address well-known measurement challenges (Soto et al., 2008; Laajaj and Macours, 2021; Rammstedt, Kemper and Borg, 2013), I correct for acquiescence bias (following Rammstedt, Kemper and Borg (2013)) and create a general locus of control index using factor analysis.[8]

[7]There are twenty-four elements in the standard Levenson IPC instrument. I drop three, one in each dimension, for issues of cultural relevance.

[8]As all questions are framed as positive statements about control in their respective dimensions, this is particularly vexing. Individual differences in the tendency to agree will inflate the correlations between unrelated items, which means that an individual's naive score could be positively correlated across all three

Factor analysis is particularly well suited for this application as each of the Likert scale items is essentially a proxy for an underlying latent variable representing a respondent's locus of control.[9]

Table 2 and Figure 3 summarize the distribution of the general locus of control index. By construction, the distribution for the full sample is centered on zero. In addition to the standard deviation of the index, I also report the mean index value for each tercile of the distribution. Because the primary purpose of the Levenson scales is to create an ordinal ranking of respondents, the raw index value is difficult to interpret. We can confidently say, however, that respondents in the upper (third) tercile exhibit significantly more external locus of control than respondents in the lower tercile. For this reason, many of the behavioral regression specifications below will use indicators for a household's tercile position in locus of control distribution rather than the raw index value. Movement across terciles, it can be noted, is equivalent to just over a one standard deviation change in the index value.

Table 2: Moments of the General Locus of Control Distribution

		$LOC_{General}$		
	σ	Tercile 1	Tercile 2	Tercile 3
Full Sample	0.85	-0.99	0.09	0.90
Tanzania	0.84	-1.26	-0.43	0.58
Mozambique	0.56	-0.11	0.53	1.06

To assess the reliability and stability of the general locus of control measure, I compute Cronbach's alpha and test-retest correlations across the three waves of data. An alpha of 0.70 is generally considered a reasonable target for early stage and field research (Nunnally et al., 1994). I compute alpha for both the full and reduced set of items in each wave of data. For the full set of items, the average alpha is 0.64. Reliability improves marginally for the reduced set of items, which have an average alpha of 0.68. The test-retest correlation was 0.36.[10]

dimensions just because she tends to agree more than she tends to disagree.

[9]The factor analysis itself is described in detail in the Supplemental Appendix Section **??**.

[10]Computed as the intracluster correlation coefficient of general locus of control index across years for an individual respondent.

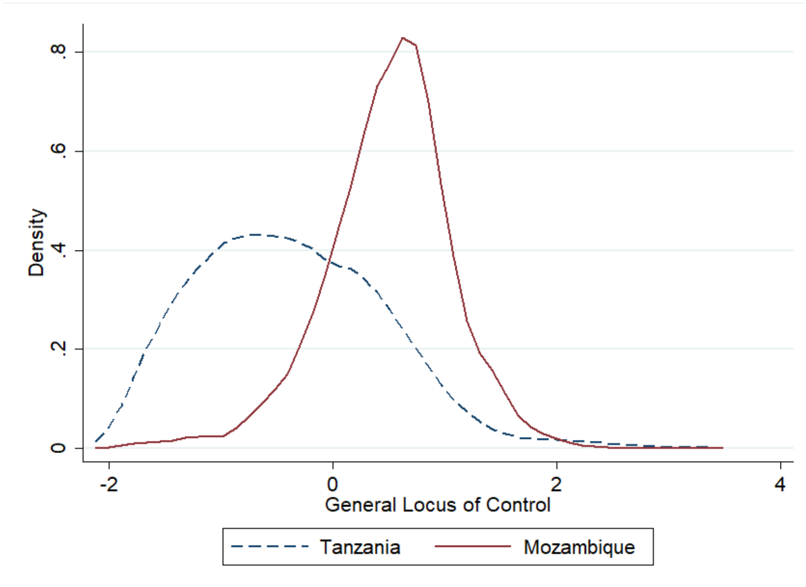


Figure 3: General Locus of Control Distributions in Mozambique and Tanzania

While studies of locus of control in economics, and particularly among poor, rural populations are uncommon, two previous studies help put the above numbers in context. Cobb-Clark and Schurer (2013) provide the first comprehensive look in economics at the stability of locus of control using the Household Income and Labor Dynamics in Australia (HILDA) data. Using a four-year panel, the authors achieve a Cronbach's alpha of 0.82. The authors also report test-retest correlations of 0.61 over one year and 0.53 over four years.

In a context similar to that of the present study, Laajaj and Macours (2021) study locus of control along with a set of technical, cognitive, and non-cognitive skills among a sample of farmers in rural Kenya. The project included two study waves, three weeks apart. The authors report Cronbach's alphas of 0.56 and 0.62 for the original and follow-up survey respectively, along with a test-retest correlation of 0.49.

The values obtained by the current study are similar to those reported by Laajaj and Macours (2021), with both studies reporting less reliability and more short-term fluctuation than Cobb-Clark and Schurer (2013).[11] The moderate test-retest correlations reported in all three studies are particularly interesting. Variability in measures of an individual's locus of

[11]Section **??** in the Supplementary Appendix reports the measures from the various studies side-by-side.

control over time reinforces the notion from the psychology literature that locus of control is not a fixed, static personality trait. Instead, Lefcourt (1982) and Cobb-Clark and Schurer (2013) conclude, it is best considered a dynamic trait reflecting current beliefs about the influence of an individuals actions on outcomes.

4.3 Maize-specific Locus of Control

Given the current focus on weather risk and the decisions of maize-producing households, there may be gains in intuition and predictive power to be had from developing a locus of control measure specific to maize production. An effective survey instrument for maize-specific locus of control will capture the extent to which a decision-maker believes that variation in maize harvest is attributable to her actions relative to forces outside of her control. For practical purposes, it must be possible to elicit the items used to create the measure credibly from farmers and in a brief timespan. In addition to differentiating between variation attributable to internal and external sources, the measure must not be mechanically related to the scale of farming operations or farmer productivity. This will allow farmers with various skill and scale to move freely through the maize-specific locus of control distribution.

I will refer to the survey module employed to collect the data necessary to create a maize-specific locus of control measure as the *hypothetical harvest activity* or HHA. To complete the HHA, survey enumerators have the following conversation with each farmer. First, a reference point is created by asking the area of a farmer's best maize plot and the quantity of maize seed typically planted on this plot. The farmer is then asked to imagine that she plants her plot with a specific input bundle. Three input bundles are presented: local seed varieties with no fertilizer, improved seed varieties with no fertilizer, and improved seed varieties with fertilizer.[12] For each input bundle, the respondent is asked how much maize she would expect to harvest under "poor", "normal", and "very good" rain conditions. The

[12] Local seed varieties refer to non-certified, saved seeds. Often, local maize seed is simply maize grain planted as seed. Improved seed varieties refer to certified maize seed. Both hybrid and open-pollinated varieties are considered improved maize seed.

top panel of Figure 4 shows the map resulting from this activity.

Two sources of variation drive harvest levels in the HHA. The first source is the weather, which plays the role of external control in this exercise. Variation in harvest attributable to the weather is visible by the vertical travel of the lines in each box in the lower left-hand panel of Figure 4. The external influence on maize production is thus captured by the variability of harvest for a given input bundle, across weather states.

The second source of variation is a farmer's choice of input bundle. Variation attributable to this dimension is observed as the vertical spread of the three points in each box of the lower right-hand panel of Figure 4. The internal influence on maize production is thus captured by the variability of harvest for a given weather state, across input bundles.

A maize-specific locus of control measure must capture the balance between external and internal control. Let the three input bundles presented to the respondent be given by $j \in \{1, 2, 3\}$ and the three states of weather be given by $k \in \{l, n, g\}$ (low, normal, good). Let y_{jk} be the harvest expected from using input bundle j in weather state k.

Averages across values of k (weather states) while holding j (input bundle) fixed will replace the k subscript with a bullet point(as in: $\bar{y}_{j\bullet}$). Likewise, averages across values of j (input bundle), holding k (weather state) fixed, will be replace the j subscript with a bullet point (as in: $\bar{y}_{\bullet j}$).

Maize-specific locus of control is defined as:

$$LOC_{Maize} = \frac{\sum_j \left(\frac{S_{j\bullet}}{\bar{y}_{j\bullet}}\right)}{\sum_k \left(\frac{S_{\bullet k}}{\bar{y}_{\bullet k}}\right)} \tag{8}$$

Where

$$S_{j\bullet} = \sqrt{\frac{\sum_k (y_{jk} - \bar{y}_{j\bullet})^2}{2}} \tag{9}$$

$$S_{\bullet k} = \sqrt{\frac{\sum_j (y_{jk} - \bar{y}_{\bullet k})^2}{2}} \tag{10}$$

$$\bar{y}_{j\bullet} = \frac{1}{3}(y_{jl} + y_{jn} + y_{jg}) \tag{11}$$

$$\bar{y}_{\bullet k} = \frac{1}{3}(y_{1k} + y_{2k} + y_{3k}) \tag{12}$$

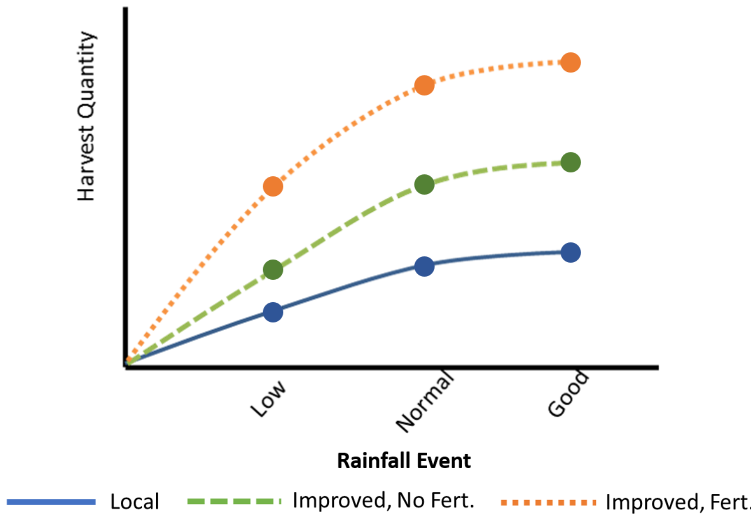
To draw direct comparisons to the diagram in Figure 4, consider the first element of the numerator:

$$\frac{S_{1\bullet}}{\bar{y}_{1\bullet}} = \frac{\sqrt{\frac{\sum_k (y_{1k} - \bar{y}_{1\bullet})^2}{2}}}{\frac{1}{3}(y_{1l} + y_{1n} + y_{1g})}$$

This element focuses on the first input bundle ($j = 1$) and thus the lowest box in the lower left-hand panel of Figure 4. The numerator, $S_{1\bullet}$, is the sample standard deviation of the three points in the box. The denominator is the simple average of the three points in the same box. Together, then, the element captures the variability of harvest due to weather when a farmer is using input one, expressed as a fraction of average harvest level associated with input one. The numerator in Equation 8 sums the three measures of external variation. The denominator is constructed in an identical fashion for the three measures of internal variation.

Consistent with the conventions from psychology, larger numbers in the maize-specific locus of control measure indicate more external locus of control. Figure 5 illustrates how the hypothetical harvest activity differs for farmers demonstrating an internal and external locus of control in maize production. The left-hand panel of Figure 5 contains data from a farmer with a strong internal locus of control. Relative to the vertical travel of each input line, significant variation is visible across lines. Contrast this with the right-hand panel, which contains data from a farmer with a strong external locus of control. Here, the vertical travel of each input line clearly dominates the variation in output across lines.

In keeping with the conditions enumerated at the beginning of the section, the maize-specific locus of control measure is invariant to the scale of farming operation and not mechanically related to the expected returns to technology adoption. Proofs of these properties are included in the Supplementary Appendix Section ??.



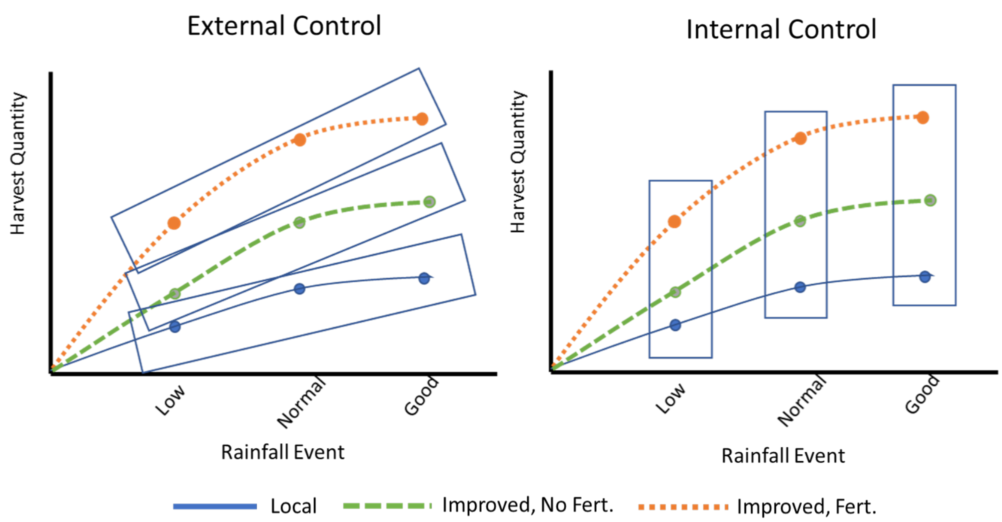


Figure 4: Hypothetical Harvest Activity & Locus of Control in Maize Production

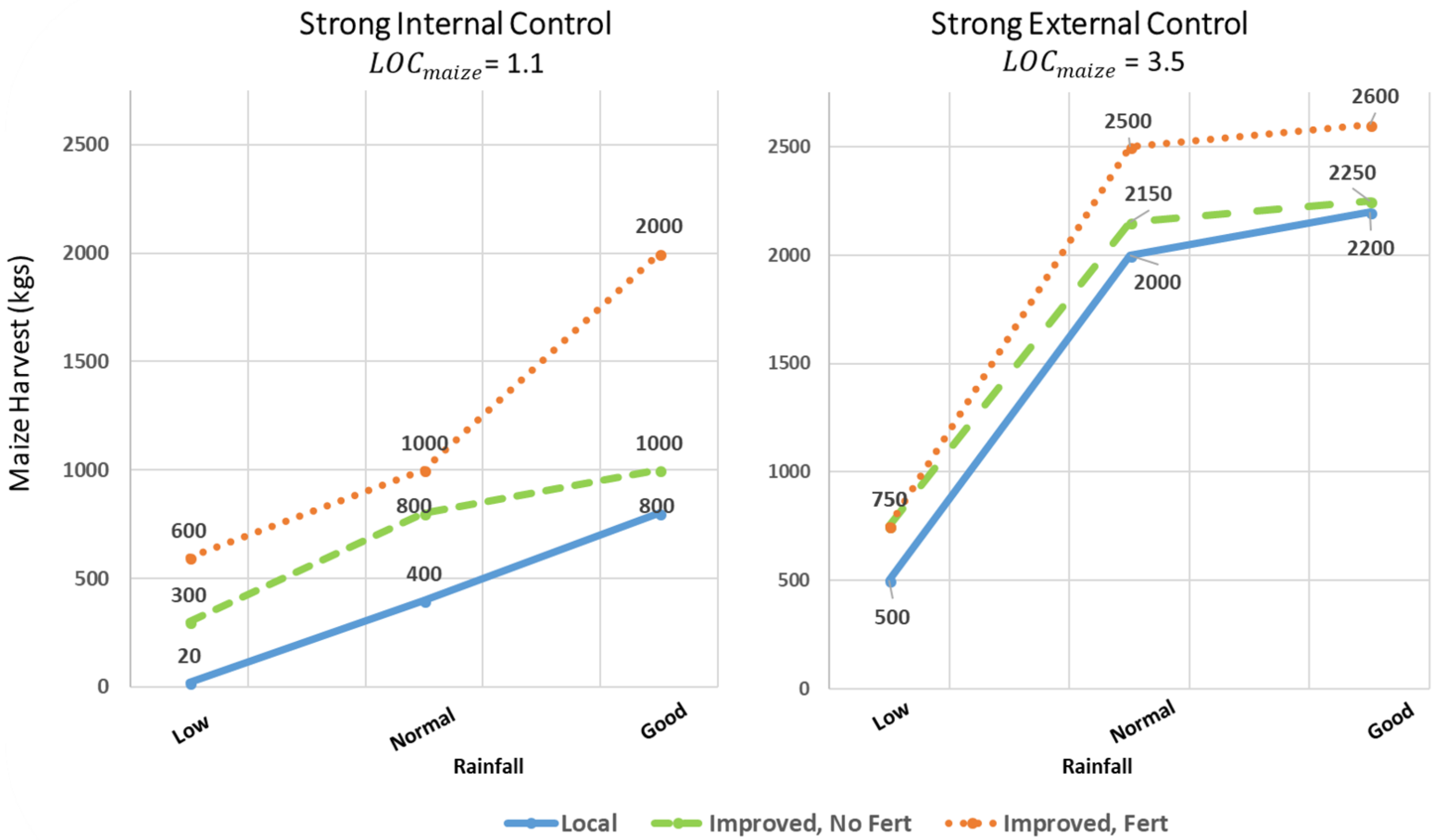


Figure 5: Hypothetical Harvest Activity - Empirical Examples

Table 3 and Figure 6 summarize the distributions of the maize-specific locus of control measure in Mozambique and Tanzania. As with the general locus of control measure, Table 3 reports the mean locus of control for farmers in each tercile of the distribution. Figure 6 compares density plots of maize-specific locus of control across the two countries. A horizontal line has been placed at the value of one, indicating equal balance between the influence of input choice and weather on variation in production outcomes. On average, farmers in Mozambique once again demonstrate more external locus of control than their Tanzanian counterparts.

Table 3: Moments of the Maize-specific Locus of Control Distribution

	LOC_{Maize}				
	Mean	SD	Tercile 1	Tercile 2	Tercile 3
Full Sample	1.49	1.04	0.80	1.24	2.44
Tanzania	1.24	0.61	0.76	1.11	1.85
Mozambique	2.01	1.43	1.01	1.67	3.33

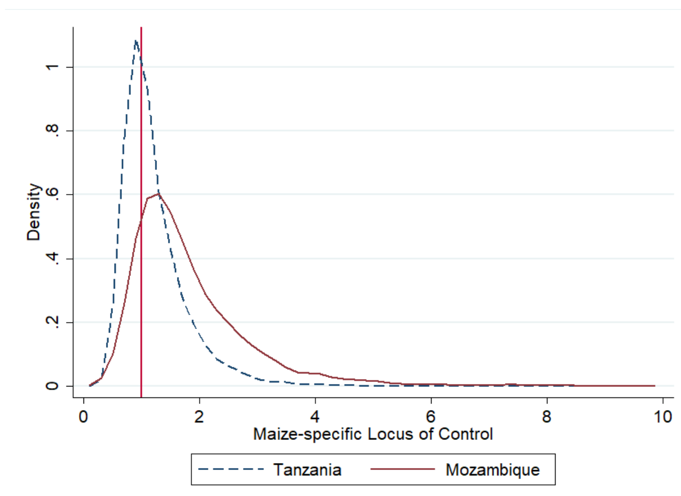


Figure 6: Maize-specific Locus of Control Distributions in Mozambique and Tanzania

The Supplemental Appendix (Section **??**) contains a similar analysis of the reliability and stability of the maize-specific locus of control as that presented for the general locus of control instrument. Maize-specific locus of control seems to be less stable than general locus of control. Using a one year test-retest, the correlation coefficient is 0.19, or about half the magnitude of the coefficient for general locus of control over the same time period. I also look at stability in a farmer's position in the distribution of maize-specific locus of control. To do this, I first assign each farmer her rank in the maize-specific locus of control distribution in each year. I then regress her current rank on her rank the previous year. In a model looking back only a single period, the coefficient on previous season rank returns a positive an statistically significant coefficient of 0.20. Focusing exclusively on the final round of data in order to include twice-lagged rank suggests that rank is persistently relevant, if small in magnitude.[13]

Section **??** of the Supplemental Appendix also contains an investigation of the relationship between the general and maize-specific locus of control instruments. We would expect a positive correlation between general and maize-specific locus of control. That is to say, those farmers with a more external general locus of control are also expected to exhibit a more external maize specific locus of control. In regression analysis using both normalized continuous measures of the instruments and an individual's ranking, I find statistically significant relationships in the expected direction. In the linear model, a one standard deviation change in general locus of control is associated with a 0.165 standard deviation change, in the same direction, in maize-specific locus of control.

5 Locus of Control and the Production Function

The primary avenue through which I hypothesize that locus of control will affect investment decisions is by influencing beliefs about the production function. Most notably, I hypothesize that individuals with different locus of control will hold systematically different beliefs about the marginal returns to the input under their control. As locus of control becomes more external, Equation 4 posits that the marginal product of investment falls. In this section, I construct a measure of the perceived increase in maize harvest resulting from use of improved

[13]Cronbach's alpha cannot be calculated for maize-specific locus of control as it requires various items each seeking to measure a shared, underlying variable.

maize varieties and test its relationship to locus of control.

I use data from the hypothetical harvest activity (HHA) described above to measure an individual's expected yield gain from using improved maize varieties over local maize varieties. Moving from quantities to yields is straight-forward as the HHA frames each question to explicitly keep a farmer's plot size and seed quantity constant. I focus only on the yield gain from changing seed technology (excluding the use of fertilizer) to best foreshadow the behavior studied below. Studying the yield gain across technologies does not allow for a direct test of the Equation 4 hypothesis about locus of control and the marginal product of investment, which concerns a continuous function within a single technology. It is, however, conceptually similar and feasible with the current data.

The HHA provides a measure of the expected yield return at three points – one for each type of growing season (bad, normal, good). Figure 7 illustrates. Note that the vertical axis is now in yield rather than harvest level.

Let $f^x_{i,L}$, $f^x_{i,N}$, and $f^x_{i,G}$ represent the increase in yield from planting improved maize seed rather than local maize seed if the farmer receives low, normal, and good rain respectively. That is:

$$f^x_{i,L} = F^x_{i,L} - F^l_{i,L}$$
$$f^x_{i,N} = F^x_{i,N} - F^l_{i,N}$$
$$f^x_{i,G} = F^x_{i,G} - F^l_{i,G}$$

Where $F^x_{i,k}$ is the yield using improved seeds for individual i in weather state k and $F^l_{i,k}$ is the yield using local seed for individual i in weather state k. Yield here refers to harvest per kilogram of seed rather than per unit area.[14]

The return to adoption in each weather state can be used to create a weighted average of the expected returns to adoption across weather states. This can be done using either a

[14]Seed use rates are more reliable than maize area. The analysis could also be done using area yields.

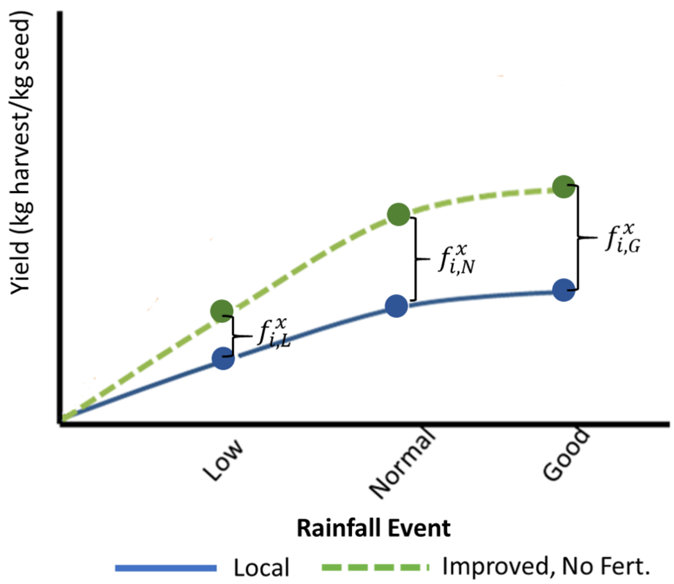


Figure 7: Expected Yield Gain From Improved Maize Seed

respondent's subjective beliefs about the probability of each weather state or by weighting each state of nature equally. In order to focus attention fully on the production function, I construct the expected return weighting each state of nature equally. Using subjective probabilities instead of equal weights does not change the results in any meaningful way.

Figure 8 plots the locus of control measures against the expected yield return (right-hand axis) from adopting improved maize varieties.[15] The dashed line is a quadradic best fit line, with the associated 95% confidence interval shown in gray. The solid black line shows the empirical cumulative density function for (left-hand axis) each locus of control measures, with the vertical red-dashed lines indicating the tercile break points.

Using local prices for maize grain and improved maize seed, I calculate the yield return that would be necessary for adoption to be profitable.[16] The "break even point" for each

[15]Despite being constructed with the same data, the expected harvest gain and maize-specific locus of control measure are conceptually and empirically distinct. This proof appears in the Supplemental Appendix Section **??** . In summary, I show that locus of control is invariant to scaling all outcomes by a positive constant, while expected return is not. In the other direction, expected harvest is invariant to adding a positive constant to all outcomes, while this preserves the maize-specific locus of control measure only as a special case.

[16]Hybrid seeds ($\sim$ 15 kg) OPV seeds ($\sim$ 8 kg)

type of seed is represented by a horizontal line on the second vertical axis in Figure 8.

As locus of control becomes more external, in terms of both the maize-specific and general measure, the expected yield gain from adopting improved seed varieties falls. For the majority of the population, however, the expected return would still make adopting improved maize varieties cost effective along the full locus of control distribution.

More formally, I regress the expected yield return on both locus of control measures

$$E[f_{it}^{x}] = \alpha + \beta_1 LOC_{maize,it} + \beta_2 LOC_{General,it} + \nu_v + \nu_t + \epsilon_{it}, \tag{13}$$

where ν_v and ν_t are village and year fixed effects.

Table 4: Expected Harvest Gain Per Kg of Seed Used

	E[Yield Increase From Improved Maize]	
	(1)	(2)
Maize-specific LOC		
Tercile 2	-17.03***	
	(1.682)	
Tercile 3	-27.65***	
	(1.897)	
LOC_{Maize}		-7.887***
		(1.253)
General LOC		
Tercile 2	-4.470*	
	(2.354)	
Tercile 3	-6.339***	
	(2.257)	
$LOC_{General}$		-3.911***
		(1.127)
Year FE	Yes	Yes
Village FE	Yes	Yes
Observations	8376	8376
R^2	0.235	0.222

Expected yield return calculated by assigning equal weights to each weather state.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A more external locus of control is associated with decreases in the expected returns from adopting improved maize varieties (Table 4). The differences are especially large for the maize-specific measure, where being in the second tercile is associated with a decrease of seventeen kilograms of harvest per kilogram of improved seed and being in the most external tercile is associated with a drop of nearly twenty-eight kilograms per kilogram of seed.

While the above estimates are not causal, they are suggestive of a strong association between locus of control and subjective beliefs about the production function.

Supplemental Appendix Section **??** takes a similar approach to testing the relationship between locus of control, subjective probabilities and preferences, notably risk preferences using both general risk attitudes and an incentivized risk aversion elicitation activity. The empirical association between locus of control and the expected return to adoption is much stronger than with either risk preferences or subjective probabilities. Nevertheless, the direction of any causal relationship cannot be determined from the current data. It also remains possible that some third factor – such as risk exposure, soil quality, or agricultural skill – is both depressing expected returns and creating external locus of control.

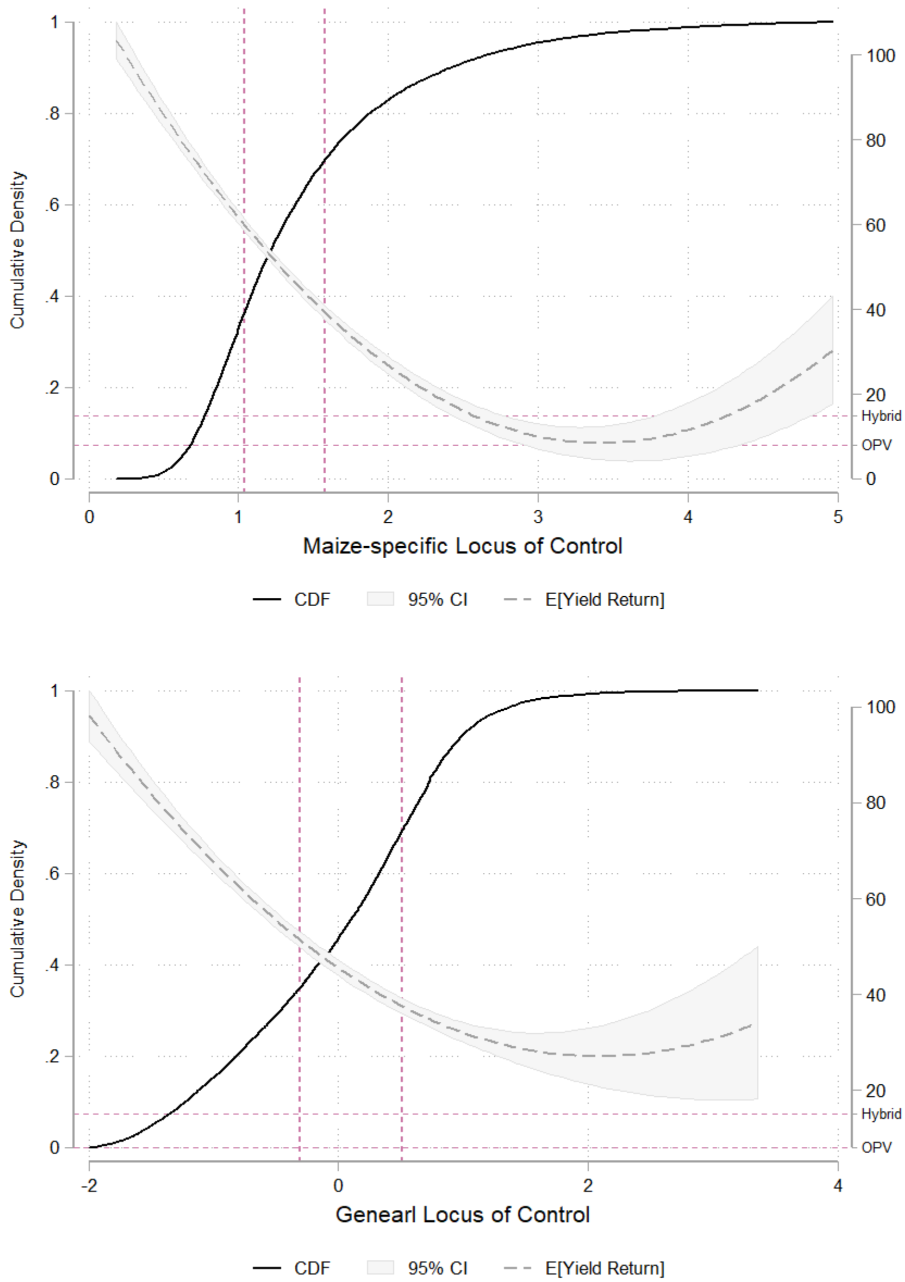


Figure 8: Profitability of Improved Maize Varieties over the Locus of Control Distribution

6 Locus of Control and Decision-making

Figure 9 depicts the agricultural calendar and the timing of survey enumeration associated with the data introduced earlier.[17] Each year, household surveys began just after the maize harvest had been completed. At this point in time, the farmer had had the opportunity to internalize the previous year's experiences but had not yet made investment decisions for the coming year.

The three survey rounds provide complete data on two agricultural seasons: 2016/2017 and 2017/2018. In this case, complete data means a measure of household characteristics and beliefs at the beginning of the season, agricultural decisions within the season, and agricultural outcomes at the end of the season. Time subscripts (t) throughout this section refer to an agricultural season.

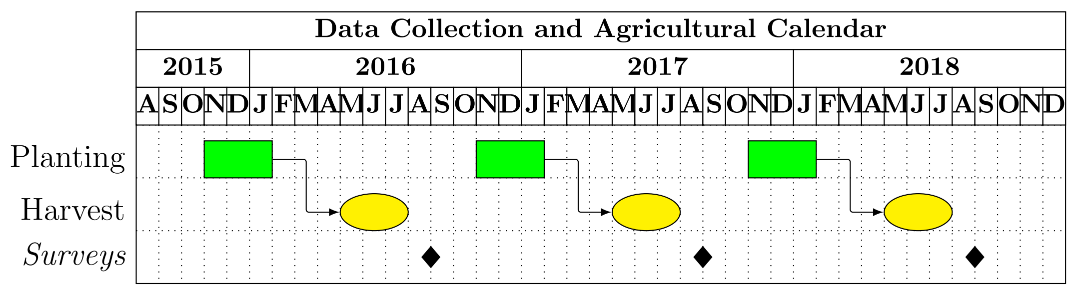


Figure 9: Calendar of Events

Relating beliefs, personality traits, and skills to behavior in a plausible causal framework presents well-known challenges (Borghans et al., 2008; Almlund et al., 2011). When individuals are asked to recall behavior at the same time that beliefs are elicited, there is a clear danger of simultaneity and recall biases. At the very least, the experiences resulting from an individual's actions are already reflected in her beliefs. Drawing from multiple survey rounds to create complete data on an agricultural season provides a way around: beliefs assigned to the 2016/2017 agricultural season using were elicited in the 2016 survey round

[17]The timing of planting, harvest, and enumeration differ slightly between Mozambique and Tanzania. In both countries, however, yearly surveys were carried out shortly after harvest and before planting decisions were made for the following year.

while agricultural decisions assigned to the 2016/2017 agricultural season were elicited in the 2017 survey round. [18]

As a first task, I examine the simple correlation between locus of control and use of improved maize seed varieties. Hypothesis 1 would imply that a more external locus of control will be associated with a decreased probability of using improved maize seed.

$$Pr(y_{it} = 1) = \alpha + \beta LOC_{it} + \nu_c + \delta_t + \epsilon_{it} \tag{14}$$

I estimate Equation 14 as a linear probability model using pooled ordinary least squares. With no prior reason to suspect that the conditional expectation function follows a particular non-linear functional form, linear probability models provide a good approximation of the conditional expectation function and facilitate comparison of marginal effects across models (Angrist and Pischke, 2008). This also allows for a smooth transition to the panel methods in the next section. I use robust standard errors in all specifications, due to the inherent heteroskedasticity of the linear probability model. Standard errors are clustered at the level of geographic strata.

I begin by estimating the model separately for each locus of control measure – general and maize-specific – including only dummy variable controls for country and year. Locus of control measures enter into the model as a set of dummy variables indicating a farmer's tercile position in the locus of control distribution. Table 5 shows that being located in a more external tercile of either the general locus of control distribution (Column 1) or the maize-specific locus of control distribution (Column 2) is associated with significant declines in the probability of using an improved maize seed variety. These results persist when both locus of control measures are included. Using the Akaike Information Criterion as a basis for model selection indicates that including both measures is preferred to either measure individually.[19]

[18] Because the 2016 survey round occurred shortly before planting decisions in for the 2016/2017 agricultural season, there is little scope for beliefs to change substantially prior to agricultural decision-making.

[19] All results are qualitatively identical using raw measures of locus of control rather than terciles

The results presented in Table 5 could only be interpreted as causal in the unlikely case that controlling for country and year effects removes all components of the error term that are correlated with both locus of control and use of improved maize varieties. That is:

$$E[\epsilon_{it}|LOC_{it}, \nu_c, \delta_t] = 0 \tag{15}$$

Table 5: Pooled OLS Relating Locus of Control to Use of Improved Maize Seed Varieties

	Report Using an Improved Maize Variety		
	(1)	(2)	(3)
Maize-specific LOC			
Tercile 2		-0.0857***	-0.0841***
		(0.0166)	(0.0164)
Tercile 3		-0.113***	-0.112***
		(0.0184)	(0.0187)
General LOC			
Tercile 2	-0.0544***		-0.0543***
	(0.0201)		(0.0197)
Tercile 3	-0.0848***		-0.0857***
	(0.0226)		(0.0223)
Mozambique	-0.111**	-0.108***	-0.0682
	(0.0435)	(0.0401)	(0.0408)
2018	-0.0473***	-0.0416**	-0.0417**
	(0.0156)	(0.0160)	(0.0161)
Observations	5609	5398	5398
R^2	0.028	0.029	0.033
AIC	7989.8	7676.5	7660.7

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Locus of control's roots in lived experience creates a high potential for unobservable factors to both influence actions and correlate with locus of control. I now make use of both observable farm household characteristics and the panel nature of the data to attempt to purge the associations reported in Table 5 of as many confounding influences as possible. I continue to estimate linear probability models, now acknowledging the potential existence of individual components of the error term that may be correlated with locus of control or other explanatory variables (Z_{it}) in Equation 16.

$$Pr(y_{it} = 1) = \beta LOC_{it} + \gamma Z_{it} + \alpha_i + \epsilon_{it} \tag{16}$$

Equation 16 is estimated under the assumptions of both random and fixed effects, including a vector of observable farm household characteristics. In addition to the country and year effects from the previous section, the control set includes a measure of household economic status (SPS Points), the number of maize plots planted, the education level of the farmer, and recent shocks due to drought[20]. I also control for a farmer's beliefs about the probability of weather events and risk attitudes. Like locus of control, the set of controls correspond to household characteristics at the start of the agricultural season.

As an intermediate step between the random and individual fixed effect models, I include a set of dummy variables for a farmer's village into the Z_{it} vector of the random effects model. The rational behind the intermediate step is to remove localized issues of access and economic shocks that might affect improved seed use and correlate with locus of control. The danger, on the other hand, is that village fixed effects will also remove time invariant village characteristics – like weather history – that might play an important role in the development of an individual's locus of control.

The first column of Table 6 contains the results of regressing use of improved maize varieties on locus of control and a set of farm household characteristics using the random effects model. As in Table 5, being located in the most external tercile of the locus of control distributions is associated with substantial declines in the likelihood of using improved maize seed varieties. Being located in the most external tercile of the maize-specific locus of control distribution is associated with a seven percentage point decrease in the probability of using improved maize seed. Similarly, being in the most external tercile of the general locus of control distribution is associated with nearly a three-and-a-half percentage point decrease in

[20]The drought variable is an indicator equal to one if the household experienced sub-optimal rainfall the previous season. Optimal rainfall for maize is between 500-800 millimeters. The indicator variable constructed here takes a value of one if cumulative rainfall for the 120 days following planting is less than 400 millimeters.

the probability of using improved maize seed.

The second column in Table 6 contains the estimation results using village-level fixed effects. The magnitudes of the association between locus of control and use of improved maize varieties falls for both measures, though it remains an economically meaningful and statistically significant three percentage points for the third tercile of the maize-specific locus of control measure.

The final column in Table 6 reports the results of using a fixed effect regression approach, exploiting variation in an individual's reported locus of control across the two agricultural seasons represented in the panel. Locus of control is not believed to be a fixed trait, thus the within-groups estimator may provide a way to remove correlation between α_i and the variables of interest. More precisely, the estimating equation becomes:

$$Pr(y_{it} = 1) - Pr(\bar{y}_i = 1) = \beta(LOC_{it} - L\bar{O}C_i) + \gamma(Z_{it} - \bar{Z}_i) + \epsilon_{it} - \bar{\epsilon}_i \qquad (17)$$

While earlier sections documented significant variation in locus of control in the current data, previous studies, such as Cobb-Clark and Schurer (2013), have demonstrated that short term fluctuations in locus of control are less meaningful for predicting behavior than average levels over time. Consistent with Cobb-Clark and Schurer (2013), removing time invariant individual characteristics in Equation 16 erases the effects of locus of control. This suggests that short term fluctuations in these beliefs are less important than their longer-term levels. Also consistent with this interpretation, a Hausman test rejects the equivalence of the estimates in the fixed and random effects models, suggesting that the unobserved individual components of the error term are meaningfully related to the decision to use improved maize varieties and correlated with the included explanatory variables.

While the data do not contain experimental variation in locus of control, the simple association and panel estimates provided an interesting foundation for future inquiry. While the descriptive elements of Section 4 suggest that locus of control is dynamic, the evidence presented in this section suggests that it is the more persistent components of the construct

Table 6: Locus of Control and Use of Improved Maize Varieties: Panel Estimation

	Report Using an Improved Maize Variety		
	(1)	(2)	(3)
Maize-specific LOC			
Tercile 2	-0.0556***	-0.0237	-0.00512
	(0.0158)	(0.0149)	(0.0200)
Tercile 3	-0.0745***	-0.0300*	0.00550
	(0.0169)	(0.0161)	(0.0219)
General LOC			
Tercile 2	-0.0232	-0.00993	0.0157
	(0.0170)	(0.0159)	(0.0219)
Tercile 3	-0.0344*	-0.0120	0.0261
	(0.0188)	(0.0176)	(0.0244)
Fixed Effects	Country	Village	Individual
Controls	Yes	Yes	Yes
Observations	5355	5355	5355

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: All specifications include indicator variables for country an dyear. The control set also includes the respondent household's simple poverty scorecard score, number of maize plots managed, education level of the household head, risk index score, subjective rainfall probabilities, and an indicator for having experienced drought during the previous maize growing season.

that most strongly affect behavior.

With the exception of the final within-groups fixed effect model, the various estimates presented reaffirm and expand on previous evidence of the empirical relationship between locus of control and the decision to use improved maize varieties. Using a general measure of locus of control, both Abay, Blalock and Berhane (2017) and Laajaj and Macours (2021) find that locus of control helps predict use of improved maize seed. Abay, Blalock and Berhane (2017) find that a one standard deviation change toward the internal pole is associated with a one to one-and-a-half percentage point increase in the probability of using improved maize seed. Laajaj and Macours (2021) do not isolate the impact of locus of control but find that a set of non-cognitive skills, including general locus of control, accounts for up to eleven percent of the variation in use of hybrid maize seeds.

7 Conclusions

Vulnerable households, which are often the target for technologies that seek to increase resilience, likely hold beliefs about their ability to control outcomes that make them less likely to invest in disaster prevention. Locus of control provides one way to elicit these beliefs and has proved descriptively useful in understanding technology adoption and investment decisions in a variety of contexts. In this paper, I have sought to link the locus of control construct the the expected utility maximization problem and empirically test the resulting insights.

As noted by Rotter (1975), for understanding decisions in a specific activity domain, focused locus of control measures can lead to more informative predictions than general measures. This paper expands on existing work by developing a maize-specific locus of control measure, demonstrating its relationship to a general locus of control measure, and showing how both measures fit into the decision-making process. Namely, for both measures, a more external locus of control is associated with a lower expected return to adopting improved maize seed varieties. Subsequently, a more external locus of control is also associated with a reduced probability of using improved maize seed varieties in the season following belief elicitation.

These results are not meant to suggest locus of control as a target for intervention, as has recently been suggested for hope and aspirations. Instead, the point is to acknowledge that an individual's beliefs are a function lived experience and contain valuable information related to expectations regarding the returns to investment. It is often precisely because decision-makers suffer frequent and inescapable shocks to their production and livelihoods that they are unwilling, perhaps rightly so, to devote limited resources to unknown technologies — even when those technologies seek to reduce the impact of those shocks.

Unfortunately, the sample of households from Mozambique represented in this data bear out that truth with painful clarity. Soon after the collection of these data, Cyclone Idai slammed into the coast of south eastern Africa near the port city of Beira, Mozambique. The households from Mozambique in this data were located in the provinces of Sofala and Manica, the provinces hardest hit by Cyclone Idai. Those households are sure to have been affected by the cyclone. Many likely lost their maize crop – which in March would have been entering its grain filling stage and starting to provide green maize to ease the burden of the lean season. Others likely lost assets: houses, livestock, fields. Transportation infrastructure, which was tenuous at best in many rural areas, will have been damaged, cutting off access to food and medical aid.

The impact of such shocks linger, both through their decapitalizing effects on households' ability to invest and through their effects on households' belief in the extent to which their own actions matter. If you believe that what you do does not matter, then why invest? The unfortunate truth is that, for many, this belief is not entirely incorrect: for the most vulnerable, outcomes are often dominated by forces outside of their own control. Creating a plan to increase resilience necessitates understanding both the objective reality of control and how exposure to repeated risks affects individual's perceptions of the return to investment.

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