Locus of Control and Investment Behavior Among Smallholding Maize Farmers: An Empirical Study from Mozambique and Tanzania

Jonathan G. Malacarne

March 2, 2018

Abstract

This paper brings to bear insights from psychology and behavioral economics to better understand the way in which perceptions of self-efficacy influence investment behavior – and through behavior, welfare. Using both analytical and empirical methods, the paper demonstrates that control beliefs affect investment decisions and shape the way in which decision makers interpret success and failure. General and activity-specific locus of control beliefs are elicited for a sample of maize-producing households in Mozambique and Tanzania. Households attributing more variation in production to external factors relative to input choice, such as the weather, are shown to be significantly less likely to adopt improved maize varieties. This reduction is greater than fifteen percent in Tanzania and over ten percent in Mozambique. Control beliefs are also show to affect the choice of crop portfolio.

In an ideal world, maize would produce to its yield potential without the need to consider questions of soil quality, weather, or pests. Failing this, control of production can be wrested back from nature by use of irrigation, stress-resistant seed varieties, and chemical inputs. The welfare of farm households can be further insulated from external forces by transferring resources directly across states-of-the-world via insurance. These technological solutions, however, must be adopted to be effective. This paper begins from the intuitive observation that believing outcomes to be primarily determined by forces outside their control likely reduces an agent's willingness to invest in the production process. Put more simply, if the weather is all that matters, why invest in improved seed and fertilizer?

Farmer beliefs are fundamental building blocks for decisions about how to allocate resources across uses with different returns and risk profiles. While farmers know that both weather and input choices affect production, they do not necessarily know the precise parameters that determine the returns to these factors. A long and active literature into the psychological construct known as *locus of control* suggests that control beliefs – an agent's beliefs about the extent to which outcomes are determined by their own actions relative to uncontrollable factors – are not only influenced by decision makers' experiences in a target activity but also in life more broadly.

While the actions and outcomes that constitute these experiences are not directly observable, psychologists have developed instruments to elicit the resulting beliefs. In this paper, I make use of these instruments to consider the adoption of improved agricultural inputs and cropping choices of farm households across a large set of communities in Mozambique and Tanzania. Building on behavioral theory from psychology, I focus on how farmers' locus of control shapes their beliefs about the returns to investment and affects adoption decisions. This approach provides new insight into how reliance on an unpredictable production process influences farmer's beliefs about control of outcomes and how these beliefs feed back into the adoption and investment decision.

Much like earlier efforts to explain uptake and investment[1], the best characterization of the decision facing farm households is likely a combination of behavioral influences and traditional economic constraints. This is especially true for rainfed maize production. Rainfed maize production epitomizes the challenges of relying heavily on a stochastic process for food and economic security. While staple crops remain a dominant source of calories for poor households worldwide, that role is particularly strong in the maize-producing countries of Eastern Africa. According to FAO estimates, households in the region derived nearly sixty percent of calories from cereals, roots, and tubers. In some countries this number is significantly higher. Households in Mozambique, for example, are estimated to derive over seventy percent of calories from staple foods (FAOSTAT, 2017). Those who rely on this level of staple consumption are highly exposed to fluctuations in the production and prices of the commodities on which their economic and food security are based. This vulnerability is born out in high rates of undernourishment, stunting in children under five years old, and anemia in pregnant women (FAO, 2015). Agricultural innovations that improve the yields and resilience of staple crops hope to lessen the impacts of weather shocks, and subsequently, shocks to nutrition and income.

[1]Summarized nicely by Smale et al. (1994) for the debate on the roles of input fixity, portfolio selection, safety-first behavior, and learning by doing

Despite the seemingly high returns to agricultural technologies that improve yields and reduce exposure to weather risk, their adoption by the most vulnerable households is often low. In the combined sample of farm households from Mozambique and Tanzania surveyed in this paper, less than half report using any improved seed variety and only five percent report using chemical fertilizers. While these low levels of adoption may speak to issues of access[2], they do not result from a lack of innovation. In 2016 alone, the CGIAR Research Program, MAIZE, (MAIZE CRP) had a budget of 11.6 million dollars focused on developing and promoting stress-resistant and nutritious maize varieties (CGIAR, 2016). Drought Tolerant Maize for Africa (DTMA), one of the MAIZE CRP's flagship programs, released 233 drought-tolerant maize varieties over it's lifetime, across thirteen countries in sub-Saharan Africa[3] from 2007 - 2015 (CIMMYT, 2015). Even so, local seed companies face significant challenges in marketing these technologies successfully. This is especially true in the remote and resource poor communities that stand to benefit the most from drought-tolerant seed technology.

The rest of this paper is organized as follows. Section 1 presents a brief introduction to locus of control and its suitability for analyzing economic investment problems. In this section, I also present a brief analytical model demonstrating the impact of activity-specific control beliefs on expected profit, investment, the potential for disillusionment in a profit maximization problem. I then turn to the primary focus of the paper, presenting the context of rainfed maize agriculture in Tanzania and Mozambique in Section 2. Section 3 details the construction of the control belief measures used in the analysis and their distributions among farmers in the two countries. Section 4 contains the primary empirical analysis of the paper, relating control beliefs to use of improved agricultural inputs, investment levels, and choice of cropping portfolios. Most notably, I show that attributing more of the variation in maize production to weather relative to input choice – that is, external activity-specific control beliefs – result in significant decreases in the probability of adopting improved inputs in both Tanzania and Mozambique. Finally, Section 5 concludes with a discussion of these results and a framework for future analysis.

1 Locus of Control and Economic Investment Decisions

The psychological construct known as *locus of control* will serve as the starting point for the behavioral analysis in this paper. Locus of control is a concept that rose to prominence starting with the work of Rotter (1966) and focuses on what psychologists call *expectancies*, one of the four primary variables of interest in social learning theory (Rotter, 1975). In more familiar economic language, expectancies refer to the expected reward from a particular action in a given situation. Locus of control measures were developed to help explain observed differences in the way individuals updated their expectations following a round of actions and reinforcements. These differences are thought to be driven by whether outcomes are seen as resulting primarily from an individual's own actions or from factors outside of their control. Broadly speaking, *internal* control refers to the belief that actions are determined by one's own actions, while *external* control refers to the belief that outcomes are strongly

[2]The three dimensions of access being availability, affordability and acceptability

[3]In reference to the countries studied in this paper, twenty drought tolerant maize varieties were released in Tanzania and nine were released in Mozambique

influenced by forces other than the agent herself.

Control beliefs can be thought of with varying levels of generality. At their broadest, they capture an individual's beliefs about the way the world works. For example, the following two statements refer to general attitudes about control of outcomes.

1. It is not always wise for me to plan too far ahead because many things turn out to be a matter of good or bad fortune.

2. When I get what I want, it's usually because I worked hard for it.

Rotter's original scale to measure locus of control was constructed from a series of forced choice statements and condensed locus of control into a single measure between zero and unity (Rotter, 1966). Subsequent work, including that of Hanna Levenson, whose instruments I use in the empirical section of this paper, have shown that control can be better represented by a series of scales–usually elicited via sets of Likert scales–generating a separate score for various dimension of control (Levenson, 1981). There are three dimensions of the Levenson scales: *Internal* defined in the same way as Rotter's use of the term; *Chance*, which captures stochastic, impersonal factors; and *Powerful Others*, capturing the influence of actors such as community leaders and politicians. A higher score within a given scale indicates that agents believe this dimension exerts a high level of control over outcomes.

For specific economic decisions, such as whether or not to invest in agricultural inputs, more activity-specific control beliefs are likely to be operative. In his 1966 monograph, Rotter describes the interplay between general and activity-specific beliefs as follows. When activities are relatively new to the decision maker, she will rely more heavily on her general beliefs. As she acquires experience in the activity (or in activities she deems to be similar), more specific beliefs will take over. For the purposes of economic analysis, we can interpret this as a statement about how general control beliefs will influence an agent's prior beliefs about the parameters governing the returns to various factors in new production processes. To restate this in the context of this paper, those agents who believe, generally, that outcomes are out of their control will be more likely to also believe that investment in agricultural inputs have little influence on production relative to stochastic factors such as weather and pest pressure.

The analysis in this paper considers the relationship between and influence of both general and activity-specific control beliefs on the investment decisions of farmers engaged in rainfed agriculture in Mozambique and Tanzania. In doing so, it contributes to a small but growing literature on the role of non-cognitive traits on economic investment behavior. The unique dataset collected on farmer beliefs and behaviors allows me to treat this topic in a more comprehensive way than most existing work, with particular application to locus of control and agriculture. In the development context, the most extensive treatment of psychological constructs, their measurement, and their ability to explain behavior is conducted by Macours and Laajaj (2017) with a large sample of farmers in Kenya. The authors find that, while difficult to measure, non-cognitive traits such as locus of control are significant predictors of both yield and behavior. Due to the large number of other psychological traits and skills considered in that paper, including the Big Five personality traits, risk aversion, optimism, and attitudes toward change, the instruments used to elicit locus of control are extremely general and contain few elements. Other studies outside of the development context, such as Coleman and DeLeire (2003) for human capital investment among high school students and Cobb-Clark (2015) and McGee (2015) for labor market outcomes, similarly find that control beliefs are significant predictors of behavior. The current paper adds to this body of work in its approach to measuring control beliefs, by giving attention to both general and activity-specific components of belief, and in providing empirical evidence of the link between control beliefs and economic investment behavior.

1.1 Model

As noted in in Section 1, both general and activity-specific components of locus of control are of interest for understanding economic behavior. While it is the activity-specific component of belief that enters into a decision making problem directly, general locus of control beliefs exert their influence on whether agents over or under value the parameters that govern the returns to various factors of production. To make this more concrete, consider the following production function which translates farmer-controlled inputs (x), a fixed land input (T) and an index of growing season quality (ϵ) into farm output. Let the objective[4] production process be given by:

$$f(x_{it}, \epsilon_{it}) = (z \cdot x_{it})^{\alpha} T_i^{1-\alpha} \epsilon_{it}^{\theta}$$

Assume that ϵ is imperfectly observable and distributed uniformly between zero and unity. It may be the case that some information on this input can be inferred – farmers know whether or not it has rained recently – but the exact level is not observable. The quality of a growing season is a good example of this, as it depends on agroecological zone and complicated interactions of rainfall and temperature. Let z be a technological scalar and assume that production exhibits constant returns to scale in x and T. With T fixed the farmer can focus on:

$$f(x_{it}, \epsilon_{it}) = (zx_{it})^{\alpha} \epsilon_{it}^{\theta} \tag{1}$$

$$\frac{\partial f}{\partial x} = \alpha z (zx_{it})^{\alpha-1} \epsilon_{it}^{\theta} \tag{2}$$

The production function made explicit in Equation 1 implies that investment in the farmer-determined input x is risk increasing, with risk being driven by ϵ, which the agent takes as random. Just and Pope (1978) point out this feature of Cobb-Douglas-style production functions and argue that modelers should justify their chosen representation of the production process with an awareness of its implication for production risk. Here, the chosen form apt for two reasons. First, that investment levels in basic agricultural inputs should increase risk is logical. If you plant with better inputs, the best harvest you could receive goes up but the floor remains zero. Across technologies, the distribution of outcomes can be adjusted by defining different parameters for the sensitivity of output to inputs, but within a technology the risk-increasing nature of investment would still hold. Second, as demonstrated in Equation 2, this form implies that marginal returns to the farmer-controlled input depend directly on the sensitivity of the production process to the stochastic input. In our

[4] To later be contrasted with the subjective.

example, the quality of a growing season is not a random nuisance or a degree of uncertainty in the farmer's knowledge, but rather a factor affecting the returns to all other inputs. This is in contrast to the production function behind the target-input models often used to study learning[5].

Let the objective production function be defined as in Equation 1. Activity-specific locus of control is then best described as a farmer's beliefs about the importance of x and ϵ – captured by her subjective beliefs about the exponents in Equation 1. The agent's subjective production function can then be represented by:

$$f_s(x_{it}, \epsilon_{it}) = (zx_{it})^{\beta}\epsilon_{it}^{\gamma} \tag{3}$$

$$\frac{\partial f}{\partial x} = \beta z(zx_{it})^{\beta-1}\epsilon_{it}^{\gamma} \tag{4}$$

If β and γ are not equal to the scalar values α and θ, we will call these beliefs *incorrect*, or *incorrect control beliefs*. As the Cobb-Douglas parameters capture the extent to which investment and the externally determined ϵ impact production, any error or uncertainty in the agent's beliefs about β and γ lead to differences between Equations 1 and 3. As noted earlier, farmers general locus of control is expected to affect their valuation of β and γ. For an unfamiliar technology – a new crop, seed variety, or chemical input – farmers with an internal general locus of control would tend to overvalue β. Those with an external general locus of control, would tend to undervalue β and or overvalue γ. Looking at the expression for the marginal product of x in Equation 4 begins to make clear the impact these deviations in beliefs will have on investment levels.

To further understand the role of control beliefs on the investment decision, I now consider the decision of a profit maximizing farmer choosing a level of investment x. While farmers are generally assumed to be risk averse, focusing on the profit maximization problem allows for a direct and concise view of the role of the two control parameters without the added assumptions and confounding influence of utility functions.

Let β and γ be assumed to be scalar and ϵ be known to be distributed as $U(0, 1)$:

$$E[f_s(x_{it}, \epsilon_{it})] = (z \cdot x_{it})^{\beta} E\left[\epsilon_{it}^{\gamma}\right]$$

Because ϵ is distributed uniformly between zero and one, ϵ^{γ} is Beta distributed:

$$\epsilon^{\gamma} \sim Beta(\frac{1}{\gamma}, 1)$$

In a sense, control beliefs are a more primitive construct that risk attitudes. Figures 1 and 2 demonstrate the role of the control parameters on the distribution of expected production outcomes. For a given investment level, the variance a farmer expects in the production process depends on the importance she assigns to x and ϵ.

Now consider the decision facing a risk neutral, profit maximizing agent:

[5]Target input models are notably used to study learning and adoption in Foster and Rosenzweig (1995) and are described in detail in Jovanovic et al. (1994) and Prescott (1972)

$$\max_x E[\pi] = E[pf_S(x_{it}, \epsilon_{it}) - cx] \qquad s.t. \quad x_{it} \cdot c \leq A_{it}, \quad x_{it} \geq 0$$
$$\max_x E[\pi] = (z \cdot x_{it})^{\beta} E\left[\epsilon_{it}^{\gamma}\right] - cx] \qquad s.t. \quad x_{it} \cdot c \leq A_{it}, \quad x_{it} \geq 0$$

Appendix 7.1 contains the full derivation, consideration of corner solutions, and comparative statics. For now, I focus on the interior solution and comparative statics on the two primary parameters of interest. The interior solution, which holds for a wide range of prices and productivity parameters, is given by:

$$x_{it}^{\star} = \frac{1}{z}\left(\frac{c \cdot (1+\gamma)}{p \cdot \beta \cdot z}\right)^{\frac{1}{\beta-1}} \tag{5}$$

Investment levels are decreasing in gamma, that is, when farmers believe that weather realizations play a greater role in determining production outcomes, investment declines. Investment is also increasing in beta for most values of prices and parameters[6]. These results lead to the following expression for a farmer's subjective expected profit given her beliefs about the production technology and her investment behavior.

$$\pi(x_{it}^{\star}(\beta,\gamma)) = p(zx_{it}^{\star})^{\beta} E[\epsilon_{it}^{\gamma}] - cx^{\star} \tag{6}$$

The first order impacts of control beliefs on adoption behavior come from these results. Farmers who believe they have more control, invest more and expected to earn higher profits. Ass the probability of adoption should be increasing in expected profit, I will expect those households expressing more internal control beliefs to adopt improved agricultural technologies at a higher rate than their externally oriented peers.

In looking at Equation 6, an important disconnect becomes evident between the farmer's expectation of profit and the objective distribution of production outcomes and profits. Recall that the true production function is given by Equation 1 and governed by the parameters α and θ rather than β and γ. Given the farmer's choice of $x^{\star}$, objective expected profit is given by:

$$\pi(x_{it}^{\star}(\beta,\gamma)|\alpha,\theta) = p(zx_{it}^{\star})^{\alpha} E[\epsilon_{it}^{\theta}] - cx^{\star} \tag{7}$$

While Equation 6 was said to drive the first order impact of control belief on adoption behavior, the tension between Equations 6 and 7 are likely a driving factor in the second order effects. Namely, the unfounded expectation of high profits sets the stage for potential disillusionment, especially among those farmers who believe that their success or failure is driven by their own actions. Recall that Rotter's original hypothesis linking locus of control to behavior focused importantly on this behavioral response to success and failure.

> *"In its simplest form, our basic hypothesis is that if a person perceives a reinforcement as contingent upon his own behavior, then the occurrence of either a positive or negative reinforcement will strengthen or weaken potential for that behavior to recur in the same or similar situation."* (Rotter, 1966)

[6] See Appendix section 7.1.3 for formal condition.

What agents learn or infer from their experiences is likely contingent on their control beliefs and the more general locus of control that underlies them. Agents with strong internal locus of control expect their actions to drive outcomes. They can therefore be expected to be among the first to invest and innovate. At the same time, they may take failure hard, attributing it to their decisions rather than to an unfortunate action by nature. The stickiness of beliefs toward internal control may also mean that these agents are slow to learn that they have little control over certain production processes. If there is no outside option, no menu of other technologies, these agents may be appear resilient and maintain high levels of investment. If outside options exist, however, these agents may switch technologies–an active, internal control oriented response to believing that what they were doing was not working and it was up to them to do something else.

Those agents with strong external control beliefs can be expected to behave differently. At the outset, they may invest little. Even when things go well, these agents may attribute their success to and not follow up by increasing investment activity. On the other hand, where internally oriented agents may become discouraged by early losses, externally oriented agents may be less discouraged by losses they attribute to fate and maintain their behavior.

Even in the brief analytical model presented in this section, the economic implications of locus of control are evident. While clearly evident, however, they are not simple. That control beliefs affect the perceived variance of production outcomes and the multiple order impacts of control beliefs, first affecting adoption and then influencing how farmers interpret outcomes, invites more thorough analytical and simulation-based modeling. Such modeling is beyond the scope of this paper, which now turns to the empirical case of control beliefs and investment behavior among a sample of maize-producing households in Tanzania and Mozambique.

2 Rainfed Maize Production in Mozambique and Tanzania

In 2015, researchers from the University of California, Davis and the International Center for the Improvement of Maize and Wheat (CIMMYT) began a randomized control trial on the impact of drought-tolerant (DT) maize seed and index-based agricultural insurance on the welfare of small farm households. Parallel projects were launched in the countries of Mozambique and Tanzania. In each country, the research team worked with local seed and insurance companies to promote the new technologies. Households in the study area are exposed to high levels of drought risk and rely heavily on maize production for their economic and nutritional provisions. As part of the study, yearly surveys are carried out with just over 3,000 households[7] in 153 communities. While the analysis presented here does not make use of the random variation introduced through assignment to treatment, the introduction and promotion of new agricultural technology offers the opportunity to study the interaction of control beliefs, learning, and investment.

Tables 1 - 3 summarize the sample from the two countries with respect to their economic position, portfolio of income generating activities, and food security status. While all households in the study grow maize, they differ significantly in their other activities as well as in

[7] Households were randomly selected for survey participation from rosters of all maize-growing households provided by community leaders.

their economic position. Most households are engaged in a number of activities to generate income, including wage labor and operating business. There is a significant fraction however, thirty-seven percent in Tanzania and thirty-four percent in Mozambique, that report having no source of income other than maize production.

In terms of agriculture, most households grow a combination of staple crops and cash crops in addition to maize. Table 2 reports the most commonly produced cash crops in each country. Maize, however, remains central to households' economic and food security. The average household cultivates between one and three hectares of maize[8] and plants predominantly local seed varieties. As noted earlier, relying so heavily on rainfed agriculture makes households vulnerable to suffering food and economic insecurity during years characterized by drought or flood. This vulnerability is clearly visible in our data, particularly for the sample from Mozambique which is both poorer and suffered broadly from a severe drought in the year prior to the beginning of the project.

Table 3 shows just how vulnerable this sample of households is. Nearly forty-percent of households in Tanzania suffered a food insecure even in the year prior to our first round of surveys. This number was almost eighty-percent in Mozambique. The lower half of the table, showing access to formal credit and savings, highlights another dimension of why weather fluctuations so quickly turn into food insecure events for these households. Less than ten percent of households in the study have access to formal credit or savings products. While most claim they could access a small informal loan (less than USD 5), this number drops off quickly when asked about slightly larger values. What's more, these informal networks have difficulty dealing with large covariate shocks such as drought.

The sample and environment described above is the motivating force behind efforts by organizations such as CIMMYT and its DTMA project to increase food and economic security by promoting stress-resistant and nutritious maize varieties. It is also the motivations for collaborations such as the one between CIMMYT and the UC Davis research team, which seeks to further improve the ability of drought-tolerant seed to improve household welfare by bundling it with an index insurance product. As noted earlier, these innovations are only effective if they are valued and adopted by households currently experiencing low yields and high exposure to weather risk. Longterm exposure so such a risky environment, however, may result in the kind of external belief which led to low levels of expected profit and therefore adoption in Section 1.1. The next section lays out the instruments used to measure these beliefs before turning to their influence on the adoption decision.

3 Measuring Control Beliefs

Recall from Section 1 that control beliefs capture the extent to which an agent believes that outcomes are influenced by her own actions relative to forces outside of her control. These beliefs can range from fully general beliefs about how the world works down to beliefs about the parameters governing the returns to factors of production in a specific process. One contribution of this paper is to advance the elicitation of these constructs in a development setting, with particular attention to the relationship and influence of both general and specific control beliefs. This section details the measures used to elicit those beliefs,

[8]Though these self-reported areas are somewhat suspect.

their construction, and their distributions in the sample of farmers from Mozambique and Tanzania.

3.1 General Locus of Control: The Levenson IPC Scales

The Leveonson IPC scales (Levenson, 1981) seek to capture the extent to which individuals attribute outcomes to each of three dimensions. The internal dimension (I), reflects control by one's own actions. The powerful others dimension (P), attributes control to agents such as community leaders, politicians, spouses, or other figures of power. Finally, the chance dimension (C) attributes outcomes to stochastic factors. Like the original Rotter scales, Levenson's scales are a broad measure of locus of control capturing general attitudes rather than beliefs about specific activities. In fact, the two statements listed in Section 1 are elements from this set of scales, the first belonging to the Chance scale and the second belonging to the Internal scale.

One particularly appealing feature of the Levenson IPC scales is that each dimension is measured independently. Survey respondents are presented a set of statements to which they assign a Likert scale value. Of twenty-one total statements, seven belong to each of the three scale dimensions[9]. As such, it is possible for an agent to attribute significant influence to multiple dimensions.

Naive scores – as they are called in Macours and Laajaj (2017) – are obtained summing the elements traditionally associated with each dimension. The authors point out, however, that estimating an individuals control beliefs using a set of items is really a latent variable problem. Each individual question is an imperfect proxies for the underlying construct. While the scales have been used and validated in many countries and cultures, there is significant evidence that the relevance of individual items varies across populations (Rammstedt et al., 2013). Measurement challenges are also well documented, especially with less educated populations (Soto et al., 2008)[10].

Of particular concern is acquiescence bias (Macours and Laajaj, 2017; Rammstedt et al., 2013; Soto et al., 2008), or "yea-saying", in which respondents are more likely to agree with statements than to disagree. 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 correllations between unrelated items, which in this case means that an individual's naive score could be positively correlated across all three dimensions just because they tend to agree way more than they disagree.

I adjust for acquiescence bias following Rammstedt, subtracting the mean item score from a the full twenty-one element set. Figures 3 - 4 show the distribution of scores with and without the correction for acquiescence bias in the two countries.

With the adjusted scores, I then undertake a process of improving the constructs via factor analysis. Exploratory factor analysis on the full set of 21 items indicates that there is substantial noise not assoicated with the factor structure we would expect from the Levenson

[9] There are 24 elements in the standard Levenson IPC instrument. I drop three, one in each dimension, for issues of cultural relevance.

[10] I take up the full challenge of analyzing the responses to the Levenson IPC modules for reliability and creating the scales that capture the most consistent information in other work, making use of additional data rounds and a three week test-retest validation exercise.

scales. This means that a number of questions do not contain information related to the latent variables representing beliefs about control of outcomes. To sort out which questions do and do not contain such information, I re-do the exploratory factor analysis by country for each of the three dimensions of the Levenson scale (see Appendix 7.2). I use varimax rotation to produce orthogonal factors, as recommended for identifying related variables for index creation (Kim and Mueller, 1978). It should be noted that if differs from over-fitting a models to data in an important way. Based on the assumed structure of control beliefs, I am looking for the set of questions that serves as the best proxy for each dimension. I am not choosing the set of variables that best predicts the behaviors investigated later.

I drop items with negative factor loadings in their primary dimension of control. Table 5 shows the original and retained items in each scale. With the selected items, I once conduct the analysis and rotate the facotrs before predicting individual factor scores. Table 4 shows the correlations between factor scores across the three dimensions for both countries. Consistent with intuition about the relationship between internal and external dimensions of control, factor scores in the Internal dimension are negatively correlated with those of Chance and Powerful Others in both countries. Similarly, Chance and Powerful Other factors scores are positively correlated. In keeping with the interpretation of locus of control measurements suggested in Rotter (1975) households are sorted into terciles by country for use in the later analysis. The rationale for this is that the raw locus of control scores are not cardinal, but seem to be effective in an ordinal sense for predicting behavior.

3.2 Maize-Specific Control Beliefs

While the Levenson IPC scales capture general attitudes toward control, it is possible to elicit control beliefs in agriculture more directly. To capture the operative control belief for decision making in maize production, I create measures of the variation in production believed to be driven by an agent's choice of inputs and by uncontrollable weather outcomes. This is accomplished by presenting respondents with a series of hypothetical scenarios varying the choice of input bundle and weather outcome. Respondents are first asked the size and quantity of inputs used on their best maize plot. With this reference point fixed, the respondent is then asked to imagine that she has planted her best maize plot with a specific input bundle[11]. For each input bundle, the respondent is asked how much she would expect to harvest under "poor", "normal", and "very good" rain conditions. Figure 6 shows the map resulting from this activity.

I then construct internal (choice of inputs) and external (weather-related) locus of control measures from the resulting nine points. Recall from Equation 3, we are interested in a measure that proxies the role of the Cobb-Douglas parameters on the investment and weather variables. If we had continuous data on inputs and weather, we would be able to estimate the parameters directly for each individual. Instead, I only have a discrete approximation of the input space.

Let the three input bundles 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). To create a measure of internal control, I will look at

[11]Three input bundles are presented: "local" seed varieties with no fertilizer, improved seed varieties with no fertilizer, and improved seed varieties with fertilizer

variability in production outcomes within a weather state and across input bundles (Figure 7). Three such measures can be constructed: one for each weather state. For now, I will not be concerned with the likelihood of each weather state, but rather how, given a weather state, choice of input bundle affects production outcomes. I therefore summarize a farmer's internal control beliefs with the average of variability measures across the three weather states, weighting each equally. The process and intuition is identical for constructing farmer control beliefs about the influence of weather on production outcomes. Rather than holding weather state constant, however, I hold the input bundle constant and look at variation across the weather dimension (Figure 8).

The internal and external control dimensions for an individual farmer are thus calculated as:

$$AG_E = \frac{1}{3}\sum_j \left(\frac{S_j}{\bar{y}_j}\right) \tag{8}$$

$$AG_I = \frac{1}{3}\sum_k \left(\frac{S_k}{\bar{y}_k}\right) \tag{9}$$

Where S_j and S_k are sample standard deviations defined as follows. Let y_{jk} is harvest expected from using input bundle j in weather state k.

$$S_j = \sqrt{\frac{\sum_k (y_{jk} - \bar{y}_j)^2}{2}} \tag{10}$$

$$S_k = \sqrt{\frac{\sum_j (y_{jk} - \bar{y}_k)^2}{2}} \tag{11}$$

And

$$\bar{y}_j = \frac{1}{3}(y_{jl} + y_{jn} + y_{jg}) \tag{12}$$

$$\bar{y}_k = \frac{1}{3}(y_{1k} + y_{2k} + y_{3k}) \tag{13}$$

To further build the intuition behind these measures, consider one element of the summation in Equation 9. Specifically, the element corresponding to internal control in the "low" weather state (l).

The question we seek to answer with this construct is this: For a given weather state, how much do farmers believe they can affect agricultural output? Put another way, within a weather state, how much does output vary when the input bundle changes? Variation in production outcomes within the low weather state can be summarized by the sample standard deviation for the three input bundles (y_{1l}, y_{2l}, y_{3l}). Call this standard deviation S_l as in Equation 11. For comparability across individuals and states of the world, I normalize S_l by the mean expected production across all input bundles in the low weather state. That is, $\bar{y}_l$ as in Equation 13. In the low weather state, I can therefore say that variability due to input choice is on the order of $\frac{S_l}{\bar{y}_l} * 100\%$ of the mean expected harvest in this state.

3.3 The External-Internal (EI) Ratio

A final construct, and the principle measure I will use to analyze household decisions, is the ratio of external to internal control in agriculture. This is given by the ratio of Equations 8 and 9. In this ratio, larger numbers indicate households who believe that weather drives more variability in production outcomes relative to their own choice of input bundle[12].

$$AG_{EI} = \frac{\sum_j \left(\frac{S_j}{\bar{y}_j}\right)}{\sum_k \left(\frac{S_k}{\bar{y}_k}\right)} \tag{14}$$

This construct is my preferred measure of maize-specific control beliefs because it allows the two dimensions to balance each other. Note that the internal solution to the profit maximization problem given by Equation 5 has an infinite number of solutions over the space defined by the internal control parameter (β) and the external control parameter (γ).

4 Predicting Agricultural Investment Behavior With Control Beliefs

I now use the control belief constructs laid out in the previous section to predict agricultural investment behavior. I focus on three principle decisions: the choice to adopt improved maize seed, adoption of fertilizer, and the choice of a cropping portfolio. This set of behaviors captures decisions made by farmers with an eye to both producing food and income and mitigating weather risk. The choice of seed variety and fertilizer both carry with them increased expenditures but hold the possibility of high returns if the weather is good. Diversifying into cash crops carries similar risks, while devoting more resources to staple crops such as millet, sorghum, or cassava can be seen as a strategy for coping with weather stress.

With the exception of the regressions in Figure 10 on maize seed quantities, all of the results reported in Figures 9 - 13 are linear probability models regressing a farmer decision on her tercile position in general and maize-specific locus of control measures. All models are estimated separately for Mozambique and Tanzania, and include a set of controls for the scale of agricultural operation and household wealth.

The linear probability model is sufficient for this task for two principle reasons. First, I am not generating predicted probabilities and so there is no need to worry about the model generating predictions below zero or above one. Second, the regressors of interest are indicator variables for a farmer belonging to a given tercile of control beliefs. The linear probability model simplifies interpretation of these discrete jumps over non-linear models.

The primary challenge for interpreting the results presented below as informative about the direction of the relationship between control beliefs and investment behavior is one of mutual causality. In fact, the Section 1 discussion focused largely on how experiences informed beliefs and Section 1.1 argued that these beliefs informed behavior. This problem is, then, both what we are hoping to see and the thing that is stopping us from being able to

[12] The ratio is constructed in this direction to more closely resemble traditional locus of control scales, in which larger numbers are associated with external control attitudes

see it clearly. To address this, I make use of the timing of survey collection and agricultural decisions.

$$Pr(X_{it} = 1) = \alpha + \beta_1' General_{it-1} + \beta_2' Specific_{it-1} + \beta_3' Z_{it-1} + e_{it} \tag{15}$$

Each year, household surveys are conducted during the months of June to August in both Mozambique and Tanzania. At this point in time, the household has had the opportunity to include their experiences the previous year into their beliefs but have not yet made investment decisions for the coming year. The maize preparation and planting season then begins in September and continues through January, depending on the rains and the agroecological zone. I can then use control beliefs elicited during the previous survey round to predict agricultural investment decisions made a few months later without worrying that farmer's recent good or bad experiences will bias their control beliefs or their recall of their input decisions.

Equation 15 shows the form of the linear probability models estimated throughout this section. The probability that a farmer makes a decision X at time t is regressed on both her general and specific locus of control beliefs. These beliefs are those elicited from the farmer at time $(t-1)$ and enter into the regression as a set of indicator variables marking the farmer's position in terciles of the belief distribution within her country.

4.1 Improved Seed and Fertilizer Use

The first set or results come from estimating the Equation 15 model on whether or not a farmer decides to invest in improved maize seed and fertilizer. Full results can be found in Figure 9. Recall that about half of the combined sample use some level of improved maize seed, with use rates being higher in Tanzania. Very few farm households report using any amount of chemical fertilizer.

The pattern of impacts that we expect to see, both from intuition and from the analytical model, would have the probability of investment increasing along internal control measures and decreasing along external control measures[13]. We also expect that, given these specifications deal with maize production, the maize-specific measures of control belief should be more influential. The primary role of the general beliefs will have already been exerted in its influence over the maize-specific control parameters.

For the Tanzania sample, this is almost exacdtly what we see. Belonging to the upper terciles of the Ag E.I. Ratio – which indicates that more variation is attributed to the weather than to the choice of inputs – is associated with a nearly eighteen percent reduction in the probability of using improved seed. The impacts of holding general beliefs about chance and internal control are also in the expected direction, though smaller than those of the agriculture specific component. Like adoption of improved seed, the same pattern emerges in fertilizer, though the percentage changes are smaller, owing likely to the fact that so few households use fertilizer at all.

In Mozambique, as well, belonging to the upper tercile of the sample in terms of the Ag E.I. Ratio is associated with an eleven percent reduction in the probability of using improved

[13] At least in reference to the first-order influence, setting aside any potential disillusionment effect.

seed. Once again, a similar though smaller pattern can be observed in fertilizer use. For the Mozambique sample, the influence of the general control belief measures is muted.

Interestingly, no clear pattern emerges when we move to Figure 10 and look at the quantity of maize seed that farmers report. The pattern of signs is nearly reversed for the two countries and, if anything, external control seems to be associated with slightly higher use rates. It is worth noting that the seed quantities reported here are a sum of both improved and traditional varieties. Anecdotal evidence suggests that farmers use higher quantities of traditional varieties to make up for low germination rates.

4.2 Crop Portfolio Choice

The second set of results that we consider are on crop portfolio choice. Like choice of inputs, the choice of crop portfolios has implications for both a farm household's income generating potential and for its ability to weather adverse production years without sacrificing the wellbeing of its members. Figures 11 - 13 contain these results. I first look at the decision of whether or not to plant cash and staple crops, before turning to the decision to plant specific crops.

Like the models for total seed use, no clear picture emerges from this first pass at understanding crop portfolio choice. Because we are no longer focused exclusively on maize, it seems reasonable that general control attitudes would begin to play a larger role. We see this a bit in the results for Tanzania, where the probability of planting cash crops is rising monotonically across terciles of internal control. There still appears to be weak evidence that external beliefs in the maize-specific measure are associated with less diversification into both staples and cash crops. It may be the case that production of staple and cash crops are sufficiently similar in the mind of farmers that this agricultural belief is still more operative than the fully general control belief.

The final results we consider involve the choice to plant specific cash and staple crops in the two countries. For this exercise, I consider horticulture crops and the three most common cash crops in each country. For Tanzania, this is sesame, sunfower, and groundnuts. For Mozambique, the three most common cash crops are sesame, cashews, and pineapple. In both countries, I also consider sorghum, millet, and cassava, which are staple crops that have lower production potential than maize but are more resistant to weather stress.

While searching across this number of specifications and variables inevitably turns up a few stars, there are a few systematic patterns that emerge across the two countries that are worth considering. First, while general control beliefs do seem to play a role in predicting some cropping choices – particularly the internal control dimension in Tanzania – the maize-specific control measure continues to play a larger and more consistent role. Believing that weather drives agricultural outcomes to a greater extent than input decisions (in maize, though perhaps proxying for other crops through this) seems to have a particularly strong impact on *which* cash crop farmers choose. In Tanzania, farmers with external beliefs seem to avoid sunflower in favor of sesame. In Mozambique these farmers avoid cashews.

5 Conclusions

The analysis presented in this paper, both analytical and empirical, seeks to use behavioral insight from psychology to help develop a better understanding of how farm households' beliefs about the forces that control outcomes in agriculture affect their investment decisions. It is an early attempt at doing so, and as such generates as many questions as answers.

Activity-specific control beliefs, in this case, the belief that weather outcomes play a stronger role in determining maize production than farmers' input decisions, is shown to drastically reduce take-up of improved inputs. Given all of the effort and resources being poured into developing technologies to help farm households increase their food and economic security, identifying such a strong behavioral dimension of decision-making is intriguing. The analytical model also provides a word of caution, however, to those who would interpret the empirical results as evidence that efforts should be made to increase households' perceptions of their own agency as a way to induce greater investment. Increasing perceptions of internal control brings with it an increased chance of disillusionment when high expectations are not met. Both the empirical and analytical models thus both open many avenues for further study, both about the environment factors that give rise to a farmer's control beliefs and the longer term impacts of these beliefs on continued investment. Rather than a direct target, low investment resulting from strong external control beliefs may be a signal of exposure to high levels of unmitigated risk both in the activity of interest and more broadly.

6 Tables and Figures

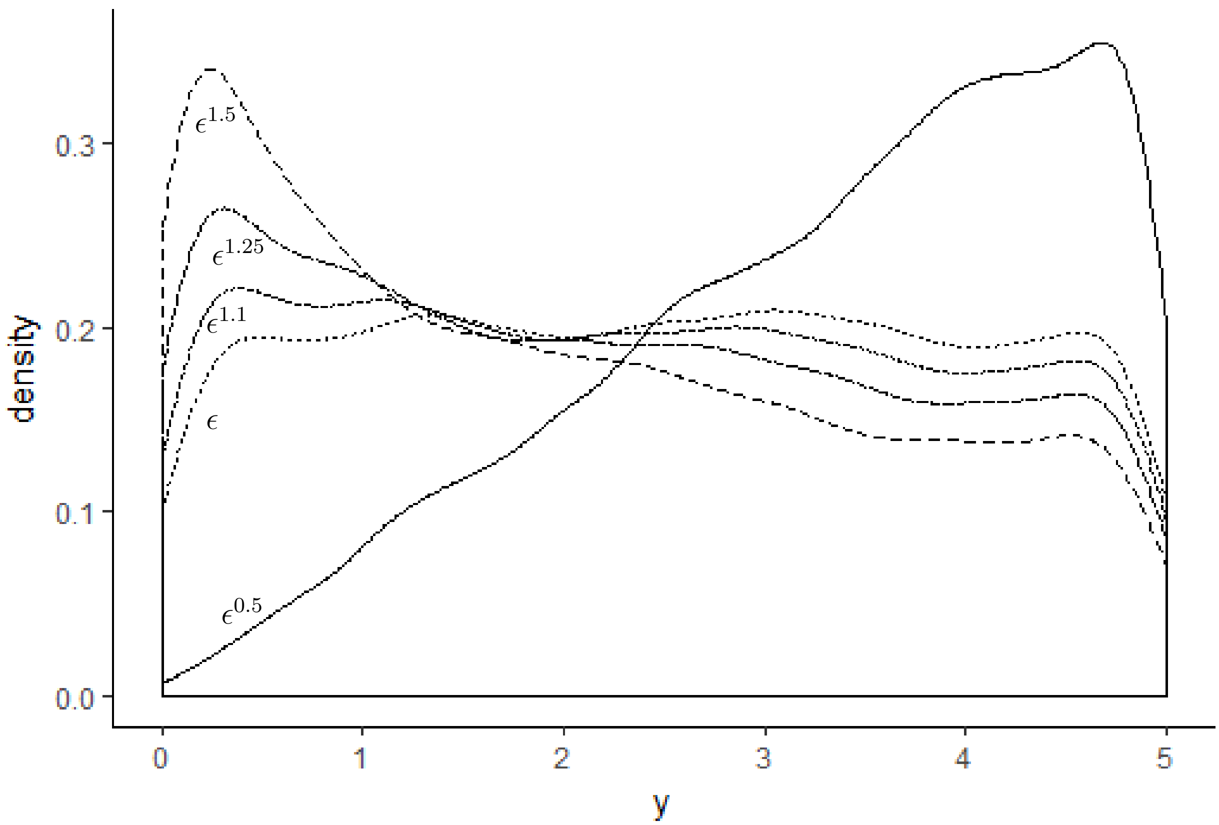

Figure 1: Distribution of outcomes when $y = 5\epsilon^{\gamma}$ and $\epsilon \sim U(0, 1)$. 10,000 Draws.

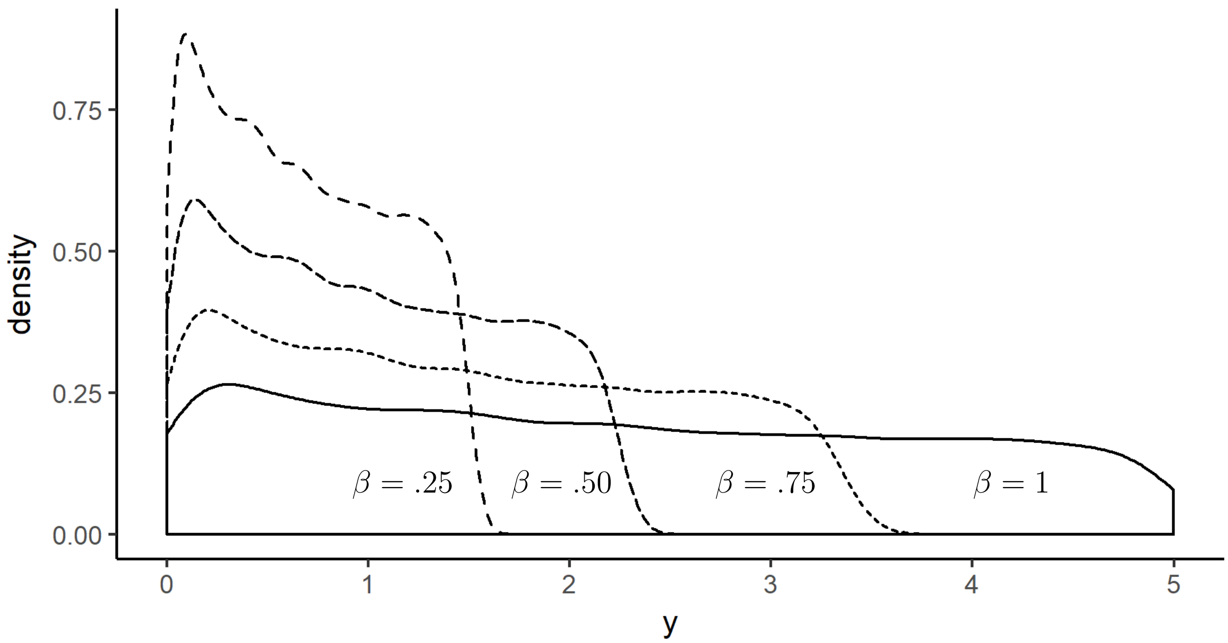

Figure 2: Distribution of outcomes when $y = 5^{\beta}\epsilon^{1.25}$ and $\epsilon \sim U(0,1)$. 10,000 Draws.

	Tanzania	Mozambique
Average HH Members	6	6.9
Highest Level of Education (HH Head)		
None or Below Lower Primary	.18	.39
Lower Primary	.08	.36
Upper Primary	.67	.15
Secondary or Above	.07	.10
Average Simple Poverty Score+	37.4	25.7
Probability Below National Poverty Line	20.2	72
Probability Below International $1.25/Day Line	35.2	78.3
Asset Ownership		
Mobile Phone	.80	.56
Bicycle	.53	.76
Radio	.60	.57
Solar Panel	.37	.45

+ (Schreiner, 2012; Schreiner and Lory, 2013). Tanzania probabilities are upper bounds as one question necessary to calculate the full SPS Score is missing.

Table 1: Summary of Household Characteristics and Asset Ownership

	Tanzania	Mozambique
Maize Production and Practices		
Area Planted (ha)	1.7	2.7
Use Improved Seed	0.59	0.46
Use Chemical Fertilizer	0.02	0.03
Average Seed Use (kgs)	23	32
Average Yield (kgs/ha)	975	325
Income Generating Activities		
Maize Only	.37	.34
Salaried Job	.04	.16
Operate A Business	.39	.34
Labor For Wages	.29	.32
Receive Pension	.02	.05
Receive Remittances	.11	.17
Crop Portfolio		
Grow Staples	.79	.79
Grow Cash Crops	.68	.67
Top Cash Crops		
#1	Sesame	Sesame
#2	Sunflower	Cashews
#3	Groundnuts	Pineapple

Table 2: Income Generating Activities and Crop Portfolio

	Tanzania	Mozambique
Fraction of Households That:		
Experienced Food Insecurity In Past Year	.37	.78
Had to Rely on Less Preferred Foods	.28	.63
Limited Variety of Meals	.13	.50
Reduced Meal Size	.26	.62
Had No Food in the House	.13	.41
Went Without Food for 24 Hours	.06	.44
Fraction of Households That:		
Have Access to Formal Credit	.05	.03
Have Access to Formal Savings	.09	.05
Could Get a Small, Informal Loan[++]	.79	.43
Could Get a Medium, Informal Loan	.48	.22
Could Get a Large, Informal Loan	.31	.08

[++] Small = USD 5, Medium = USD 25, Large = USD 100

Table 3: Food Security and Credit Access

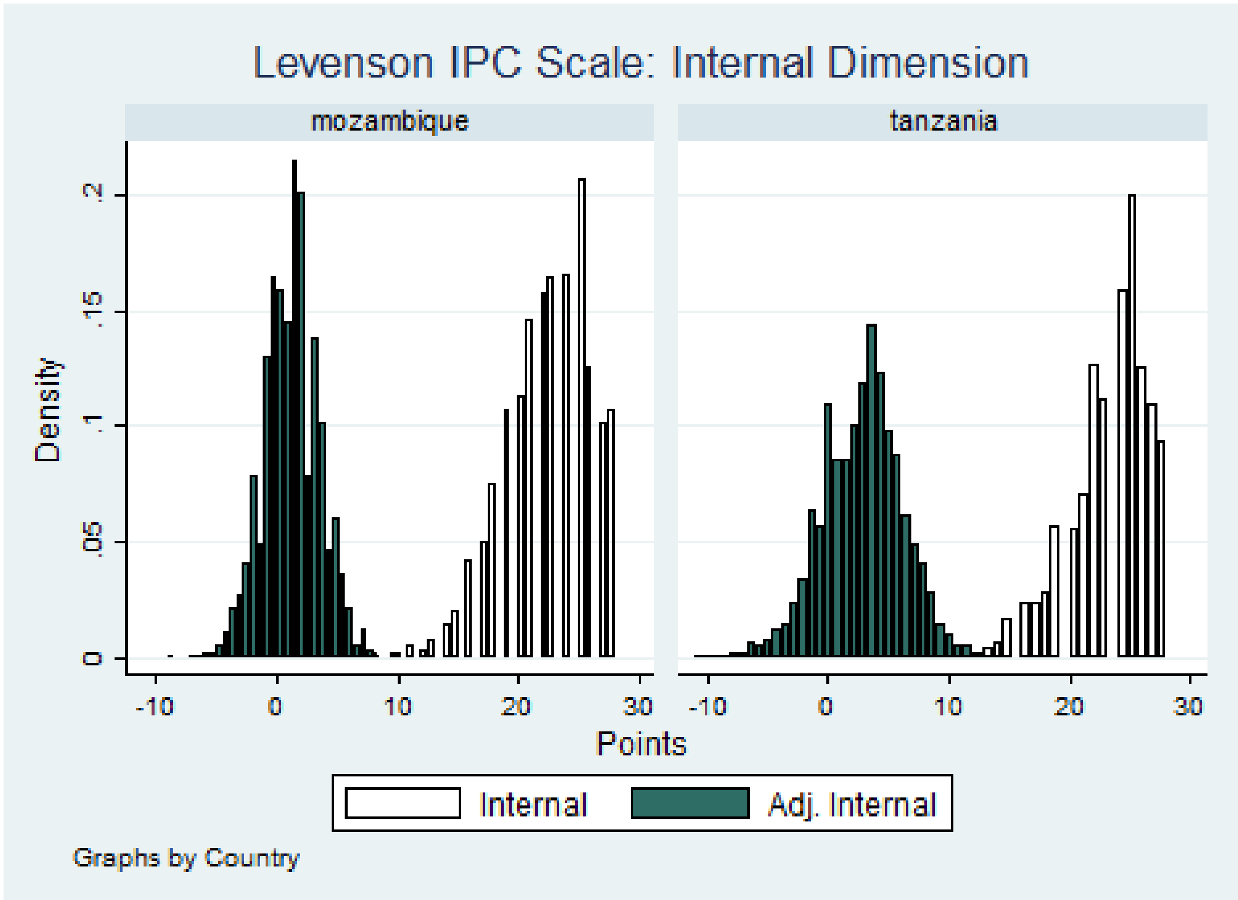

Figure 3: Internal Locus of Control Scores: Naive and Adjusted

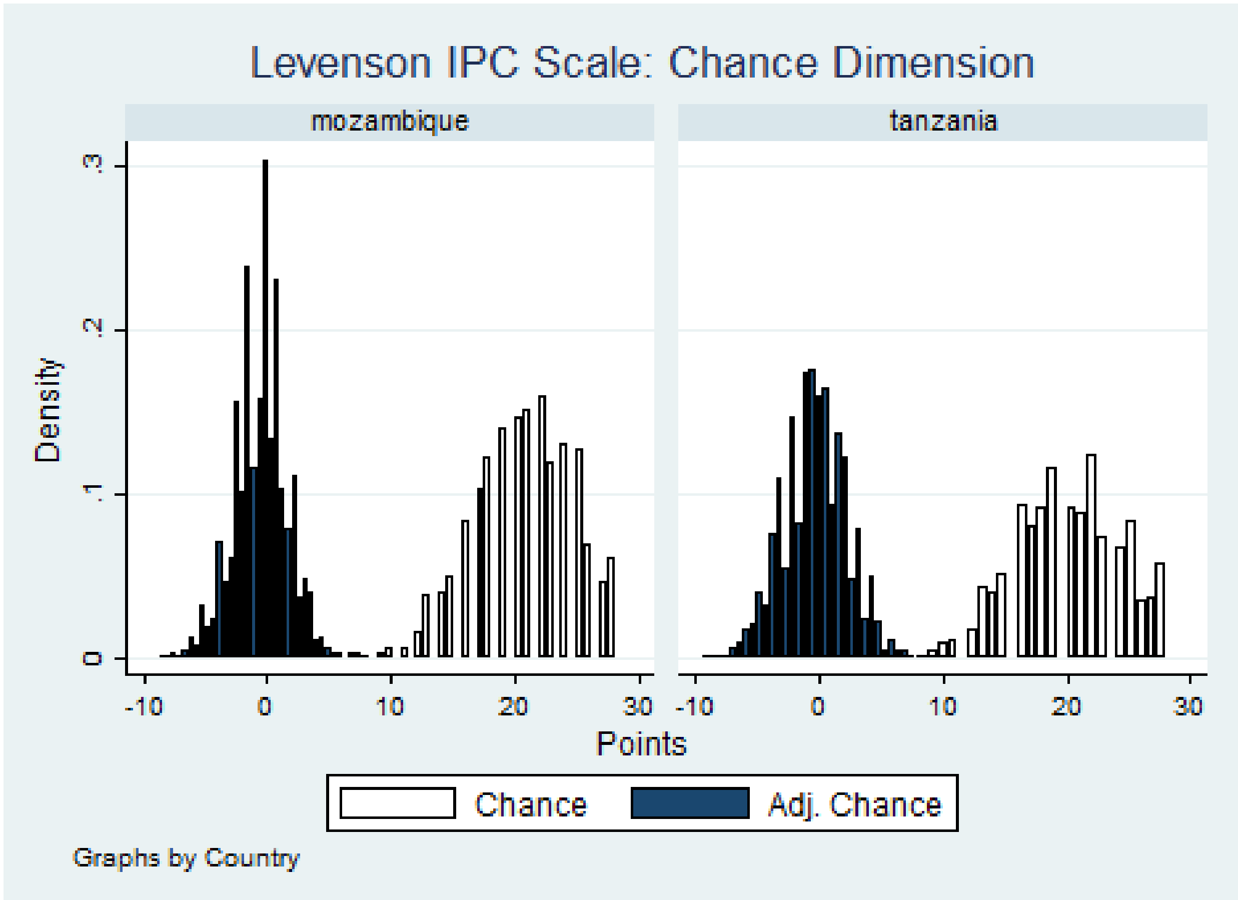

Figure 4: Chance Locus of Control Scores: Naive and Adjusted

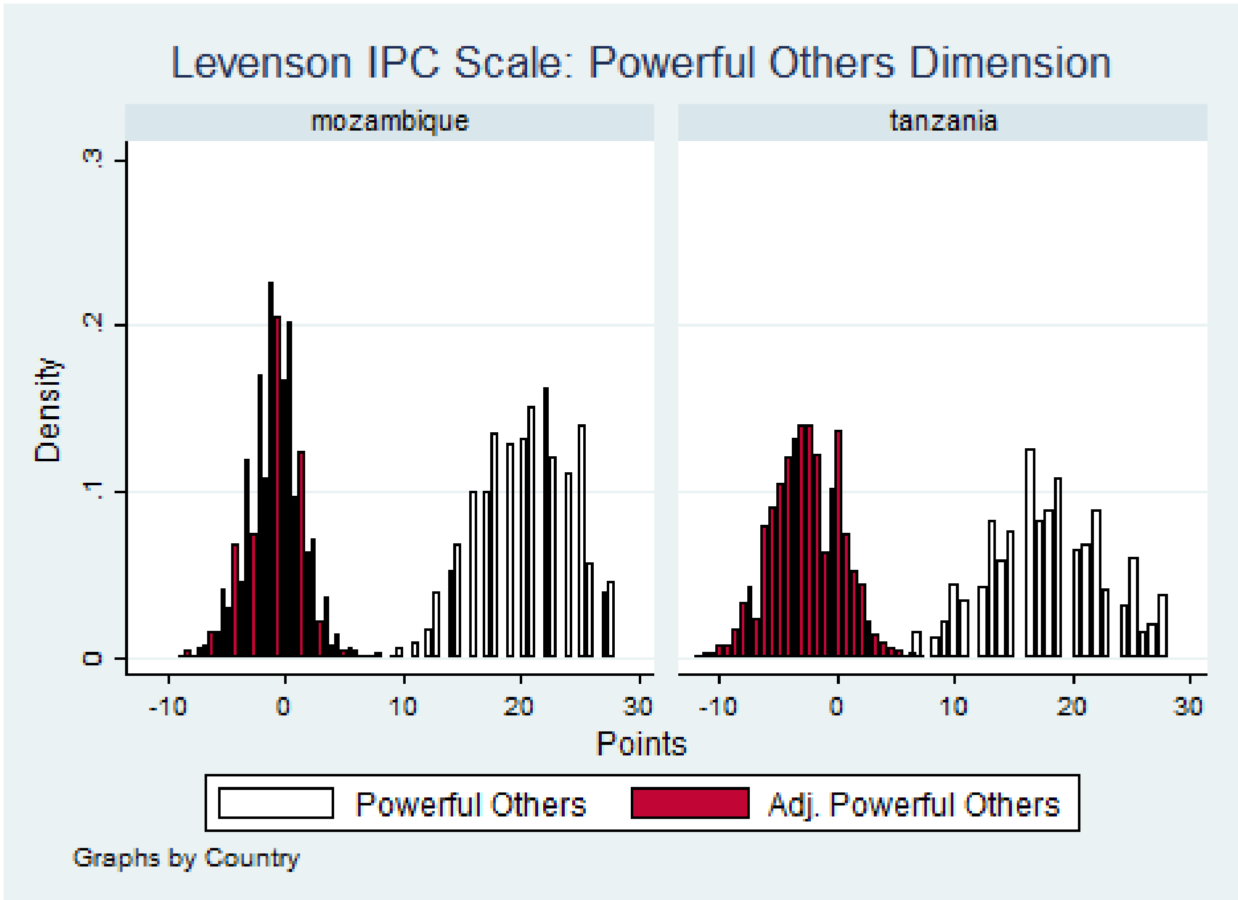

Figure 5: Powerful Others Locus of Control Scores: Naive and Adjusted

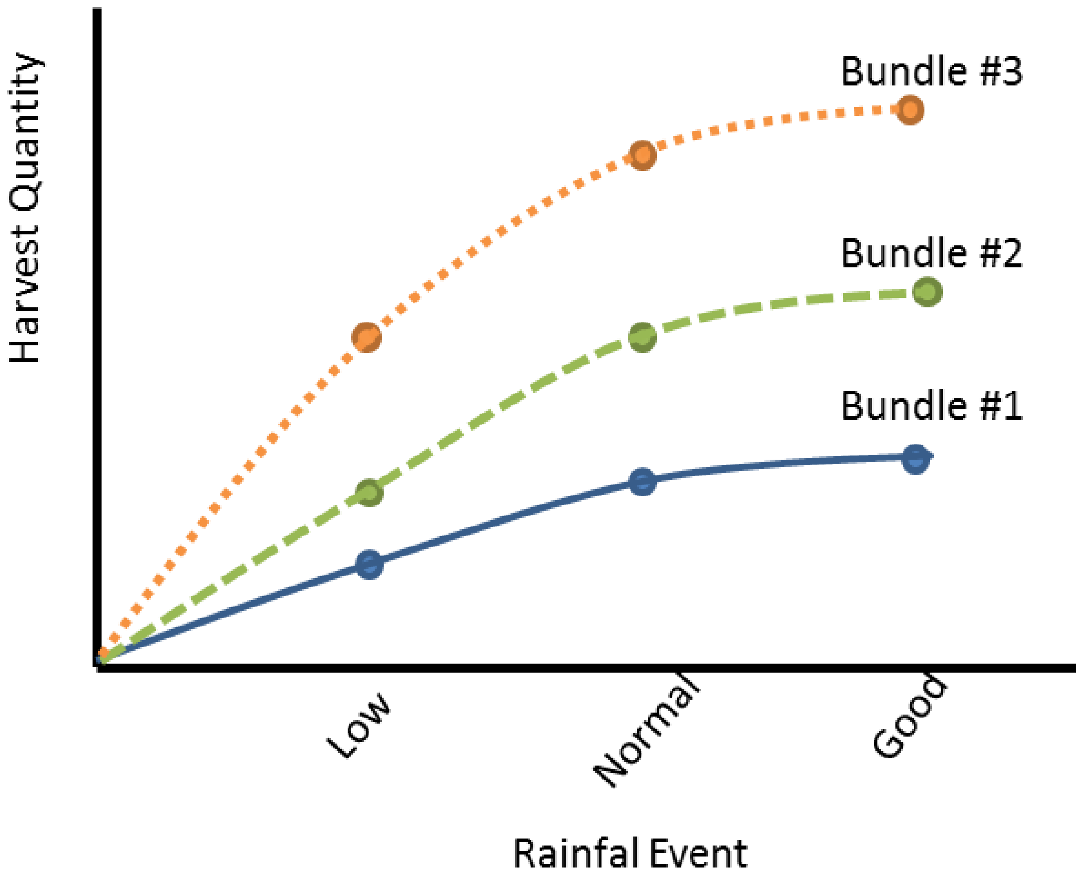

Figure 6: Maize Production: Harvest Under Various Weather-Input Combinations

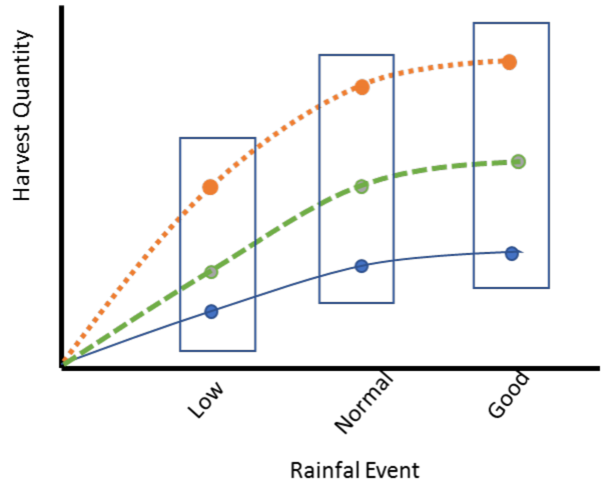

Figure 7: Maize-Specific Internal Control: Variation Within Weather States Across Input Bundles

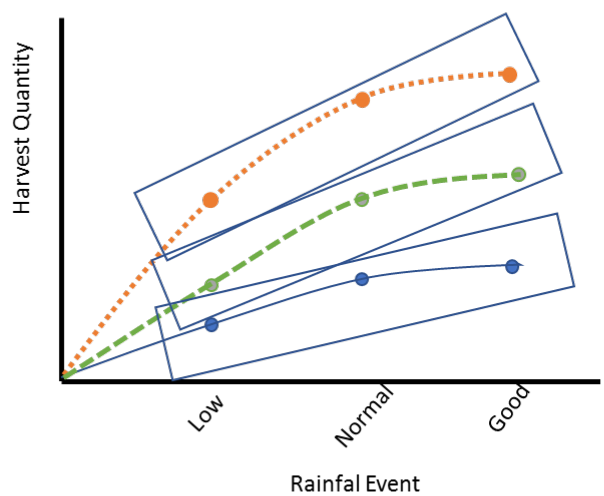

Figure 8: Maize-Specific External Control: Variation in Production for a Given Input Bundle, Across Weather States

Tanzania			
	Internal	Chance	P.O
Internal	1.0000		
Chance	-0.3988	1.0000	
P.O.	-0.5161	0.0959	1.0000

Mozambique			
	Internal	Chance	P.O.
Internal	1.0000		
Chance	-0.1181	1.0000	
P.0.	-0.2134	0.1715	1.0000

Table 4: Correlation Among Locus of Control Factor Scores

	Tanzania		Mozambique	
	Seed	Fert	Seed	Fert
Internal				
Tercile 2: I	0.0529*	0.00809	0.0112	-0.0178
	(0.0320)	(0.0126)	(0.0389)	(0.0138)
Tercile 3: I	0.0815**	0.0366**	0.000557	-0.0185
	(0.0350)	(0.0149)	(0.0380)	(0.0130)
P.O.				
Tercile 2: P	0.0207	-0.00728	0.0561	0.0254**
	(0.0290)	(0.0129)	(0.0361)	(0.0119)
Tercile 3: P	0.00421	0.00830	0.00767	-0.00952
	(0.0319)	(0.0147)	(0.0385)	(0.00862)
Chance				
Tercile 2: C	-0.0680**	-0.0281**	0.0566	-0.0133
	(0.0285)	(0.0132)	(0.0372)	(0.0105)
Tercile 3: C	-0.0874***	-0.0145	0.000110	0.00348
	(0.0326)	(0.0143)	(0.0364)	(0.0120)
Ag E.I. Ratio				
Tercile 2: E.I	-0.130***	-0.0113	-0.0389	-0.0247**
	(0.0282)	(0.0140)	(0.0371)	(0.0110)
Tercile 3: E.I	-0.175***	-0.0363***	-0.115***	-0.00488
	(0.0284)	(0.0121)	(0.0367)	(0.0133)
Simple Poverty Score	0.00505***	0.000697*	0.00235*	0.000864*
	(0.000787)	(0.000378)	(0.00124)	(0.000495)
Num. Plots	0.0266	0.00466	0.0426***	0.00360
	(0.0171)	(0.00445)	(0.0140)	(0.00529)
Constant	0.463***	0.0287	0.332***	0.0173
	(0.0593)	(0.0259)	(0.0634)	(0.0214)
Observations	1657	1658	1100	1100

Standard errors in parentheses

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

Figure 9: Linear Probability Model of Adoption of Improved Maize Seed

	Tanzania Total Seed (kg)	Mozambique Total Seed (kg)
Internal		
Tercile 2: I	0.974	6.977
	(2.311)	(4.737)
Tercile 3: I	-3.896	5.663
	(2.642)	(4.376)
P.O.		
Tercile 2: P	-1.125	0.829
	(2.040)	(3.607)
Tercile 3: P	-2.322	4.174
	(2.332)	(5.044)
Chance		
Tercile 2: C	-1.842	8.412*
	(2.490)	(4.501)
Tercile 3: C	-3.583	4.033
	(2.626)	(3.442)
Ag E.I. Ratio		
Tercile 2: E.I.	2.305	-2.910
	(2.265)	(2.664)
Tercile 3: E.I.	5.785**	1.932
	(2.218)	(5.039)
Improved	-2.873	-0.0807
	(2.336)	(3.141)
Simple Poverty Score	0.187**	-0.0242
	(0.0893)	(0.124)
Num. Plots	8.559***	8.192***
	(3.160)	(2.110)
Constant	8.602	8.876
	(6.900)	(7.144)
Observations	1657	1100

Standard errors in parentheses

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

Figure 10: Total Maize (kgs) Seed Regressed on Control Beliefs

	Tanzania		Mozambique	
	Staple Crops	Cash Crops	Staple Crops	Cash Crops
Internal				
Tercile 2: I	-0.000206	0.0514*	-0.0228	0.0418
	(0.0245)	(0.0311)	(0.0246)	(0.0386)
Tercile 3: I	0.0305	0.124***	-0.0215	0.0359
	(0.0259)	(0.0336)	(0.0234)	(0.0375)
P.O.				
Tercile 2: P.O.	-0.0267	-0.0428	0.0290	0.0497
	(0.0216)	(0.0283)	(0.0243)	(0.0356)
Tercile 3: P.O.	-0.0303	0.0146	0.0115	0.0302
	(0.0247)	(0.0306)	(0.0255)	(0.0380)
Chance				
Tercile 2: C	0.00482	0.000819	0.0264	0.0721**
	(0.0216)	(0.0276)	(0.0244)	(0.0362)
Tercile 3: C	0.0196	0.0244	0.0189	-0.00264
	(0.0232)	(0.0316)	(0.0249)	(0.0366)
Ag E.I. Ratio				
Tercile 2: E.I.	-0.0562***	-0.0644**	0.0640***	-0.0517
	(0.0209)	(0.0273)	(0.0240)	(0.0362)
Tercile 3: E.I.	-0.0472**	-0.0652**	0.0149	-0.0418
	(0.0209)	(0.0274)	(0.0259)	(0.0359)
Simple Poverty Score	-0.000274	-0.00149*	0.00151*	0.000989
	(0.000646)	(0.000782)	(0.000910)	(0.00123)
Num. Plots	-0.00361	0.0359	0.0216**	0.0131
	(0.0135)	(0.0257)	(0.00973)	(0.0161)
Constant	0.903***	0.678***	0.765***	0.522***
	(0.0459)	(0.0651)	(0.0413)	(0.0651)
Observations	1658	1658	1100	1100

Standard errors in parentheses

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

Figure 11: Linear Probability Model of Cultivation of Cash and Staple Crops

	Tanzania						
	Hort.	Sesame	Sunflower	Groundnuts	Sorghum	Millet	Cassava
Internal							
Tercile 2: I	-0.0499*	-0.0101	0.0698**	-0.0263	0.0191	0.0482***	-0.0481**
	(0.0298)	(0.0157)	(0.0325)	(0.0273)	(0.0294)	(0.0161)	(0.0226)
Tercile 3: I	-0.0717**	0.00470	0.100***	-0.00770	0.0736**	0.0381**	-0.0479*
	(0.0321)	(0.0191)	(0.0355)	(0.0293)	(0.0327)	(0.0160)	(0.0255)
P.O.							
Tercile 2: P.O.	0.00718	-0.0103	-0.0408	-0.0232	0.00907	-0.00390	0.00119
	(0.0270)	(0.0162)	(0.0299)	(0.0243)	(0.0274)	(0.0156)	(0.0212)
Tercile 3: P.O	-0.0120	-0.0206	0.0349	0.0164	0.0432	0.0156	-0.0103
	(0.0292)	(0.0169)	(0.0325)	(0.0278)	(0.0299)	(0.0164)	(0.0230)
Chance							
Tercile 2: C	-0.0399	0.00326	-0.00645	-0.0614**	0.00180	0.0311**	-0.0162
	(0.0258)	(0.0147)	(0.0294)	(0.0254)	(0.0277)	(0.0158)	(0.0204)
Tercile 3: C	0.0530*	0.0260	-0.0233	-0.0933***	-0.0239	0.00233	0.00652
	(0.0308)	(0.0179)	(0.0335)	(0.0273)	(0.0307)	(0.0157)	(0.0240)
Ag E.I. Ratio							
Tercile 2: E.I.	0.0314	0.0403***	-0.123***	-0.0317	-0.0661**	-0.00939	-0.00364
	(0.0261)	(0.0152)	(0.0291)	(0.0251)	(0.0274)	(0.0153)	(0.0216)
Tercile: E.I.	0.0369	0.0150	-0.105***	-0.0704***	-0.0575**	-0.0153	-0.0387*
	(0.0262)	(0.0138)	(0.0292)	(0.0242)	(0.0276)	(0.0152)	(0.0205)
Simple Poverty Score	0.00191***	0.000959**	-0.00296***	-0.000101	-0.00433***	-0.00149***	0.00145**
	(0.000740)	(0.000436)	(0.000822)	(0.000668)	(0.000736)	(0.000413)	(0.000608)
Num. Plots	-0.000394	-0.00485	0.0465*	0.0361*	0.0263*	0.00262	0.00156
	(0.00886)	(0.00356)	(0.0277)	(0.0194)	(0.0151)	(0.00365)	(0.00730)
Constant	0.206***	0.0217	0.636***	0.260***	0.419***	0.0818***	0.134***
	(0.0513)	(0.0291)	(0.0696)	(0.0554)	(0.0559)	(0.0275)	(0.0412)
Observations	1658	1658	1658	1658	1658	1658	1658

Standard errors in parentheses

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

Figure 12: Linear Probability Model of Decision to Cultivate Various Crops in Tanzania

	Mozambique						
	Hort.	Sesame	Cashews	Pineapple	Sorghum	Millet	Cassava
Internal							
Tercile 2: I	-0.0263	0.0426	0.0278	-0.0170	0.00259	0.00370	-0.0107
	(0.0299)	(0.0383)	(0.0344)	(0.0256)	(0.0388)	(0.0327)	(0.0391)
Tercile 3: I	0.0121	0.0132	0.0477	0.00801	0.0184	0.00968	-0.0102
	(0.0305)	(0.0373)	(0.0331)	(0.0252)	(0.0375)	(0.0316)	(0.0384)
P.O.							
Tercile 2: P.O.	0.000928	0.0608*	0.0148	0.0215	0.0359	-0.0319	0.123***
	(0.0278)	(0.0354)	(0.0325)	(0.0227)	(0.0357)	(0.0298)	(0.0364)
Tercile 3: P.O	-0.00256	0.0495	-0.0252	0.0363	-0.0131	0.00558	0.0481
	(0.0300)	(0.0378)	(0.0335)	(0.0251)	(0.0383)	(0.0331)	(0.0389)
Chance							
Tercile 2: C	0.0467	0.0276	0.0449	0.0496*	0.0697*	0.0697**	-0.00431
	(0.0288)	(0.0365)	(0.0338)	(0.0257)	(0.0363)	(0.0322)	(0.0374)
Tercile 3: C	0.0205	0.00397	-0.00564	-0.0193	0.00320	-0.0322	0.00862
	(0.0276)	(0.0360)	(0.0320)	(0.0224)	(0.0366)	(0.0292)	(0.0369)
Ag E.I. Ratio							
Tercile 2: E.I.	-0.00890	0.0370	-0.110***	-0.0493**	0.0556	-0.00386	0.0317
	(0.0284)	(0.0359)	(0.0345)	(0.0249)	(0.0362)	(0.0318)	(0.0372)
Tercile 3: E.I.	0.000706	0.0956***	-0.175***	-0.0477*	0.00433	-0.0416	-0.0227
	(0.0285)	(0.0362)	(0.0332)	(0.0250)	(0.0368)	(0.0309)	(0.0371)
Simple Poverty Score	0.000128	0.00227*	-0.00100	0.000993	0.00134	0.000815	0.00320**
	(0.000964)	(0.00121)	(0.00110)	(0.000794)	(0.00124)	(0.000986)	(0.00126)
Num. Plots	0.0281**	0.0259	-0.00450	0.00813	0.0355**	0.0109	0.00819
	(0.0123)	(0.0161)	(0.0118)	(0.00916)	(0.0146)	(0.0118)	(0.0144)
Constant	0.109**	0.183***	0.365***	0.0872**	0.446***	0.192***	0.357***
	(0.0515)	(0.0627)	(0.0565)	(0.0424)	(0.0635)	(0.0532)	(0.0652)
Observations	1100	1100	1100	1100	1100	1100	1100

Standard errors in parentheses

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

Figure 13: Linear probability Model of Decision to Cultivate Various Crops in Mozambique

7 Appendix

7.1 Appendix: Profit Maximization Problem Derivations

Let:

$$y_{it} = x_{it}^{\beta}\epsilon_{it}^{\gamma}$$

Let the price of output and the cost of input be given by p and c respectively. Also assume that the agent is constrained to not spend more than A on inputs.

The profit maximizing agent solves:

$$\max_{x} \quad p \cdot E[f(x,\epsilon)] - x \cdot c \qquad s.t. \quad x \cdot c \leq A, \quad x \geq 0$$

Defining the Lagrangian

$$\mathcal{L} = p \cdot E[f(x,\epsilon)] - \lambda(x \cdot c - A) + \lambda_x \cdot x$$

The first order conditions of which are:

$$\begin{aligned}
&(1) \quad \frac{\partial \mathcal{L}}{\partial x} = p \cdot E\left[\frac{\partial f(x,\epsilon)}{\partial x}\right] - c - \lambda \cdot c + \lambda_x = 0 \\
&(2) \quad \lambda(c \cdot x - A) = 0 \\
&(3) \quad \lambda_x \cdot x = 0
\end{aligned}$$

And the second order condition:

$$f_{xx} < 0$$

With the production process defined above:

$$E\left[\frac{\partial f(x,\epsilon)}{\partial x}\right] = \beta z(z \cdot x_{it})^{\beta-1} \cdot E[\epsilon_{it}^{\gamma}]$$

$$= \beta z(z \cdot x_{it})^{\beta-1} \cdot \frac{1}{1+\gamma}$$

Rewriting the first and second order conditions:

$$\begin{aligned}
&(1) \quad \frac{\partial \mathcal{L}}{\partial x} = \frac{p \cdot \beta z(z \cdot x_{it})^{\beta-1}}{1+\gamma} - c - \lambda \cdot c + \lambda_x = 0 \\
&(2) \quad \lambda(c \cdot x - A) = 0 \\
&(3) \quad \lambda_x \cdot x = 0
\end{aligned}$$

And the second order condition:

$$(\beta - 1)\frac{p\beta z}{1+\gamma} \cdot (z \cdot x_{it})^{\beta-2} < 0$$

The second order condition holds for all $\beta \leq 1$, which is satisfied by the assumption of no increasing returns to scale in x and T.

7.1.1 Zero Investment Corner

First consider the possibility that $x^\star = 0$. Let $\lambda_x > 0$. Then by FOC (3) $x = 0$. At $x = 0$, FOC (2) becomes $\lambda(-A) = 0$ and thus $\lambda = 0$

FOC (1) then becomes:

$$p \cdot E\left[\frac{\partial f(x,\epsilon)}{\partial x}\right]_{x=0} - c + \lambda_x = 0$$

$$p \cdot E\left[\frac{\partial f(x,\epsilon)}{\partial x}\right]_{x=0} < c$$

This condition says that, for zero investment to be optimal, the value marginal product of x must be less than the cost of investment as x approaches zero. Reorganizing slightly:

$$E\left[\frac{\partial f(x,\epsilon)}{\partial x}\right]_{x=0} < \frac{c}{p}$$

Now substituting in the functional form:

$$\left[\frac{p\beta z}{1+\gamma}(z \cdot x_{it})^{\beta-1}\right]_{x=0} < \frac{c}{p}$$

All prices and parameters are positive. By the assumption that production is decreasing returns to scale in x, $\beta < 1$. Thus:

$$lim_{x\to 0}(z \cdot x)^{\beta-1} = \inf$$

While failure to adopt a technology will be of significant in sections discussing adoption, it will not come from the solution to the profit maximization problem occurring at the zero investment corner. If the Inada conditions hold on the production function, as they do here, this will not be feasible. It is worth nothing, however, that if the input is at all bulky then the optimal investment could be smaller than the available unit, resulting in zero investment. Agents solving the profit maximization problem and comparing expected profits across technologies could also fail to adopt, but I will put off discussing this behavior until later. The inequality therefore cannot hold and zero investment is not a feasible solution.

7.1.2 Liquidity Constrained Corner

One of the primary populations of interest in studying rainfed agriculture is small-holding households producing primarily for subsistence purposes. This will certainly be true of the empirical application in this paper. As such, it is likely that many households make decisions in the proximity of liquidity constraints. While this will not be the only constraint of interest, it will certainly be one of them.

Let $\lambda > 0$, then by FOC (2) $x^\star = \frac{A}{c}$.

With $x > 0, \lambda_x = 0$ by FOC (3).

At $x^{\star} = \frac{A}{c}$, FOC (1) then becomes:

$$p \cdot E\left[\frac{\partial f(x,\epsilon)}{\partial x}\right] - c - \lambda \cdot c = 0$$

$$p \cdot E\left[\frac{\partial f(x,\epsilon)}{\partial x}\right] > c$$

Substituting in the current production process at $x^{\star} = \frac{A}{c}$:

$$\frac{p\beta z}{1+\gamma}\left(z \cdot \frac{A}{c}\right)^{\beta-1} > c$$

This condition is the opposite of the zero investment condition. The liquidity constraint binds if the value marginal product of x is still greater than the cost of investment when all available resources are being used for investment.

The level of liquidity, $\underline{\mathrm{A}}$, an agent needs to avoid being constrained in her choice of $x^{\star}_{it}$ is thus given by the cost of the input multiplied by the profit maximizing input level. That is, the agent is liquidity constrained if:

$$A < \frac{c}{z} \cdot \left(\frac{c \cdot (1+\gamma)}{p \cdot \beta \cdot z}\right)^{\left(\frac{1}{\beta-1}\right)}$$

Ththat is to say, the level of A necessary to avoid being liquidity constrained moves opposite the optimal investment level. This is intuitive, but worth noting.

Liquidity Constraint: Comparative Statics The intuition behind the comparative statics on the asset level at which the liquidity constraint begins to bind are straightforward: As the optimal investment level decreases, the tighter the asset constraint would have to be before it would bind. In other words, you need less money to invest optimally, so it is less likely that the constraint binds.

Consider the condition for A to bind:

$$A < \frac{c}{z} \cdot \left(\frac{c \cdot (1+\gamma)}{p\beta z}\right)^{\left(\frac{1}{\beta-1}\right)}$$

The term in parenthesis on the right-hand side is the optimal investment level $x^{\star}$ as derived in 5. As the intuition suggested, the constraint will become more binding as the optimal level of investment increases. The effects of the two parameters of interest, β and γ, on optimal investment levels are derived in the next section.

7.1.3 Interior Solution

Now assume that $0 < c \cdot x < A$.

Both λ and λ_x are then equal to zero.

FOC (1) can now be rewritten as:

$$p \cdot E\left[\frac{\partial f(x,\epsilon)}{\partial x}\right] = c$$

Substituting in the current production process:

$$\frac{p\beta z(z \cdot x_{it})^{\beta-1}}{1+\gamma} = c$$

Solving for $x_{it}^{\star}$:

$$(z \cdot x_{it})^{\beta-1} = \frac{c \cdot (1+\gamma)}{p\beta z}$$

$$x_{it}^{\star} = \frac{1}{z}\left(\frac{c \cdot (1+\gamma)}{p\beta z}\right)^{\frac{1}{\beta-1}}$$

Interior Solution: Comparative Statics I now consider the impact of a change in prices p and c, the technology scalar z, and parameters γ and β on the optimal choice of investment $x_{it}^{\star}$. Because optimal investment is determined only by parameters and prices, this can be accomplished by taking partial derivatives of $x_{it}^{\star}$ with respect to the parameter or interest.

The External Belief Parameter γ I begin with the impact of a change in the external belief parameter γ on the optimal investment level.

$$x_{it}^{\star} = \frac{1}{z}\left(\frac{c \cdot (1+\gamma)}{p\beta z}\right)^{\frac{1}{\beta-1}}$$

$$\frac{\partial x_{it}^{\star}}{\partial \gamma} = \frac{1}{\beta-1}\left(\frac{c+c\gamma}{p\beta z}\right)^{\frac{1}{\beta-1}-1}\frac{c}{p\beta z^2}$$

$$\frac{\partial x_{it}^{\star}}{\partial \gamma} = \frac{1}{\beta-1}\left(\frac{c+c\gamma}{p\beta z}\right)^{\frac{2-\beta}{\beta-1}}\frac{c}{p\beta z^2} \tag{16}$$

The second two terms in Equation 16 are positive. The partial derivative thus takes its sign from the first term, which, given the assumption of decreasing returns to scale in the input and thus $\beta < 1$, is negative. An increase in γ reduces the optimal level of investment $x_{it}^{\star}$.

The Internal Belief Parameter β The impact of a change in the internal belief parameter β is more complicated than the previous case.

$$x_{it}^{\star} = \frac{1}{z}\left(\frac{c \cdot (1+\gamma)}{p\beta z}\right)^{\frac{1}{\beta-1}}$$

$$ln(x_{it}^{\star}) = \left(\frac{1}{\beta-1}\right) ln\left(\frac{c+c\gamma}{p\beta z}\right) + ln\left(\frac{1}{z}\right)$$

$$ln(x_{it}^{\star}) = (\beta-1)^{-1} ln\,(c+c\gamma)) - (\beta-1)^{-1} ln\,(p\beta z) + ln(1) - ln(z)$$

$$\frac{\partial ln(x_{it}^{\star})}{\partial \beta} = \frac{\partial}{\partial \beta}\left[(\beta-1)^{-1} ln\,(c+c\gamma)) - (\beta-1)^{-1} ln\,(p\beta z) + ln(1) - ln(z)\right]$$

$$\frac{1}{x_{it}^{\star}}\frac{\partial x_{it}^{\star}}{\partial \beta} = \frac{ln(c+c\gamma)(-1)}{(\beta-1)^2} - \left[\frac{ln(p\beta z)(-1)}{(\beta-1)^2} + (\beta-1)^{-1}\frac{pz}{pz\beta}\right]$$

$$\frac{1}{x_{it}^{\star}}\frac{\partial x_{it}^{\star}}{\partial \beta} = \frac{ln(c+c\gamma)(-1)}{(\beta-1)^2} - \left[\frac{ln(p\beta z)(-1)}{(\beta-1)^2} + \frac{1}{\beta(\beta-1)} \cdot \frac{(\beta-1)^2}{(\beta-1)^2}\right]$$

$$\frac{1}{x_{it}^{\star}}\frac{\partial x_{it}^{\star}}{\partial \beta} = \frac{ln(p\beta z) - ln(c+c\gamma) - \frac{\beta-1}{\beta}}{(\beta-1)^2}$$

$$\frac{1}{x_{it}^{\star}}\frac{\partial x_{it}^{\star}}{\partial \beta} = \frac{ln\left(\frac{p\beta z}{c+c\gamma}\right) - \frac{\beta-1}{\beta}}{(\beta-1)^2}$$

$$\frac{1}{x_{it}^{\star}}\frac{\partial x_{it}^{\star}}{\partial \beta} = \frac{ln\left(\frac{p\beta z}{c+c\gamma}\right) + \frac{1-\beta}{\beta}}{(\beta-1)^2}$$

Multiplying both sides by $x_{it}^{\star}$:

$$\frac{\partial x_{it}^{\star}}{\partial \beta} = \frac{ln\left(\frac{p\beta}{c+c\gamma}\right) + \frac{1-\beta}{\beta}}{(\beta-1)^2} \cdot \frac{1}{z}\left(\frac{c \cdot (1+\gamma)}{p\beta z}\right)^{\frac{1}{\beta-1}} \tag{17}$$

The second term and the denominator of the first term are positive. The sign of the derivative is thus determined by the numerator of the first term. Taking a closer look at the numerator:

$$ln\left(\frac{p\beta z}{c+c\gamma}\right) + \frac{1-\beta}{\beta}$$

The right-hand term is positive given the assumption of decreasing returns to scale in x. I can then define two conditions for which the overall derivative is positive and one for which it is negative.

If $p\beta z \geq (c + c\gamma)$, then $\frac{\partial x^{\star}_{it}}{\partial \beta} \geq 0$.

Slightly less strict, if $ln\left(\frac{p\beta z}{c+c\gamma}\right) + \frac{1-\beta}{\beta} > 0$, then $\frac{\partial x^{\star}_{it}}{\partial \beta} > 0$.

If, conversely, $\frac{ln(p\beta z)}{c+c\gamma} + \frac{1-\beta}{\beta} < 0$, then $\frac{\partial x^{\star}_{it}}{\partial \beta} < 0$.

7.2 Appendix: Factor Analysis on the Levenson IPC Scales

As described in Section 3.1, I use factor analysis to remove noise from the twenty-one element version of the Levenson IPC scales and obtain unidimensional measures in each of the three scales. To do this, I follow the below process.

1. For each country, I run an exploratory factor analysis routine on the seven items pertaining to each dimension of the Levenson IPC Scales, using varimax factor rotation.

2. This exercise, shown in the left-hand block of results on the following pages, makes clear that substantial noise exists in the answers to individual items. We see this as the set of questions pertaining to each scale fail to load predominantly on a single factor.

3. Because we know that each scale should load on a single factor, I restrict the number of factors to one (using a confirmatory factor analysis approach).

4. Items with negative factor loadings in the confirmatory factor analysis are dropped. The factor analysis is then repeated and factor scores are predicted using regression prediction.

The retained elements for each scale and country are reported in Table 5 below.

Tanzania - Factor Analysis

Internal		Factor1	Factor2	Factor3
	locus-1a	0.179714382	0.182493633	0.055222482
	locus-4a	0.376475393	0.109904916	0.156155613
	locus-8a	0.328809499	0.116084912	0.062849127
	locus-16a	0.222597941	0.00997546	0.181542404
	locus-17a	0.561823218	0.038782492	0.054562568
	locus-18a	0.559213298	0.054658884	0.020140234
	locus-20a	0.26058525	0.126164411	-0.023455668

Internal		Factor1
	locus-1a	0.218518666
	locus-4a	0.411003242
	locus-8a	0.35093393
	locus-16a	0.246758675
	locus-17a	0.559778127
	locus-18a	0.554761609
	locus-20a	0.272887165

Chance		Factor1	Factor2	Factor3	Factor4
	locus-2a	0.557837469	-0.010613014	-0.004675677	0.002213294
	locus-5a	-0.209858576	-0.131532444	-0.164171432	-0.007671404
	locus-6a	0.54963044	0.034474041	0.017986991	-0.01293548
	locus-9a	-0.181099016	-0.012305846	0.011199439	0.121246655
	locus-12a	-0.042668566	0.242474678	0.02948894	0.02280328
	locus-14a	-0.009685252	0.278003721	0.06660859	-0.036794819
	locus-21a	-0.137197439	-0.229262793	0.081017366	-0.049603404

Chance		Factor1
	locus-2a	0.551448458
	locus-5a	-0.230953931
	locus-6a	0.550173273
	locus-9a	-0.183860897
	locus-12a	-0.012358545
	locus-14a	0.027909703
	locus-21a	-0.158731522

P.O.		Factor1	Factor2	Factor3
	locus-3a	0.072211064	0.226015558	-0.088888961
	locus-7a	-0.010067808	-0.107655551	0.265310912
	locus-10a	0.233229559	0.297590951	-0.148898223
	locus-11a	-0.125581723	-0.084102329	0.230937505
	locus-13a	0.461452328	0.053718367	-0.02340161
	locus-15a	-0.109440799	-0.275470609	0.011271155
	locus-19a	0.459023638	0.073145701	-0.029858944

PO		Factor1
	locus-3a	0.1910594
	locus-7a	-0.133196727
	locus-10a	0.376346487
	locus-11a	-0.209405276
	locus-13a	0.418583247
	locus-15a	-0.223585913
	locus-19a	0.427432823

Mozambique - Factor Analysis

I		Factor1	Factor2	Factor3	Factor4
	locus-1a	-0.247858051	-0.143414234	-0.023100225	-0.025290967
	locus-4a	-0.12439986	-0.007167478	-0.009656018	0.128732248
	locus-8a	-0.10078615	0.131975567	0.149517382	-0.00054233
	locus-16a	0.254742704	-0.043886607	-0.081269678	0.021290448
	locus-17a	0.277837167	-0.068124132	-0.018805531	-0.079880662
	locus-18a	-0.050332461	0.321858038	0.039265042	0.010244985
	locus-20a	0.055143941	0.277628695	-0.00904827	-0.008721601

I		Factor1
	locus-1a	0.11232461
	locus-4a	0.108198818
	locus-8a	0.185933966
	locus-16a	-0.243585277
	locus-17a	-0.272792085
	locus-18a	0.225356261
	locus-20a	0.103867535

C		Factor1	Factor2	Factor3	Factor4	Factor5
	locus-2a	0.269654954	0.040059949	0.046871462	-0.145916366	-0.060219452
	locus-5a	0.142676682	0.292771944	0.027854532	-0.037520547	-0.039391286
	locus-6a	0.073508688	-0.30120418	-0.037973749	-0.050756346	-0.051021792
	locus-9a	-0.3861168	-0.00759658	0.058641999	0.009638687	-0.022729608
	locus-12a	-0.106076995	0.043820764	0.087549591	0.203707197	0.053399506
	locus-14a	0.065672281	0.024873308	0.075024061	0.072102251	0.192951034
	locus-21a	0.101810848	-0.071718346	-0.250265631	-0.033100097	-0.036341043

C		Factor1
	locus-2a	0.294329883
	locus-5a	0.160035495
	locus-6a	0.078250331
	locus-9a	-0.367382592
	locus-12a	-0.182482836
	locus-14a	0.003033248
	locus-21a	0.152319306

P.O.		Factor1	Factor2	Factor3	Factor4
	locus-3a	-0.210735456	0.135645356	-0.034716218	0.095591163
	locus-7a	0.17806989	0.30864012	-0.104898725	-0.008632191
	locus-10a	-0.349428552	-0.028797917	0.031172067	0.044615749
	locus-11a	0.319702315	0.126231486	-0.036051533	0.010546575
	locus-13a	-0.10407475	-0.141802007	0.175010665	-0.000567771
	locus-15a	0.013611957	-0.327821443	-0.014610872	0.007886133
	locus-19a	0.15356633	0.141083253	-0.012154184	-0.137254143

PO		Factor1
	locus-3a	-0.085406464
	locus-7a	0.342892263
	locus-10a	-0.297161537
	locus-11a	0.326823642
	locus-13a	-0.199631242
	locus-15a	-0.182935133
	locus-19a	0.22082404

	Tanzania	Mozambique
	(Retained in **bold**)	
Internal		
	locus-1a	**locus-1a**
	locus-4a	**locus-4a**
	locus-8a	**locus-8a**
	locus-16a	locus-16a
	locus-17a	locus-17a
	locus-18a	**locus-18a**
	locus-20a	**locus-20a**
Chance		
	locus-2a	**locus-2a**
	locus-5a	**locus-5a**
	locus-6a	**locus-6a**
	locus-9a	locus-9a
	locus-12a	locus-12a
	locus-14a	**locus-14a**
	locus-21a	**locus-21a**
PO		
	locus-3a	locus-3a
	locus-7a	**locus-7a**
	locus-10a	locus-10a
	locus-11a	**locus-11a**
	locus-13a	locus-13a
	locus-15a	locus-15a
	locus-19a	**locus-19a**

Table 5: Original and Retained Items of Levenson IPC Scales by Country

References

CGIAR. Cgiar financial report 2016. 2016.

CIMMYT. Quarterly belletin of the drought tolerant maize for africa project. *DTMaize*, 4 (4), December 2015.

Deborah A Cobb-Clark. Locus of control and the labor market. *IZA Journal of Labor Economics*, 4(1):3, 2015.

Margo Coleman and Thomas DeLeire. An economic model of locus of control and the human capital investment decision. *Journal of Human Resources*, 38(3):701–721, 2003.

FAO. Regional overview of food insecurity: African food security prospects brighter than ever. Technical report, Food and Agriculture Organization of the United Nations, 2015.

FAOSTAT. Share of dietary energy supply derived from cereals, roots and tubers. *Food and Agriculture Organization of the United Nations*, 2017.

Andrew D Foster and Mark R Rosenzweig. Learning by doing and learning from others: Human capital and technical change in agriculture. *Journal of political Economy*, 103(6): 1176–1209, 1995.

Boyan Jovanovic, Yaw Nyarko, et al. *The Bayesian foundations of learning by doing*. National Bureau of Economic Research, 1994.

Richard E Just and Rulon D Pope. Stochastic specification of production functions and economic implications. *Journal of econometrics*, 7(1):67–86, 1978.

Jae-On Kim and Charles W Mueller. *Factor analysis: Statistical methods and practical issues*, volume 14. Sage, 1978.

Hanna Levenson. Differentiating among internality, powerful others, and chance. 1981.

Karen Macours and Rachid Laajaj. Measuring skills in developing countries. *Policy Research Working Papers*, (January):82, 2017. doi: doi:10.1596/1813-9450-8000.

Andrew D McGee. How the perception of control influences unemployed job search. *ILR Review*, 68(1):184–211, 2015.

Edward C Prescott. The multi-period control problem under uncertainty. *Econometrica: Journal of the Econometric Society*, pages 1043–1058, 1972.

Beatrice Rammstedt, Christoph J Kemper, and Ingwer Borg. Correcting big five personality measurements for acquiescence: An 18-country cross-cultural study. *European Journal of Personality*, 27(1):71–81, 2013.

Julian B Rotter. Generalized expectancies for internal versus external control of reinforcement. *Psychological monographs: General and applied*, 80(1):1, 1966.

Julian B Rotter. Some problems and misconceptions related to the construct of internal versus external control of reinforcement. *Journal of consulting and clinical psychology*, 43 (1):56, 1975.

Mark Schreiner. A simple poverty scorecard for tanzania, 2012.

Mark Schreiner and Hélia Nsthandoca Dezimahata Lory. A simple poverty scorecard for mozambique, 2013.

Melinda Smale, Richard E Just, and Howard D Leathers. Land allocation in hyv adoption models: An investigation of alternative explanations. *American Journal of Agricultural Economics*, 76(3):535–546, 1994.

Christopher J Soto, Oliver P John, Samuel D Gosling, and Jeff Potter. The developmental psychometrics of big five self-reports: Acquiescence, factor structure, coherence, and differentiation from ages 10 to 20. *Journal of personality and social psychology*, 94(4):718, 2008.