

**Empirical Studies in Production Economics and International Agricultural
Development Issues**

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Dissertation submitted to the faculty of the Virginia Polytechnic Institute and State
University in partial fulfillment of the requirements for the degree of

Doctor of Philosophy
In
Agricultural and Applied Economics

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June 24th, 2020
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Keywords: Tillage, Nitrogen, Cocoa, Prospect Theory, Climate Change.

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ABSTRACT

This dissertation is composed of two manuscripts in Production Economics and two manuscripts in International Agricultural Development. The first two manuscripts focus on production economics, and both are an exploration of nitrogen use and its impact on continuous corn production and profitability in Colorado. The first manuscript titled “Switching Regression Stochastic Plateau Production Functions—A Comparison of Alternative Specifications” proposes an alternative approach for estimating crop yield response functions using a frequentist approach. The second manuscript titled “Profitability Effects of Different Tillage Systems in Continuous Corn Rotations” explores the interaction between different tillage systems and nitrogen fertilization in irrigated continuous corn production in northeastern Colorado. We find that strip tillage is better suited for continuous corn production under the agro-climatic conditions in northeastern Colorado.

The third and fourth manuscripts focus on international agricultural development and analyze the role of factors that influence the agricultural development of small-holder farmers in Ecuador, namely, markets, food value chains, risk preferences, and risk perceptions. The third manuscript titled “Does the Use of Specialty Varieties and Post-Harvest Practices Benefit Farmers? Cocoa Value Chains in Ecuador” analyzes the impact of the use of specialty cocoa varieties on small-scale farmers’ income. It finds that the use

of specialty cocoa varieties has a low impact on small-scale cocoa producers' income, and that post-harvest practices may lead to substantial price responses irrespective of the type of cocoa grown. Finally, the fourth manuscript titled "Linking Risk Preferences and Risk Perceptions of Climate Change Using Prospect Theory" explores how farmers' risk preferences correlate with their perceptions of climate risk. It finds that farmers that behave in accordance to the assumptions of prospect theory are more likely to perceive greater risks from climate change, that is, they are more likely to perceive the risks associated with climate change as being more threatening at a personal level. Since risk perception is a necessary prerequisite for adaptation, the results presented in this manuscript, have important policy implications for process of adoption of new technologies aimed at mitigating effects of climate change.

Empirical Studies in Production Economics and International Agricultural Development Issues

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GENERAL AUDIENCE ABSTRACT

This dissertation focuses on Production Economics and International Agricultural Development. The first two manuscripts focus on production economics, and both are an exploration of nitrogen use and its impact on continuous corn production and profitability in Colorado. The first manuscript proposes an alternative approach for estimating crop yield response functions to a single input. The second manuscript explores the interaction between different tillage practices and nitrogen fertilization in irrigated continuous corn production.

The third and fourth manuscripts focus on international agricultural development, and they analyze the role of different factors that influence the agricultural development of small-holder farmers in Ecuador. The third manuscript analyzes cocoa markets in Ecuador. It finds that the use of gourmet cocoa varieties has a low impact on small-scale cocoa producers' income, and that post-harvest practices may lead to substantial benefits. Finally, the fourth manuscript explores farmers' risk behavior. It finds that farmers that behave in accordance to the assumptions of prospect theory, are more likely to show a greater risk perception of climate change, that is, they are more likely to perceive the risks associated with climate change as being more threatening at a personal level. Since risk perception is a necessary prerequisite for adaptation, the results presented in this manuscript, have important policy implications for the adoption process of new technologies aimed at mitigating effects of climate change.

Dedication

Dedicated to mi Chikis, Doña Bella, Don Villa, Home, Yuva, y Marlon.

Acknowledgements

I would like to thank my main advisor and mentor, Jeffrey Alwang, for his unconditional support during my time at Virginia Tech. Thank you for never saying no to my ideas. Even when they were crazy, you always found the way to re-direct me into the right path. Moreover, thank you for all of your assistance with my writing and econometrics, as well as for always having the time for a conversation about agriculture, development, or causality. I wish one day I can become a mentor and researcher as good as you are. Thank you also to my committee members George Norton, Ford Ramsey, Jorge Delgado, and Matthew Holt for your help and guidance during my time at Virginia Tech. Additionally, I want to acknowledge Victor Barrera from INIAP Ecuador for helping me with my fieldwork and data collection.

I would also like to thank my wife for inspiring me and supporting me during this journey we embarked together four years ago. Thank you for jumping with me into the unknown. I could not have done this without you. Finally, my everlasting gratitude goes to my family for always being there for me and for always believing in me.

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1. Dissertation Overview

This dissertation examines two main areas within the broad field of Agricultural and Applied Economics: (i) Production Economics and (ii) International Agricultural Development. Chapters 2 and 3 focus on production economics, and both are an exploration of nitrogen use and its impact on continuous corn production and profitability in Colorado. For these studies we used data from the USDA-ARS long term experiments conducted at ARDEC (2001-2017), in combination with non-linear mixed effects models, production functions using a single input, Monte Carlo methods, and non-linear optimization. Chapters 4 and 5 focus on international agricultural development, and they analyze the role of different factors that influence the agricultural development of small-holder farmers in Ecuador, namely, markets, food value chains, risk preferences, and climate risk perceptions.

In chapter 2 of this dissertation we present a manuscript titled “Switching Regression Stochastic Plateau Production Functions—A Comparison of Alternative Specifications”. This manuscript proposes a switching regression (SR) approach for estimating crop yield response models with stochastic plateaus. In contrast to the so-called Linear Response Stochastic Plateau Model (LRSP), our proposed method treats the minimum input level necessary to reach the yield plateau as a model parameter. We find that the SR specification compares favorably to the LRSP in terms of statistical fit criteria and economic significance. We present an empirical application of the proposed model, by using data from a no-tillage continuous corn experiment in Colorado. Moreover, to illustrate the proposed methodology, in this chapter we demonstrate the process of deriving nitrogen recommendations and profit estimates.

Chapter 3 contains a manuscript titled “Profitability Effects of Different Tillage Systems in Continuous Corn Rotations”. It explores the interaction between different tillage systems and nitrogen fertilization in irrigated continuous corn production in northeastern Colorado. We use the LRSP model in combination with Monte Carlo methods to estimate corn response functions to nitrogen fertilizer and to determine profit-maximizing yields and nitrogen fertilizer rates. We also analyze the expected net returns for continuous corn under different tillage practices using the profit-maximizing nitrogen fertilizer rates and yields obtained with the LRSP. For this manuscript, we use data from a long-term study to capture year-to-year weather variability and evaluate the cumulative effects of tillage practices on profitability. The results show that strip tillage is better suited for continuous corn production under the agro-climatic conditions in northeastern Colorado. Moreover, the finding presented in this manuscript suggest that evaluation of the environmental benefits of no-tillage need to factor in the tradeoff between the improved soil health caused by the reduction of machinery use versus the increased use of nitrogen fertilizer.

In chapter 4 we present a manuscript titled “Does the Use of Specialty Varieties and Post-Harvest Practices Benefit Farmers? Cocoa Value Chains in Ecuador”. In this manuscript, we analyze the impact of the use of specialty cocoa varieties on small-scale farmers’ income. Likewise, we assess the extent to what performing on-farm post-harvest practices improve the farmers’ situation. This manuscript employs household data of 340 cocoa farms from 15 different villages collected in the coastal zone of Ecuador during 2018 to answer these questions. We find that the use of specialty cocoa varieties has in total a low impact on small-scale cocoa producers’ income. Results suggest that recommending to farmers to perform post-harvest practices of fermentation and drying may lead to substantial price responses irrespective of the

type of cocoa grown. Moreover, findings presented in this manuscript have implications for program interventions aimed at increasing cocoa farmer revenue and income.

Finally, in chapter we present a manuscript titled “Linking Risk Preferences and Risk Perceptions of Climate Change Using Prospect Theory”. In this manuscript, we explore how farmers’ risk preferences correlate with their risk perceptions of climate. For this study, we use a Prospect Theory (PT) framework and a lab-in-the-field experiment to elicit and assess risk preferences. Results show that farmers that behave in accordance to the assumptions of prospect theory, are more likely to show a greater risk perception of climate change, that is, they are more likely to perceive the risks associated with climate change as being more threatening at a personal level. These findings contribute to the understanding of farmers’ behavior in developing countries. Moreover, given risk perception is a necessary prerequisite for adaptation, the results presented in this manuscript, have important policy implications for the adoption process of new technologies aimed at mitigating effects of climate change (climate-smart agricultural technologies).

2. Manuscript 1: Switching Regression Stochastic Plateau Production Functions—A Comparison of Alternative Specifications

2.1. Abstract

We propose a switching regression (SR) approach for estimating crop yield response models with stochastic plateaus. The SR method treats the minimum input level necessary to reach the yield plateau as a model parameter. We find that the SR specification compares favorably to other stochastic plateau models suggested in the literature in terms of statistical fit criteria and economic significance. An empirical application to data from a no-tillage continuous corn experiment in Colorado demonstrates the process of deriving nitrogen recommendations and profit estimates and illustrates the proposed methodology.

2.2. Introduction

In accordance with von Liebig's Law of the Minimum, researchers frequently use plateau production functions to study the response of crop yields to inputs. Recent studies following Tembo et al. (2008) have focused on the development of plateau production functions with stochastic plateaus. Such models incorporate random effects to capture the influence of stochastic events – such as pests, weed pressure, and weather – on crop yield response. Allowing for year stochastic variations in the plateau, this approach has yielded an accurate model of producers' profit expectations and has since been applied to production data in several settings including wheat (Biermacher et al., 2009; Taylor et al., 2010; Roberts et al., 2011), winter rye (Tumusiime et al., 2011), corn (Boyer et al., 2013), and cotton (Harmon et al., 2016). Many of these studies have extended the basic stochastic plateau model of Tembo et al. (2008) to include additional random parameters and non-linearities.

We present an alternative approach for frequentist estimation of the stochastic plateau crop input response function. The suggested switching regression (SR) stochastic plateau is in the spirit of Maddala and Nelson's (1974) switching regression framework as implemented in the yield response context by Berck and Helfand (1990) and Paris (1992). It is also closely related to the Tembo et al. (2008) model, representing a re-specification that maintains year random effects. Using the proposed SR model and linear stochastic plateau models introduced in Tembo et al. (2008) and Tumusiime et al. (2011), we estimate corn yield response functions to nitrogen, derive profit maximizing nitrogen rates, and conduct profit analyses for each model. The SR model compares favorably to other stochastic plateau forms in the literature and can be used as an additional means of testing robustness to model specification and estimation technique.

Our focus on modeling plateau-type production functions with random effects through the SR methodology is motivated by the practical advantages of SR models in yield response analysis. The SR method treats the minimum level of the input necessary to reach the plateau yield as a model parameter. Adding a random effect to this parameter allows the yield plateau to shift and the stochastic variation in the yield plateau can then be decomposed into variation from the random effect and the parameter itself. This is advantageous if one wishes to explore how much of the variation can be attributed to the input. The model can be easily extended in the same directions as other stochastic plateau specifications.

There are relatively few applications of stochastic plateau models to the impacts of nitrogen on corn (*Zea mays*) yields. One exception is the work of Boyer et al. (2013) who considered corn response to nitrogen under different crop rotations. We estimate a suite of models to provide a complete comparison of alternative input response function specifications

for corn. Our analysis includes a test of the economic impact of using alternative models and we find that moderate losses to a producer can result when recommendations are based on the incorrect model. The models estimated in this paper contribute to the body of literature on expected net returns and profitability from corn production in the U.S. Similarly, this paper adds to the literature on optimal nitrogen recommendations under production uncertainty. In what follows, our primary objectives are to introduce a new method of estimating the stochastic plateau production function and provide a thorough comparison of different models (including our SR approach) as applied to an actual empirical situation.

2.3. Conceptual and Econometric Models

2.3.1. Linear Stochastic Plateau Production Functions

In the case of yield response to a single input, Tembo et al. (2008) give the general form of the linear stochastic plateau production function as:

$$(1) \quad y_{it} = F(N) + \varepsilon_{it} + u_t$$

where

$$(2) \quad F(N) = \min\{\beta_0 + \beta_1 N_{it}, P_m + v_t\}$$

and t indexes over time, i is the plot or location, y_{it} is the yield in plot i in year t , N_{it} is the nitrogen applied to plot i in year t , $\varepsilon_{it} \sim N(0, \sigma_\varepsilon^2)$ is a random error term, $u_t \sim N(0, \sigma_u^2)$ is a year random effect, and $v_t \sim N(0, \sigma_v^2)$ is a plateau year random effect. In the Tembo et al. (2008) specification, the error and random effects are assumed to be independent. The fixed effect parameters are the intercept β_0 , the slope β_1 , and the average plateau yield P_m .

Equation (1) can be estimated using frequentist techniques for the estimation of non-linear mixed effects models. Ouedraogo and Brorsen (2017) detail an alternative Bayesian approach. Let the conditional probability density functions of y_{it} , v_t , and u_t be represented as: $f_y(y_{it}|N_{it}, \beta_0, \beta_1, \sigma_\varepsilon^2, u_t, v_t)$, $f_v(v_t|\sigma_v^2)$, and $f_u(u_t|\sigma_u^2)$ respectively. The joint probability density function is then given by:

$$(3) \quad f_y(y_{it}, u_t, v_t | N_{it}, \theta) = f_y(y_{it}|N_{it}, \beta_0, \beta_1, \sigma_\varepsilon^2, u_t, v_t) \times f_v(v_t|\sigma_v^2) \times f_u(u_t|\sigma_u^2)$$

where $\theta = (\beta_0, \beta_1, \sigma_\varepsilon^2, \sigma_u^2, \sigma_v^2)$ is the vector of unknown parameters. Tembo et al. (2008) obtain the marginal likelihood function of y_{it} as:

(4)

$$l(\theta|N, Y) = \prod_{t=1}^T \prod_{i=1}^{I_t} \int_c^d \int_a^b f_y(y_{it}|N_{it}, \beta_0, \beta_1, \sigma_\varepsilon^2, u_t, v_t) f_v(v_t|\sigma_v^2) f_u(u_t|\sigma_u^2) dv_t du_t$$

where a , b , c , and d are the limits of integration for the distributions of v_t and u_t respectively and I_t is the number of cross-sectional observations in year t . Because v_t enters equation (4) in a non-linear fashion, no closed form is available and standard maximum likelihood techniques cannot be used for estimation. Tembo et al. (2008) estimated the model with SAS NLMIXED which implements non-adaptive Gaussian quadrature numerical integration techniques to estimate the likelihood.

Tumusiime et al. (2011) expanded the model of Tembo et al. (2008) by allowing for additional randomness in the slope parameter and relaxing the assumption of independence in the variance parameters. The model is then

$$(5) \quad y_{it} = G(N) + \varepsilon_{it} + u_t$$

where

$$(6) \quad G(N) = \min\{\beta_0 + (\omega_t + \beta_1)N_{it}, P_m + v_t\}$$

and $\omega_t \sim N(0, \sigma_\omega^2)$ is the slope random effect. The variance parameters ω_t , v_t , and u_t are normally distributed but allowed to be correlated. A closed form for the likelihood is, again, not available but the model can be estimated using adaptive Gaussian quadrature approximations.

In both Tembo et al. (2008) and Tumusiime et al. (2011), u_t is a random effect that shifts the plateau up or down. This random effect could represent insects, disease, poor stands, heat, freeze damage, and other weather effects. The plateau random effect v_t is described as an effect that shifts the yield plateau potential. In the case of Tumusiime et al. (2011), ω_t represents the slope random effect and is assumed to represent nitrogen losses from leaching, soil, or weather. Stochastic plateau specifications are highly flexible and can also incorporate additional non-linearities in yield response. However, the use of the most flexible specifications is often limited in practice by the relatively short samples available from most agricultural experiments.

The Tembo et al. (2008) approach and its extensions obviate the need to express the plateau production function in a switching regression format. These models do not contain a parameter giving the “minimum amount of fertilizer to reach the plateau” and used as a switching point to calculate the plateau yield. Instead, they define and estimate a parameter representing the plateau directly. Tembo et al. (2008) is the only study to compare estimation results from a stochastic plateau model with a switching regression production function. Because the comparison is made only to the switching regression production function without year

random effects, it does not provide a pure comparison between the frameworks. The stochastic plateau model is likely to fit better because it is more highly parameterized and year plateau variation is an element of the data generating process. We develop a switching regression¹ type of plateau production function that accounts for both the year and the plateau random effect. This offers a more natural model for comparison with the linear stochastic plateaus of Tembo et al. (2008) and Tumusiime et al. (2011).

Following Maddala and Nelson (1974), we propose a switching regression framework for yield response to a single input which can be expressed in the same fashion as equation (1), i.e.

$$(7) \quad y_{it} = H(N) + \varepsilon_{it} + u_t .$$

In this case, $H(N)$ has a threshold point (N_p) that includes a random effect such that

$$(8) \quad H(N) = \begin{cases} \beta_0 + \beta_1 N_{it} ; & N_{it} < (N_p + v_t) \\ \beta_0 + \beta_1 (N_p + v_t) ; & N_{it} \geq (N_p + v_t) \end{cases} .$$

The threshold point N_p is the minimum nitrogen level necessary to reach the plateau yield. As shown in equation (8), the threshold point is an unknown parameter determined by the data. Moreover, $u_t \sim N(0, \sigma_u^2)$ is an intercept year random effect, and $v_t \sim N(0, \sigma_v^2)$ represents the N_p year random effect which causes the plateau to shift up or down.

¹ Makowski and Lavielle (2006) estimated a response model using a stochastic approximation of the expectation maximization algorithm defined in two hierarchical stages: (1) a within site-year yield response to applied fertilizer and (2) a between site-year yield response to applied fertilizer. The first stage used a linear-plus-plateau function (LP) defined by a switching regression. The switching regression proposed here is closer to the specifications proposed in Cerrato and Blackmer (1990) and Bullock and Bullock (1994).

Without loss of generality, we can assume no correlation among u_t and v_t resulting in a variance covariance matrix for the random effects of the form:

$$(9) \quad \text{cov}(u_t, v_t) = \begin{bmatrix} \sigma_u^2 & 0 \\ 0 & \sigma_v^2 \end{bmatrix}.$$

The threshold function is continuous but at the knot point (N_p, y_p) its derivatives do not exist. The marginal likelihood function of y_{it} for this specification is similar to equation (4), and, consequently, no closed form is available due to v_t entering nonlinearly. In the empirical application that follows, we estimate the model using MATLAB NLMEFIT: a solver for non-linear mixed effects models. The model specification presented in equation (8) is comparable to, and has the same number of parameters as, Tembo et al.'s (2008) stochastic plateau model given in equation (2). If one wishes to compare the SR specification to the linear stochastic plateau model of Boyer et al. (2013), the parameter u_t in equation (7) must be removed as Boyer et al. (2013) did not include an intercept random effect.

By including random effects for all of the parameters, equation (8) becomes:

$$(10) \quad H(N) = \begin{cases} \beta_0 + (\beta_1 + \omega_t)N_{it} ; & N_{it} < (N_p + v_t) \\ \beta_0 + (\beta_1 + \omega_t)(N_p + v_t) ; & N_{it} \geq (N_p + v_t) \end{cases}.$$

which is similar to the Tumusiime et al. (2011) model presented in equations (5) and (6).

The variance parameters ω_t , v_t , and u_t are assumed to be correlated and normally distributed, thus the variance covariance matrix of the parameter random effects is assumed to be of the form:

$$(11) \quad \text{cov}(u_t, \omega_t, v_t) = \begin{bmatrix} \sigma_u^2 & \sigma_{u\omega} & \sigma_{uv} \\ \sigma_{u\omega} & \sigma_\omega^2 & \sigma_{\omega v} \\ \sigma_{uv} & \sigma_{\omega v} & \sigma_v^2 \end{bmatrix}.$$

Allowing for nonzero covariances permits the researcher to model a richer set of relationships between the random effects.

The key difference between the SR specification proposed in this article and previous linear stochastic plateau specifications is the selection of parameters of interest. Previous approaches treat the plateau yield P_m as a parameter and add the random effect v_t to P_m to account for stochastic effects in the plateau itself. In doing so, these models capture most of the stochastic variation of the plateau yield but do not provide the researcher with information on how much of this variation can be attributed to nitrogen (input) use. In contrast, the SR specification takes the classic approach of treating the minimum nitrogen level to reach the plateau yield as a switching parameter. The yield plateau and its variation are then influenced and determined by this parameter and its random effect v_t . This is an advantage if one wants to explore how much of the yield plateau variation can be attributed to nitrogen use, the parameter of interest when modeling crop yield responses to nitrogen.

The distinctions between different parameterizations can be shown graphically. Figure 2-1(a) represents the shifts caused by random effect u_t , which adjusts the production function across the entire domain of the input. The adjustment in terms of yield is constant across the level of nitrogen. Figure 2-1(b) shows the plateau shifts caused by the random effect v_t and figure 1(c) represents the plateau shifts caused by the random effect w_t . All of these models are extensions of plateau production functions intended to model yield response in accordance with the Law of the Minimum. But as is evident from the figures, the plateau can shift over time due

to a number of factors, some of which are unobservable to producers and uncontrollable even in experimental settings.

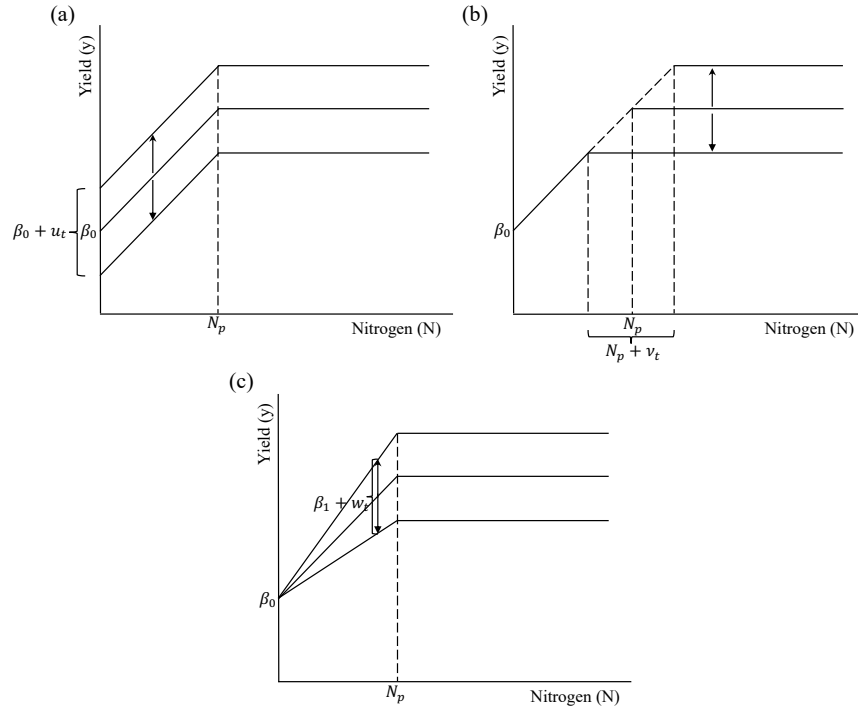


Figure 2-1. Potential shifts induced by the random effects.

The random variation of the *plateau* –also viewed as the maximum yield one can obtain due to a limiting input– leaves the producer with the task of determining the best use and management of nitrogen. Recognizing this task as being left to the producer, we estimate the alternative SR specification where N_p is modeled as a parameter instead of P_m . The implications of this alternative are contrasted with other stochastic plateau models through an empirical application.

2.3.2. Profit Maximization Theory

Because the recommended amount of nitrogen depends on the model for yield response and results from the producer's profit maximization problem, we briefly review theory related to profit maximization and explain how we arrive at an estimate of the expected yield. In the empirical context below, a risk-neutral producer's objective is to maximize expected net returns from corn production:

$$(12) \quad \begin{aligned} \max_{N_{it}} E(\pi_{it}) &= pE(y_{it}) - rN_{it} \\ \text{s. t.} \quad y_{it} &= F(N_{it}), \quad N_{it} \geq 0 \end{aligned}$$

where $E(\pi_{it})$ is the expected net return (\$/ha) for the producer, p is expected corn price (\$/kg), r is the nitrogen fertilizer price (\$/kg), N_{it} is the quantity of fertilizer applied (kg/ha), and $E(y_{it})$ is the expected yield (kg/ha).

The expected corn yield depends on the model for the yield response to nitrogen. For the model of Tembo et. al (2008), the expectation of y_{it} becomes:

$$(13) \quad \begin{aligned} E(y_{it}) &= E[F(N) + \varepsilon_{it} + u_t] = E[F(N)] \\ E(y_{it}) &= E[\min\{\beta_0 + \beta_1 N_{it}, P_m + v_t\}] \end{aligned}$$

and for the proposed SR specification, the expectation of y_{it} becomes:

$$E(y_{it}) = E[H(N) + \varepsilon_{it} + u_t] = E[H(N)]$$

$$(14) \quad E(y_{it}) = E \left[\begin{cases} \beta_0 + \beta_1 N_{it} ; & N_{it} < (N_p + v_t) \\ \beta_0 + \beta_1 (N_p + v_t) ; & N_{it} \geq (N_p + v_t) \end{cases} \right].$$

Following Tumusiime et al. (2011), the expectation of y_{it} for the model with a slope random effect becomes:

$$E(y_{it}) = E[G(N) + \varepsilon_{it} + u_t] = E[G(N)]$$

$$(15) \quad E(y_{it}) = E[\min\{\beta_0 + (\beta_1 + \omega_t)N_{it} , P_m + v_t\}]$$

while for the alternative extended SR approach, the expectation of y_{it} becomes:

$$E(y_{it}) = E[H(N) + \varepsilon_{it} + u_t]$$

$$(16) \quad E(y_{it}) = E \left[\begin{cases} \beta_0 + (\beta_1 + \omega_t)N_{it} ; & N_{it} < (N_p + v_t) \\ \beta_0 + (\beta_1 + \omega_t)(N_p + v_t) ; & N_{it} \geq (N_p + v_t) \end{cases} \right]$$

Provided that estimates for the parameters of the respective models are available, we calculate $E(y_{it})$ using standard methods of Monte Carlo integration.

2.4. Empirical Application

We estimate and compare the nitrogen response models using experimental data collected from a long-term, no-tillage continuous corn study conducted at the Agricultural Research Development and Education Center (ARDEC) located in Fort Collins, Colorado. Nitrogen fertilization treatments included a control (no nitrogen) plus eight treatment levels (34, 67, 100.8, 134.4, 168, 202, 224, and 246 kg ha⁻¹). All plots were irrigated. The study was initiated in 2001 on a clay loam soil field, with one to two percent slope, that had previously been continuously

cropped to corn for 8 years. Plots are close together and assumed to have soil uniformity. Data include 16 years of crop production, from 2001 until 2017, excluding 2008 due to an unusual and severe hail storm that decimated the corn crop.

First, we estimate the model specified in equations (1) and (2), henceforth designated LSP1. This is initially compared to the switching regression specification of equations (7) and (8), henceforth designated SR1. The mean-squared errors for both LSP1 and SR1 (Table 1) indicate superior model fit compared to models without random effects, the results of which can be found in Table A 2-1 of the Appendix. The LSP1 model estimates a yield plateau of 9,859 Kg/Ha, leading to a predicted nitrogen rate at the yield plateau of 150 Kg/Ha. In contrast, SR1 estimates a nitrogen rate at the yield plateau of 151 Kg/Ha, leading to a predicted yield plateau of 9,837 Kg/Ha. When compared to LSP1, SR1 requires a similar amount of fertilizer to reach the plateau but produces a smaller yield plateau per hectare.

Table 1 illustrates some of the differences between the LSP and SR models. LSP focuses on the estimation of the plateau yield P_m and produces a coefficient and standard error for this parameter. The standard error facilitates hypothesis testing with respect to the plateau. Since the model does not estimate the value of the minimum nitrogen to reach the plateau, N_p , it must be predicted using estimated parameters. If one is interested in the standard error of N_p , bootstrapping or other resampling methods are needed. In contrast, the SR model directly estimates the minimum nitrogen needed to reach the plateau and produces a coefficient and standard error. This represents a potential advantage over LSP as the switching level of nitrogen may be of most interest to producers.

Since the yield data are assumed to be independent and identically distributed, a natural criterion to compare the fit of the models is the Likelihood Dominance Criterion (LDC) proposed by Pollack and Wales (1991). LDC compares models based on the difference of the likelihoods adjusting for the number of parameters. As argued by Pollack & Wales (1991) and Tumusiime et al. (2011), when the number of parameters is equal – as in our application – the criterion reduces to a simple comparison of likelihood values. In this case, the likelihood comparison favors the SR1 model over the LSP1 model. Table 1 also reports the penalized-likelihood criteria AIC (Akaike information criterion) and BIC (Bayesian information criterion), often used for comparing non-nested models. Both criteria reward goodness of fit and penalize the addition of parameters to the model, as an increase in parameters always improves in-sample model fit. According to Burnham and Anderson (2002) and Raftery (1995), a difference in the range $[0,2]$ of the AIC and BIC values provides no evidence of a difference in goodness of fit.

The AIC and BIC values for the SR1 specification are smaller than those of the LSP1 model by 11.59 units. These results in combination with the LDC test provide further evidence in support of SR1 when compared to LSP1. We conclude, at least for this empirical application, that the switching regression model SR1 fits the data better than the model LSP1 specified in Tembo et al. (2008).

Both models are extended by adding additional random effects. For LSP1 this amounts to estimating the plateau function of Tumusiime et al. (2011) as specified in equations (5) and (6), and designated as LSP3. Table 1 shows the results for LSP3 and its switching regression counterpart SR3. Both models allow for a full covariance matrix of the random effects. We tested several different specifications of the covariance matrix with results reported in Table A 2-

3 of the Appendix. Allowing all parameters to have random effects, and assuming full correlation among the effects, further reduces the mean-squared error and improves the likelihood values for both models. The LDC provides minimal evidence in favor of the LSP3 model over the SR3 model. The differences in the AIC and BIC values between the LSP3 and SR3 models are 1.15 and 1.16 respectively, which suggests no difference in the goodness of fit between these two models. Thus, we cannot conclude that there is a significant difference in fit between SR3 and the model specification of Tumusiime et al. (2011) LSP3.

The nitrogen rate at the yield plateau is also similar for both models – 152 Kg/Ha for LSP3 and 153 kg/Ha for SR3. The yield plateau increases to 9,888 kg/Ha for LSP3 and 9,923 kg/Ha for SR3 relative to the more parsimonious specifications LSP1 and SR1. Model SR3 estimates a larger yield plateau when compared to LSP3 and requires slightly more fertilizer application to reach the yield plateau. Table 2-1 shows that using an intercept random effect, a slope random effect, and allowing for correlated random effects produces a model with superior fit. The MSE, penalized-likelihood criteria AIC, and BIC support the LSP3 and SR3 models over the LSP1 and SR1. This result supports the findings of Makowski and Wallack (2002) and Tumusiime et. al (2011) and is a first application of full mixed-effects modeling to no-tillage corn.

Table 2-1. Regression Results for the LSP and SR Models

Parameter	Models			
	LSP1	SR1	LSP3	SR3
Dependent Variable: Corn Yield (kg/ha)				
Intercept β_0	5,205.23 (204.29)	5,232.91 (191.70)	5,217.07 (160.93)	5,204.52 (167.49)
Slope β_1	31.05 (1.08)	30.42 (1.06)	30.66 (1.94)	30.77 (1.81)
N at Plateau N_p	- -	151.39 (4.58)	- -	153.38 (7.36)
N at Plateau (predicted) $\widehat{N}_p$	149.86	-	152.37	-
Yield Plateau P_m	9,859.02 (170.17)	- -	9,888.40 (179.82)	- -
Yield Plateau (predicted) $\widehat{P}_m$	-	9,837.54	-	9,923.73
Intercept Random Effect σ_u^2	550,754 (71,507)	469,347 (59,880)	310,455 (94,043)	347,167 (92,964)
Slope Random Effect σ_ω^2	- -	- -	39.87 (12.75)	34.90 (9.46)
N at Plateau Random Effect σ_v^2	- -	0.00 (43.51)	- -	564.55 (172.18)
Yield Plateau Random Effect σ_v^2	344,787 (91,120)	- -	413,414 (110,322)	- -
MSE	504,303	521,151	442,162	447,785
LogLikelihood	-2,075.72	-2,069.93	-2,062.21	-2,062.79
AIC	4,163.45	4,151.86	4,144.43	4,145.58
BIC	4,168.08	4,156.49	4,152.15	4,153.31
n (number of observations)	256	256	256	256

Notes: LSP1 model corresponds to equations (1) and (2). LSP3 model corresponds to equations (5) and (6). SR1 model corresponds to equations (7) and (8). SR3 model corresponds to equations (7) and (10). Standard errors are in parenthesis. We used bootstrapping techniques to obtain consistent estimates of the corresponding standard errors for the random effects parameters. The predicted parameters $\widehat{N}_p$ and $\widehat{P}_m$ are calculated using the estimation results for each model.

Boyer et al. (2013) is the only other study to estimate corn response functions using experimental data from the United States and mixed-effects plateau models. They report no-tillage continuous corn response functions using a 6-year data set (2006-2011) from an experiment conducted at Milan, Tennessee. They included a random effect on the yield plateau parameter but did not include random effects for the intercept and slope parameters. We also considered comparison with the Boyer et al. (2013) model, the results of which can be found in Table A 2-4 of the Appendix. An additional extension in Boyer et al. (2013) is the estimation

of both linear and quadratic stochastic plateau functions. The authors found no statistical distinction between the models and concluded that the linear response stochastic plateau best described yield response to nitrogen. Although not directly comparable to the results of Boyer et al. (2013) due to differences in location and agronomic characteristics, the results in Table 1 are relatively close to their reported corn yield plateau of 9,912 kg ha⁻¹ and nitrogen rate at the plateau of 137 kg ha⁻¹.

2.4.1. Correlation of Random Effects

A comparison of the random effects covariance matrix of LSP3 and SR3 highlights additional differences between the two models². Table 2-2 shows estimates of the covariance matrix represented in equation (11) for each model. We also report the covariance matrix as a correlation matrix in table 2. Recall that for both models the intercept parameter β_0 represents the case when $N_{it} = 0$ and can be interpreted as the initial productivity of the soil caused by residual nitrogen from the previous growing season. Residual nitrogen arises from mineralization of soil organic matter or nitrate that has not leached below the root zone (UC SAREP, 2018). The slope parameter β_1 represents the yield increase due to N application and can also be interpreted as the marginal productivity of the nitrogen fertilizer. The fertilizer productivity is affected by availability of organic matter, soil pH, moisture content, and other factors.

With these interpretations in mind, for LSP3, the covariance parameter σ_{uv} reflects the association between the initial soil productivity and the yield plateau. This parameter is significant at the 1% level and its strong positive correlation coefficient of 0.83 can be

² We also estimated random effects for each year of the sample. These can be found in Table A 2-5 of the Appendix.

interpreted as “when initial soil productivity increases by one standard deviation, the yield plateau increases by 0.83 standard deviations”. This robust association is expected as shifts caused by the intercept random effect u_t shift the entire yield response function, including the plateau. From an agronomic perspective, better initial soil conditions could imply a greater availability of other limiting inputs, hence a larger yield plateau.

Table 2-2. Random Effects Covariance and Correlation Matrix of Models LSP3 and SR3

	LSP3	SR3
$cov(u_t, \omega_t, v_t)$	$\begin{pmatrix} \sigma_u^2 & \sigma_{u\omega} & \sigma_{uv} \\ \sigma_{u\omega} & \sigma_\omega^2 & \sigma_{\omega v} \\ \sigma_{uv} & \sigma_{\omega v} & \sigma_v^2 \end{pmatrix}$	$\begin{pmatrix} \sigma_u^2 & \sigma_{u\omega} & \sigma_{uv} \\ \sigma_{u\omega} & \sigma_\omega^2 & \sigma_{\omega v} \\ \sigma_{uv} & \sigma_{\omega v} & \sigma_v^2 \end{pmatrix}$
Estimated Results	$\begin{pmatrix} 310,455 *** & - & - \\ (94,043) & - & - \\ 675.76 & 39.87 *** & - \\ (716.52) & (12.75) & - \\ 296,931 *** & 1,376 & 413,414 *** \\ (94,295) & (1,057) & (110,323) \end{pmatrix}$	$\begin{pmatrix} 347,167 *** & - & - \\ (92,964) & - & - \\ 402.83 & 34.90 *** & - \\ (582.64) & (9.46) & - \\ -3,257 & -127.96 *** & 564.55 *** \\ (2,664) & (36.58) & (172.18) \end{pmatrix}$
Correlation Matrix	$\begin{pmatrix} 1 & 0.19 & 0.83 \\ 0.19 & 1 & 0.34 \\ 0.83 & 0.34 & 1 \end{pmatrix}$	$\begin{pmatrix} 1 & 0.12 & -0.23 \\ 0.12 & 1 & -0.91 \\ -0.23 & -0.91 & 1 \end{pmatrix}$

Standard errors are in parenthesis for the corresponding covariance matrices. We used bootstrapping techniques to obtain consistent estimates of the corresponding standard errors for both models.

*** Significant at the 0.01 level.

For SR3, the covariance parameter $\sigma_{\omega v}$ represents the association between nitrogen fertilizer productivity and the minimum nitrogen application necessary to reach the yield plateau. This parameter is significant at the 1% level and its strong negative correlation coefficient of -0.91 can be interpreted as “when the nitrogen fertilizer productivity increases by one unit of standard deviation, the minimum nitrogen rate to reach the yield plateau decreases by 0.91 standard deviations”. This interpretation cannot be directly obtained using the LSP3 model. Moreover, this is the first study to report and analyze these covariance parameters for corn

response functions. Additional residual analyses for each model can be found in Table A 2-6 of the Appendix. Estimates of the SR3 parameter $\sigma_{\omega v}$ could allow future research to further examine the relationship between productivity and the minimum rate to reach the yield plateau for different forms of fertilizer, i.e. granular vs liquid. It would also be possible to determine if the additional costs of using fertilizers with higher productivity are offset by the gains generated by the reduction in nitrogen use.

2.4.2. Profit Analysis

We estimate the expected returns using partial budgets. Three different prices for N are taken into account: \$0.72, \$0.96, and \$1.20 per kg. These prices per kg are equivalent to prices of \$300, \$400, and \$500 per ton of 46-0-0 urea fertilizer respectively. Likewise, we assume corn prices of \$0.20 per kg or \$5 per bushel. We selected the prices to be representative of prices reported over the last decade (USDA-NASS, 2019).

Parameter estimates from Table 1 are used in combination with Monte Carlo methods to calculate expected net returns and profit maximizing nitrogen rates for the different model specifications. Ten thousand draws from the normally distributed vector $v_t \sim N(0, \sigma_v^2)$, and the jointly normally distributed vector $[\omega_t, v_t] \sim N(0, \Omega)$ are generated using the respective variance/covariance estimates of each model. Likewise, ten thousand random points representing nitrogen applications in the interval $[0, 246]$ are generated. We computed yield expectations for each of the simulated nitrogen applications evaluated at the 10,000 draws of the vectors of random effects. Finally, profit maximizing nitrogen rates are calculated for each model using the MATLAB nonlinear programming solver to solve the nonlinear optimization problem of equation (12). The solver calls the quasi-newton algorithm using the BFGS Quasi-Newton

method with a cubic line search procedure. For robustness, we also obtained results using a traditional grid search since the problem involves only one choice variable.

Figures 2-2 shows the corn yield expectations for the simulated nitrogen applications using the LSP and SR model. For reference, we also plot the actual yield averages. Results show that by using enough draws of the random effects and nitrogen applications, taking the expectation of models LSP1, LSP3, and SR3 transforms the original plateau shapes into smooth concave curves. However, taking the expectation of model SR1 does not smooth its plateau form. This is due to nitrogen at plateau random effect σ_v^2 equaling zero for this model. Nonetheless, the expectations are similar for all models.

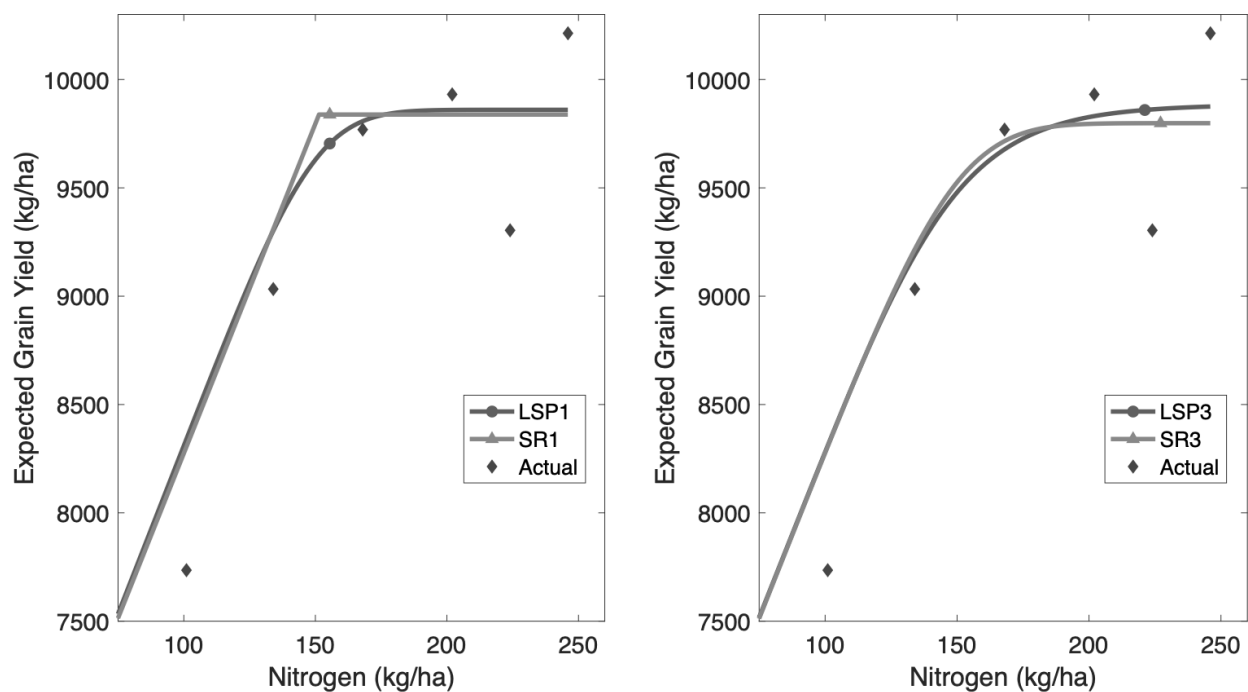


Figure 2-2. Expected grain yields for LSP and SR models

Using the expected yield estimates, expected net returns are calculated from equation (12) under the different price scenarios defined above. Figure 2-3, which uses 0.20 \$/kg as the

price of corn, and 0.96 \$/kg as the price of nitrogen, is shown below. The expected profit function generated by the different specifications of the models can be higher or smaller than the others, and depends on the amount of nitrogen applied.

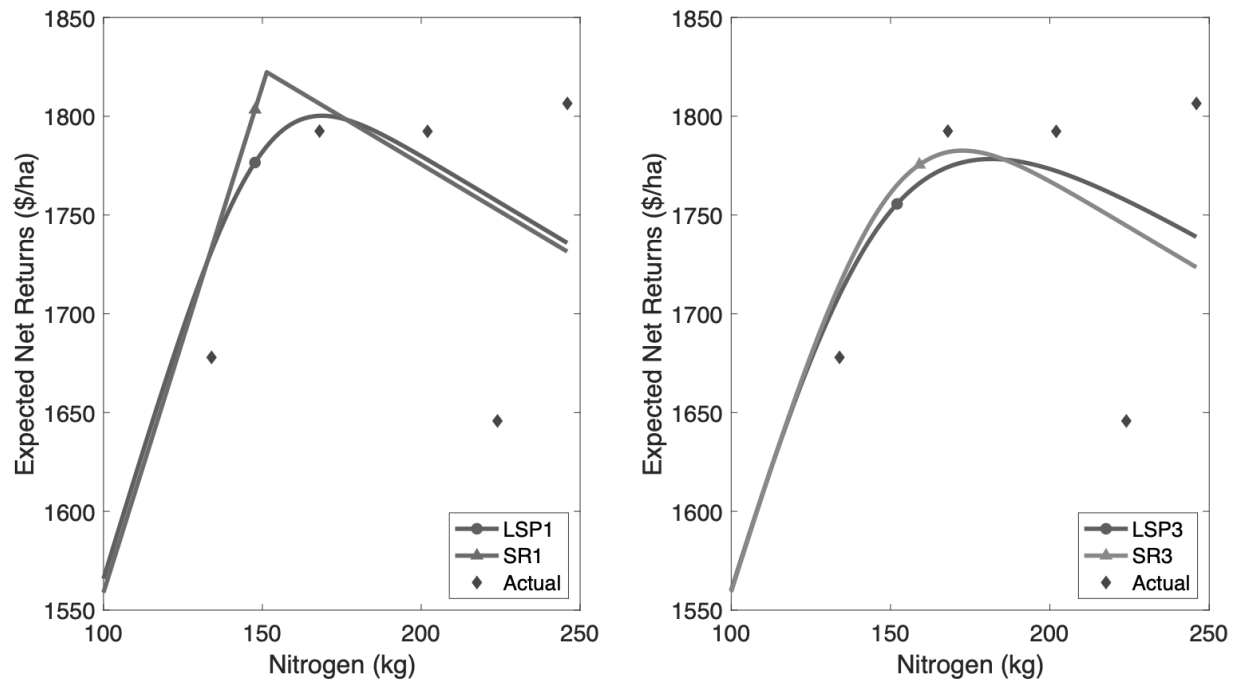


Figure 2-3. Expected net returns for LSP and SR models

Table 2-3 shows the profit-maximizing nitrogen rates, yields, and net returns for different assumed prices. The expected profit maximizing nitrogen rates ranged from 166 to 189 kg/ha for the standard stochastic plateau models and from 151 to 177 kg/ha for the SR models conditional on the price scenario.

Standard errors were estimated for the expected profit maximizing nitrogen rates and then used to construct 95% confidence intervals. These are also reported in table 3 and show that in each price scenario, the confidence interval of the stochastic plateau model overlaps with the

confidence interval of its corresponding SR model. This suggests no statistical difference in profit maximizing nitrogen rates for no-tillage corn across the model specifications.

Table 2-3. Expected Profit Maximizing Nitrogen Rates (kg/ha), Profit Maximizing Yields (kg/ha), and Net Returns (\$/ha) for LSP and SR Models

Nit. Price	Results	Corn Price = \$0.20			
		LSP Models		SR Models	
		LSP1	LSP3	SR1	SR3
\$0.72	Prof. Max. Nit. Rate (kg/ha)	172	189	151	177
	95% Confidence Interval	[166, 178]	[176, 202]	[113, 190]	[163, 191]
	Profit Max. Yield (kg/ha)	9,825	9,794	9,838	9,759
	Exp. Net Returns (\$/ha)	1,841	1,823	1,859	1,824
\$0.96	Prof. Max. Nit. Rate (kg/ha)	169	182	151	172
	95% Confidence Interval	[161, 176]	[166, 198]	[112, 190]	[161, 184]
	Profit Max. Yield (kg/ha)	9,812	9,765	9,838	9,741
	Exp. Net Returns (\$/ha)	1,800	1,778	1,822	1,783
\$1.20	Prof. Max. Nit. Rate (kg/ha)	166	176	151	169
	95% Confidence Interval	[161, 171]	[168, 184]	[117, 186]	[162, 177]
	Profit Max. Yield (kg/ha)	9,797	9,733	9,838	9,723
	Exp. Net Returns (\$/ha)	1,760	1,735	1,786	1,742

We performed an additional examination of the models by maximizing nitrogen rates over the nitrogen price range of [0.72, 1.20] \$/kg while holding fixed the price of corn at 0.20 \$/kg. Figure 2-4 illustrates the result of this sensitivity analysis. It shows that in both cases the standard plateau models always estimate larger optimal nitrogen rates than the SR model.

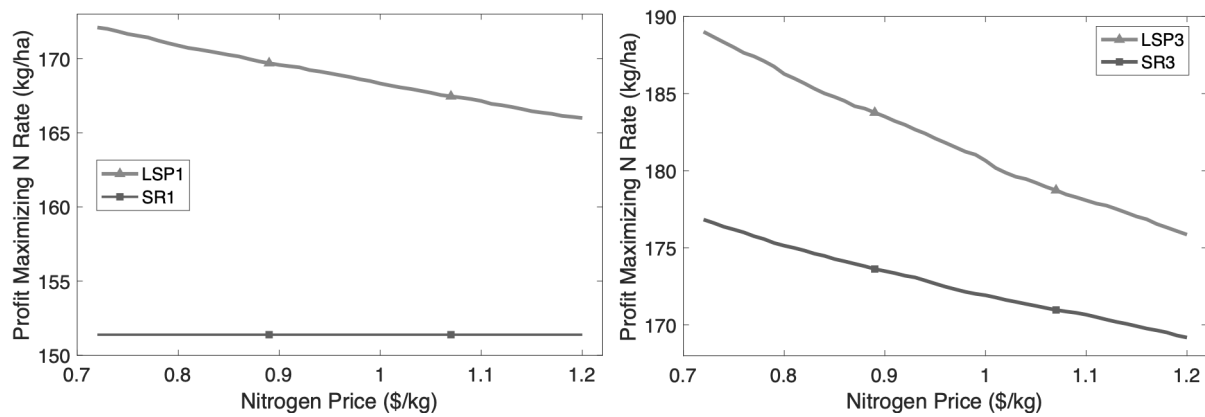


Figure 2-4. Profit maximizing nitrogen rates for LSP and SR models

Based on the LDC test, and AIC and BIC values presented in the previous section, we concluded that the SR1 model fits the data better than the model specification of Tembo et al. (2008) LSP1. Figure 2-5 shows the economic loss from using LSP1 when SR1 is the true model. As before, this was done over the nitrogen price range of [0.72, 1.20] \$/kg while holding the price of corn fixed at 0.20 \$/kg.

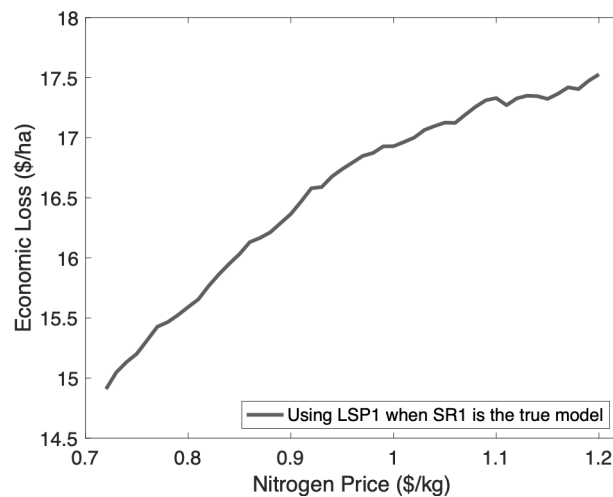


Figure 2-5. Economic loss from using LSP1 when SR1 is the true model

Results show the economic loss is increasing in nitrogen price and it ranges from \$14.90 to \$17.53 per hectare at the assumed prices. This loss is noteworthy and can moderately impact producers' profits.

Comparing over a total of 8 alternative specifications, we found models LSP3 and SR3 to have superior in-sample fit. Results indicated no clear difference in the goodness of fit between these two models. A closer examination of the models was also performed by estimating the economic loss resulting from using one model when the other model is the true model. Figure 2-6 illustrates the result of this sensitivity analysis. It shows that the economic loss from using LSP3 when SR3 is the true model is always larger than the economic loss from using SR3 when LSP3 is the true model. It also shows that the economic losses resulting from an inappropriate model are decreasing in nitrogen price. However, at the assumed prices, these economic losses are relatively small and vary from \$1.54 to \$3.28 per hectare when using LSP3 if SR3 is the true model, and from \$1.08 to \$2.47 per hectare when using SR3 if LSP3 is the true model. At this magnitude, the difference is not likely to have a major impact on producer profitability.

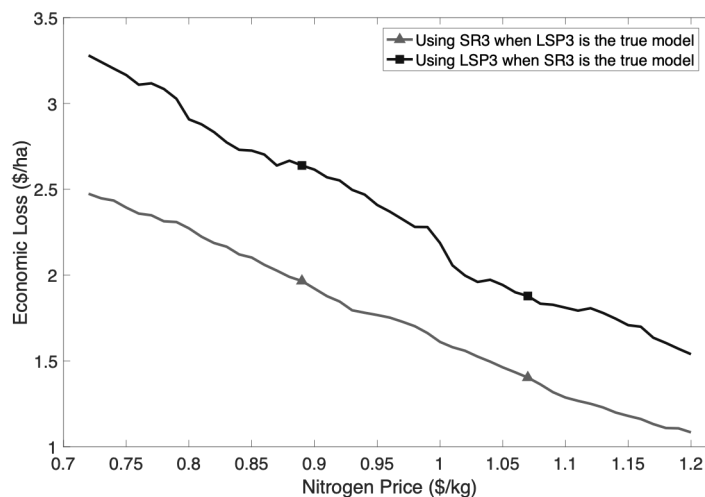


Figure 2-6. Economic loss from using an incorrect model

2.5. Concluding Remarks

We estimate corn yield response functions to nitrogen using a switching regression plateau model and the linear stochastic plateau models of Tembo et al. (2008) and Tumusiime et al. (2011). The empirical application uses data from a long-term study of corn yields conducted at the Agricultural Research Development and Education Center (ARDEC) located in Fort Collins, Colorado. Our results show that under equivalent assumptions on the random parameters and correlation of the random effects, the switching regression model(s) performs better than the specification of Tembo et al. (2008) and as good as the specification of Tumusiime et al. (2011). We suggest the switching regression specification as a useful approach for applied analyses of crop response.

The SR specification developed in this article is an alternative for the frequentist estimation of plateau-type production functions with stochastic variations. The availability of several statistical models allows the researcher to check the stability and robustness of parameter estimates. Moreover, the SR specification treats the minimum amount of nitrogen to reach the plateau as a parameter. The yield plateau and its stochastic variation are determined by this parameter and its random effect. This specification facilitates exploration of the implications of nitrogen use and management on the crop yield response. The SR specifications also represent a distinction when compared to the two alternative models, as they model the plateau yield P_m as a parameter with a random effect v_t that makes the plateau yield shifts upwards or downwards, and thus, accounts for year stochastic effects. By doing this, these models capture most of the stochastic variation of the plateau yield, but they do not provide information about how much of

this variation is caused by nitrogen use, which is of key importance when modeling crop yield response functions to nitrogen.

From a purely computational perspective, non-linear models pose a challenge for estimation as they typically have no closed form and can only be approximated numerically. This is a permanent limitation of any highly non-linear model, including the models proposed here. In our empirical application, the most highly parameterized models provided the best fit to the data. Depending on the data available, researchers may be forced to estimate more parsimonious specifications.

The models estimated in this paper contribute to the body of literature on expected net returns and profitability from corn production in the U.S. Similarly, this paper adds to the literature on optimal nitrogen recommendations under production uncertainty. At the assumed prices, standard plateau production functions always estimate a greater amount of fertilizer –to maximize expected profits– than SR models. Results also showed that using LSP1 when SR1 is the true model could result in a significant pecuniary cost to the producer, ranging from \$14.90 to \$17.53 per hectare, plus the environmental costs related to overfertilization. Similarly, using SR3 conditioned on LSP3 being the true model, results in a loss to the producer that varies from \$1.08 to \$2.47 per hectare. Overfertilization and excess nitrogen in the environment exact costs on society (Williamson, 2011).

Likelihood Dominance Criterion (LDC), Akaike information criterion (AIC), and Bayesian information criterion (BIC) indicated that the SR1 model fits the data better than LSP1 model. They showed no clear difference in the goodness of fit between the LSP3 and SR3 models. Further considerations, including: (1) minimizing the economic loss caused by using an inappropriate

model specification, and (2) minimizing the additional environmental costs related to overfertilization, suggest use of SR3 over LSP3. Naturally, our results are conditioned on the empirical situation at hand and may not hold for all data. But as a general rule, this study indicates that the switching regression (SR) stochastic plateau production function is a useful approach for measuring yield response.

Future research could apply these plateau-type functions to other crops and locations to check the validity and legitimacy of the results we obtained in this exercise. Research should also explore yield skewness and its relationship with applied nitrogen rates to determine how well the proposed production functions of this article match the pattern of skewness in the data. This could explain why the standard models estimate larger optimal nitrogen rates than the SR approach. As argued by Boyer et al. (2015), negative skewness reduces optimal nitrogen rates and positive skewness increases optimal nitrogen rates.

2.6. References

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2.7. Appendix

Fixed Effects Models

We first estimated the LSP model and the SR specification without including year random parameters. These basic versions of the models are referred to as LSP0 and SR0 respectively in Table A 2-1.

Table A 2-1. Regression Results for the Fixed Effects Models

Parameter	LSP0	SR0
Intercept β_0	5,178.10 (118.43)	5,178.10 (118.43)
Slope β_1	30.13 (1.46)	30.13 (1.46)
Nitrogen at yield Plateau (Kg/Ha) N_p	-	160.74 (6.61)
Nitrogen at yield Plateau (predicted) (Kg/Ha) $\widehat{N}_p$	160.74	-
Yield Plateau P_m (Kg/Ha)	10,022.08 (120.40)	-
Yield Plateau (predicted) (Kg/Ha) $\widehat{P}_m$	-	10,022.08
MSE	1,000,210.31	1,000,210.31
LogLikelihood	-2,128.65	-2,128.65
n (number of observations)	256	256

^a Standard errors are in parentheses.

^b Predicted parameters $\widehat{N}_p$ and $\widehat{P}_m$ are calculated accordingly using the estimation results for each specific case.

^c MATLAB package FITNLM, that fits nonlinear fixed effects models, is used for this initial estimation.

The two nonlinear specifications are completely equivalent under the scenario of fixed parameters. LSP0 and SR0 estimates a yield plateau of 10,022 Kg/Ha, which leads to a predicted nitrogen rate at the yield plateau of 161 Kg/Ha.

Table A 2-1 helps us visualize the main difference between the two models. LSP0 focuses on the estimation of the plateau yield P_m , and produces a coefficient and standard error for this parameter that can be used directly for hypothesis testing. Since the model does not estimate the

value of the minimum nitrogen to reach the plateau N_p –instead, it has to be predicted using estimated parameters. Furthermore, if one is interested in the standard error of this parameter, bootstrapping methods or other data simulations methods are needed when using the LSP0 specification.

In contrast, SR0 estimates the minimum nitrogen needed to reach the plateau N_p , and produces a coefficient and standard error for this parameter. This represents an advantage over LSP0, as that parameter may be of most use to producers. Further analysis of the LSP0 and SR0 residuals indicates the fixed effects models fail to account for year-specific effects and point toward the need to include year random effects.

In figure A 2-1 we observe the scatter plot of the data with both models super imposed. Given both models are identical we observe a single line for predicted yields.

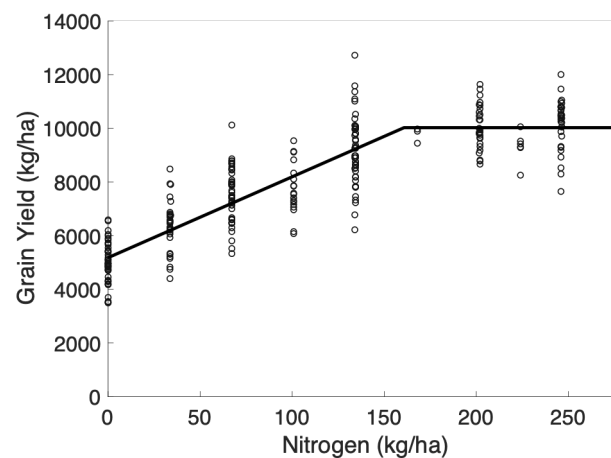


Figure A 2-1. Scatter plot of the data with model LSP0 and SR0 superimposed.

In figure A 2-2 we observe the box plot of the residuals by year, which are identical for both models as well. Figure A 2-2 shows the boxes are mostly above or below zero, indicating the

models have failed to account for year-specific effects, and hence the need and justification for the use of year random effects.

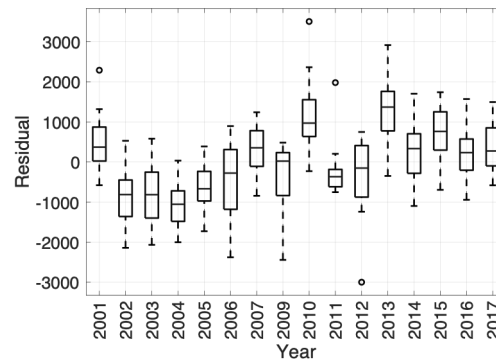


Figure A 2-2. Box-plot of residuals by year for LSP0 and SR0.

To account for year-specific effects, both models are estimated using data from each year separately. The estimates vary substantially for each year but taken as a 48-parameter model of the data, the mean-squared error of 1,000,210 in the original three-parameter model gets reduced to 459,735 for each model. Now in figure A 2-3 the box plot shows that the larger version of the models account for most of the year-specific effects. The spread of the residuals (the vertical scale of the box plot) is much smaller than in the previous box plot, and the boxes are now mostly centered on zero.

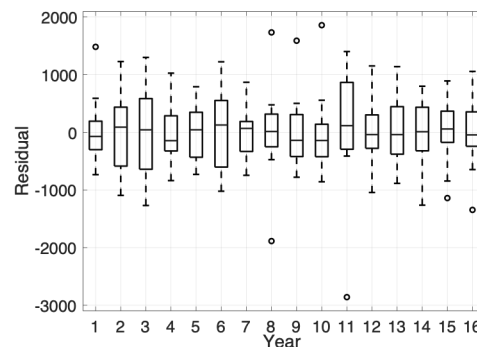


Figure A 2-3. Box-plot of residuals for LSP0 and SR0 estimated individually for each year.

While a 48-parameter model effectively accounts for variations due to specific years, it does not consider the years as representatives of stochastic events such as insects, weed pressure, and weather. For this research, the purpose of using mixed-effects models in production functions is to account for year-specific variations more generally, as random effects varying around population means.

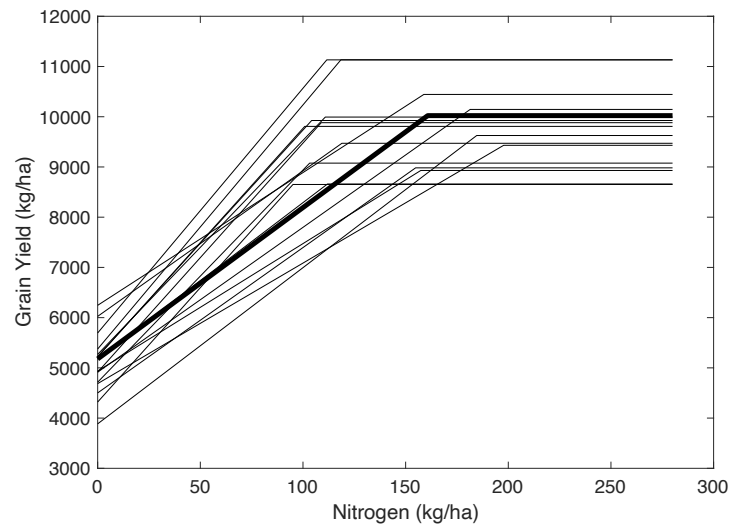


Figure A 2-4. Plot of models estimated by year.

In figure A 2-4 we observe the plot of the model estimates for each year separately, and for reference, the model with the pooled data is also super imposed and represented by the thicker line. As we can observe from figure A 2-4, the estimates for the intercept, slope, and yield plateau vary substantially for each year (See also Table A 2-2). This reinforces the argument of including random effects to account for year-specific variations.

Table A 2-2. Parameter Estimates for LSP0 and SR0 by Year

Year	LSP0			SR0		
	β_0	β_1	P_m	β_0	β_1	N_p
1	6,025.44	28.97	9,471.32	6,025.44	28.97	118.95
2	4,686.49	23.99	9,430.96	4,686.49	23.99	197.73
3	4,501.14	28.94	8,982.24	4,501.14	28.94	154.85
4	3,885.32	31.10	9,626.07	3,885.32	31.10	184.62
5	4,936.44	25.38	8,930.06	4,936.44	25.38	157.38
6	4,319.74	45.54	8,651.36	4,319.74	45.54	95.13
7	5,225.77	45.09	9,924.93	5,225.77	45.09	104.22
8	5,185.38	31.05	8,660.66	5,185.38	31.05	111.93
9	5,375.53	48.60	11,133.10	5,375.53	48.60	118.47
10	4,914.51	28.83	10,145.46	4,914.51	28.83	181.44
11	4,714.58	42.24	9,076.31	4,714.58	42.24	103.25
12	5,694.61	48.73	11,132.25	5,694.61	48.73	111.59
13	5,221.25	45.47	9,807.78	5,221.25	45.47	100.86
14	6,245.13	26.43	10,444.01	6,245.13	26.43	158.86
15	4,914.56	45.61	9,881.46	4,914.56	45.61	108.90
16	5,268.90	42.61	9,993.35	5,268.90	42.61	110.88

Regression Results Assuming no Correlation of the Random Effects.

Models LSP3 and SR3 were also estimated assuming no correlation among the parameter random effects. This implies a variance covariance matrix of the parameter random effects to be of the form:

$$\text{cov}(u_t, \omega_t, v_t) = \begin{bmatrix} \sigma_u^2 & 0 & 0 \\ 0 & \sigma_\omega^2 & 0 \\ 0 & 0 & \sigma_v^2 \end{bmatrix}$$

Table A 2-3 shows the results for LSP3 and SR3.

Table A 2-3. Regression Results for LSP3 and SR3 Assuming no Correlation of the Random Effects.

Parameter	LSP3	SR3
Intercept β_0	5,206.01 (164.49)	5,200.18 (176.86)
Slope β_1	30.66 (1.95)	30.96 (1.33)
Nitrogen at Plateau (Kg/Ha) N_p	-	148.77 (5.31)
Nitrogen at Plateau (predicted) (Kg/Ha) $\widehat{N}_p$	153.44	-
Yield Plateau (Kg/Ha) P_m	9,910.88 (173.60)	-
Yield Plateau (predicted) (Kg/Ha) $\widehat{P}_m$	-	9,806.23
Variance of Intercept Year Random Effect σ_u^2	328,040.31	390,382.31
Variance of Slope Year Random Effect σ_ω^2	40.04	11.34
Variance of Nitrogen at Plateau Year Random Effect σ_v^2	-	153.97
Variance of Yield Plateau Year Random Effect σ_v^2	369,882.60	-
MSE	444,048.10	478,163.98
LogLikelihood	-2,067.36	-2,069.53
AIC	4,148.73	4,153.07
BIC	4,154.14	4,158.47

The Stochastic Plateau Model of Boyer et al. (2013)

We also estimated the stochastic plateau model of Boyer et al. (2013), henceforth designated LSP2. This model is specified as

$$y_{it} = F(N) + \varepsilon_{it}$$

where

$$F(N) = \min\{\beta_0 + \beta_1 N_{it}, P_m + v_t\}.$$

Results are presented in Table A 2-4 and compared with an equivalent SR model designated SR2 and specified as:

$$y_{it} = H(N) + \varepsilon_{it}$$

where

$$H(N) = \begin{cases} \beta_0 + \beta_1 N_{it} ; & N_{it} < (N_p + v_t) \\ \beta_0 + \beta_1 (N_p + v_t) ; & N_{it} \geq (N_p + v_t) \end{cases}$$

Results show that when compared to LSP2, SR2 estimates the same yield plateau per hectare and requires a slightly lower amount of fertilizer per hectare to reach the yield plateau. The likelihood values of the models are similar. Nonetheless, the MSE almost doubles for both models when compared to LSP1 and SR1. This suggests that LSP2 and SR2 do not fit the data as well as LSP1 and SR1.

Table A 2-4. Regression Results for LSP2 and SR2 Models

Parameter	LSP2	SR2
Intercept β_0	5,142.55 (113.58)	5,100.04 (113.10)
Slope β_1	31.40 (1.46)	32.10 (1.45)
N at Plateau N_p	- -	147.10 (7.52)
N at Plateau (predicted) $\widehat{N}_p$	149.04	-
Yield Plateau P_m	9,821.97 (192.74)	- -
Yield Plateau (predicted) $\widehat{P}_m$	-	9,821.97
Intercept Random Effect σ_u^2	- -	- -
Slope Random Effect σ_ω^2	- -	- -
N at Plateau Random Effect σ_v^2	- -	381.47 (130.06)
Yield Plateau Random Effect σ_v^2	392,879 (132,584)	- -
MSE	907,993	908,829
LogLikelihood	-2,128.16	-2,128.27
AIC	4,266.31	4,266.54
BIC	4,270.18	4,270.41
n (number of observations)	256	256

^a Standard errors are in parenthesis. We used bootstrapping techniques to obtain consistent estimates of the corresponding standard errors for the random effects parameters.

^b The predicted parameters $\widehat{N}_p$ and $\widehat{P}_m$ are calculated accordingly using the estimation results for each specific case.

Random Effects for Each Year of the Sample

Table A 2-5. Predicted Random Effects for LSP3 and SR3 by Year

Year	LSP3			SR3		
	σ_u^2	σ_ω^2	σ_v^2	σ_u^2	σ_ω^2	σ_v^2
2001	561.65	-2.02	214.04	607.50	-2.60	-0.31
2002	-502.75	-6.31	-526.12	-537.13	-5.33	25.39
2003	-634.25	-2.49	-750.09	-626.33	-2.66	9.63
2004	-936.25	-3.15	-629.11	-1,026.37	-1.64	18.85
2005	-387.66	-4.03	-662.88	-347.61	-4.60	13.43
2006	-614.22	7.01	-931.12	-643.75	7.95	-40.08
2007	226.30	2.29	209.65	235.51	2.06	-10.71
2009	10.76	-10.86	-51.21	-83.15	-6.87	26.86
2010	604.53	7.82	1,082.73	633.34	7.07	-19.39
2011	-146.84	-2.59	41.61	-190.74	-1.55	13.14
2012	-219.61	-3.67	-219.98	-232.18	-3.02	14.04
2013	780.15	8.85	1,135.92	842.85	6.52	-19.94
2014	173.89	6.53	27.93	241.91	2.60	-16.69
2015	723.44	-0.87	590.63	753.00	-1.13	-1.07
2016	65.67	2.39	144.05	68.48	2.24	-8.43
2017	295.18	1.09	323.94	304.66	0.96	-4.72

Additional Residual Analyses for Each Model

Table A 2-6 shows the skewness and kurtosis of the residuals for each model. Results show that LSP1 and SR1 produce larger kurtosis than more highly parameterized specifications. Nonetheless, all of the models have reasonable agreement with the assumptions on the error terms.

Table A 2-6. Skewness and Kurtosis of Residuals for LSP and SR Models

Results	LSP Models			SR Models		
	LSP1	LSP2	LSP3	SR1	SR2	SR3
Skewness	-0.223	-0.005	0.038	-0.073	-0.043	0.012
Kurtosis	4.168	3.839	3.647	4.216	3.849	3.812

Figures A 2-5 and A 2-6 contain additional plots of the residuals (i.e., yields observed minus yields predicted by the model). Figure A 2-5 plots the residuals against the nitrogen rate. Points over the horizontal line suggest that the model under predicts yields and points below the line suggest that the model over predicts yields. Both LSP3 and SR3 fit the response data well with less systematic bias. The LSP2 and SR2 models fit least well.

Figure A 2-6 shows the normal probability plot of the residuals for each model. If the sample data has a normal distribution, then the data points appear along the reference line. A distribution other than the Gaussian introduces curvature in the plot (MathWorks, 2018). MATLAB Normplot draws two reference lines that represent the theoretical distribution. A solid reference line connects the first and third quartiles of the data and a dashed reference line extends the solid line to the ends of the data. Figure A 2-7 plots the residuals against year, and Figure A 2-8 shows a histogram of the residuals.

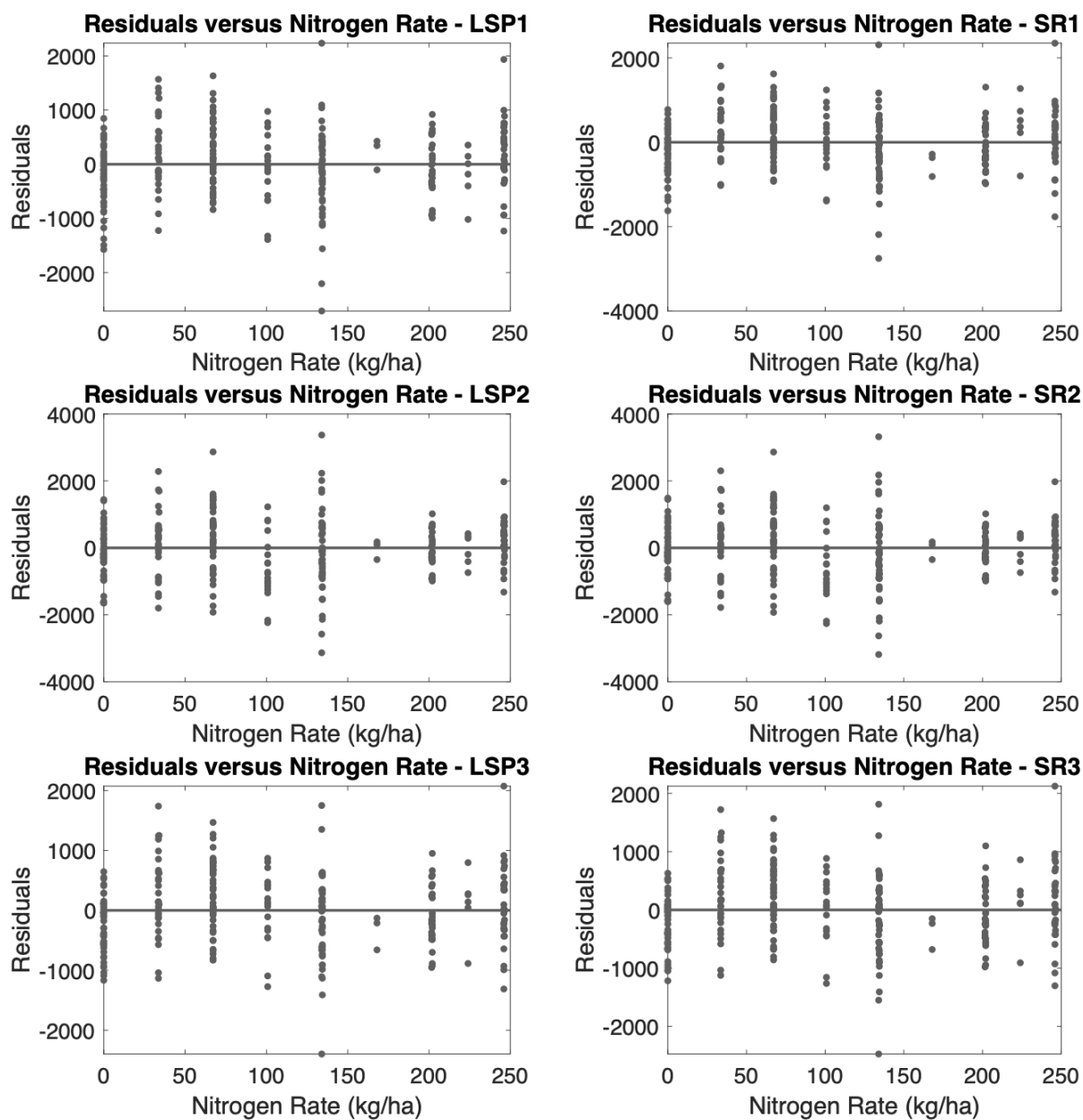


Figure A 2-5. Residuals vs. nitrogen for LSP and SR models

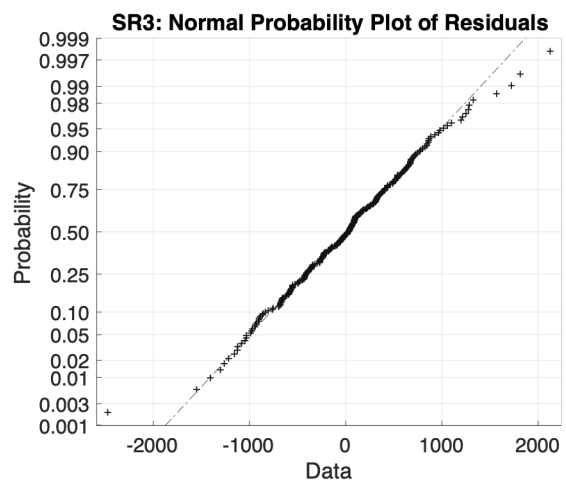
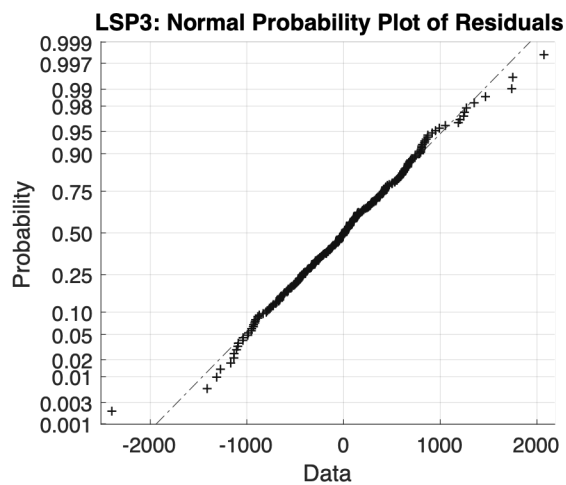
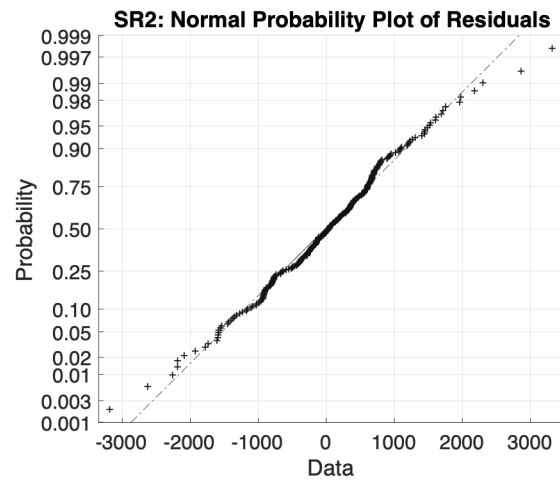
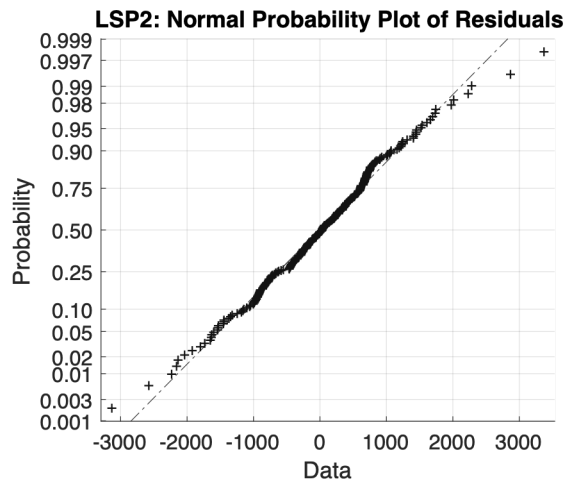
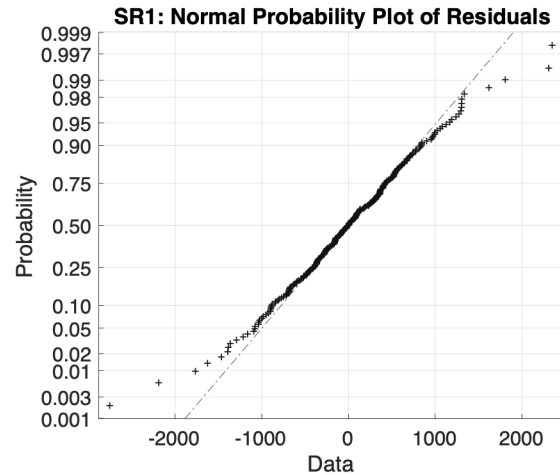
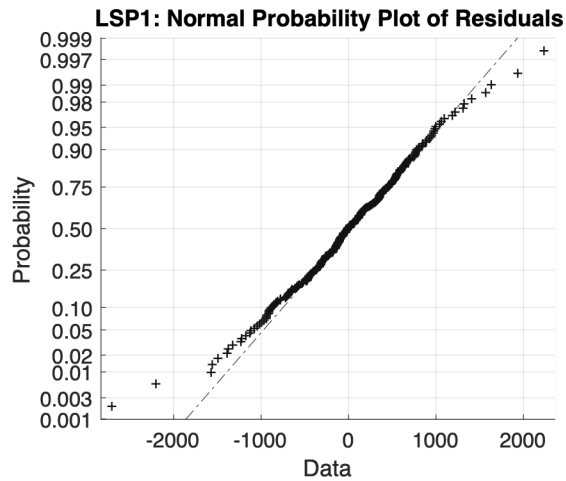


Figure A 2-6. Normal probability plots of the residuals for LSP and SR models

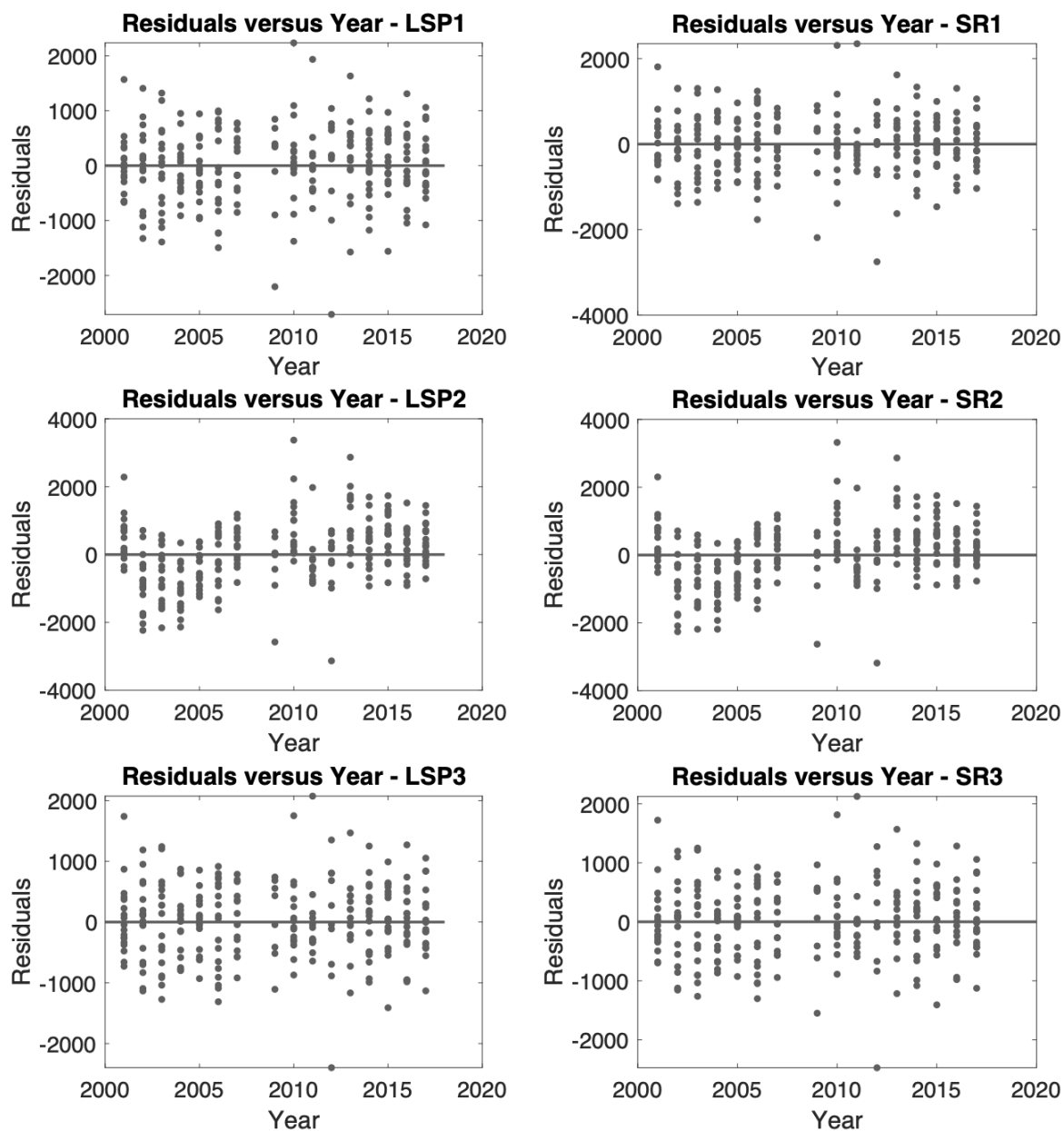


Figure A 2-7. Residuals vs. years for LSP and SR models

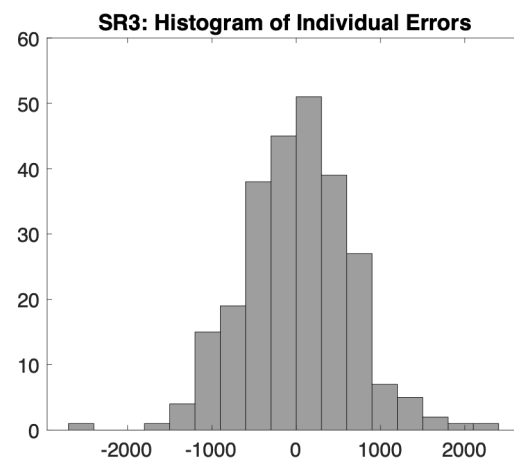
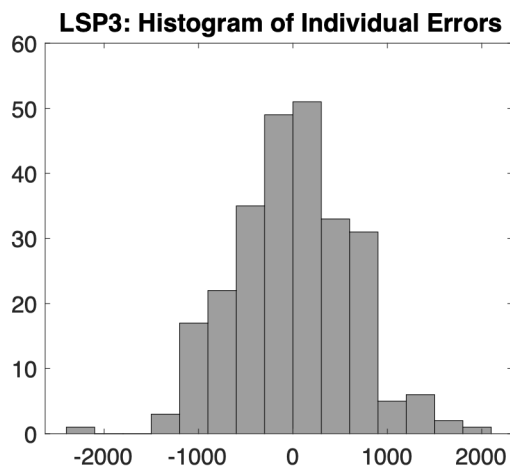
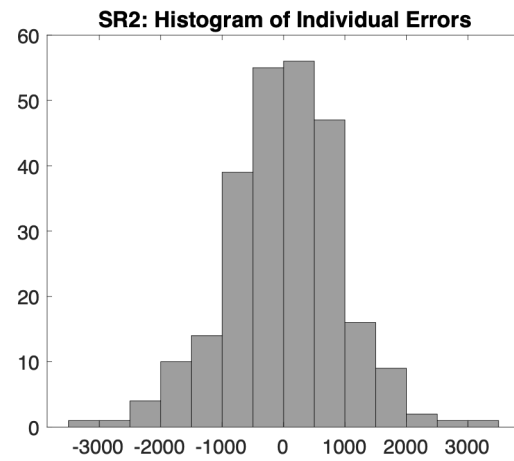
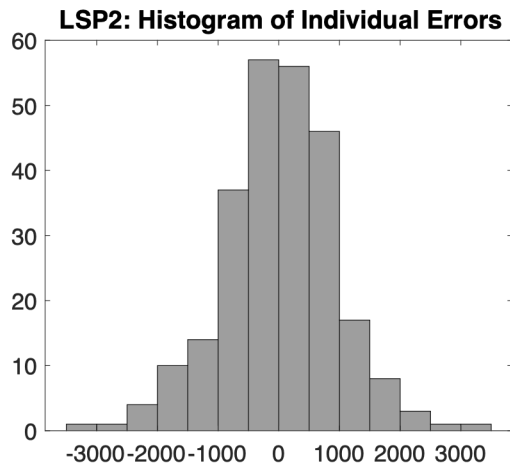
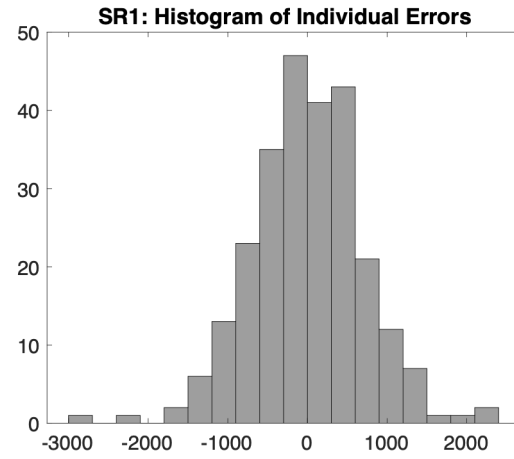
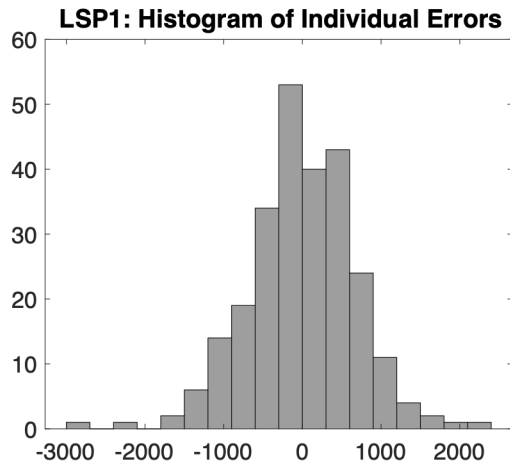


Figure A 2-8. Histogram of the residuals for LSP and SR models

3. Manuscript 2: Profitability Effects of Different Tillage Systems in Continuous Corn Rotations.

3.1. Abstract

This paper explores the interaction between different tillage systems and nitrogen fertilization in irrigated continuous corn production in northeastern Colorado. We use the linear response stochastic plateau model in combination with Monte Carlo methods to estimate corn response functions to nitrogen fertilizer and to determine profit-maximizing yields and nitrogen fertilizer rates. Expected net returns for continuous corn under different tillage practices using the profit-maximizing nitrogen fertilizer rates and yields are also analyzed. We use data from a long-term study to capture year-to-year weather variability and evaluate the cumulative effects of crop management practices on profitability.

Results show that strip tillage is better suited for continuous corn production under the agro-climatic conditions in northeastern Colorado. Moreover, no-tillage appears to be unable to yield competitive profits against other tillage practices over the long run. Even though no-till experiences significant yield increases over time, results show this practice requires significantly larger amounts of nitrogen to maximize profits in comparison to other tillage practices, hence reducing its profits. This finding suggests that evaluation of the environmental benefits of no-tillage needs to factor in this tradeoff. Environmental benefits from improved soil health caused by the reduction of machinery use might be counterweighed by the increased use of nitrogen fertilizer.

3.2. Introduction

Knowledge about the profitability of different tillage practices can help producers improve farm profits and manage risks associated with weather and market shocks. Yields, operating costs, and risk management differentials influence the profitability and adoption of the different tillage practices (Ding et al., 2009). Conventional tillage (CT), Strip tillage (ST)³, and No tillage (NT) are the most common tillage practices used in corn production in the United States (Liu & Wiatrak, 2012). Environmental implications of practices have been well documented as tillage use can affect the soil quality and productivity through soil erosion and nutrient loss (Al-Kaisi, Archontoulis, Kwaw-Mensah, & Miguez, 2015; Huggins, Allmaras, Clapp, Lamb, & Randall, 2007; Paustian, Collins, & Paul, 1997; Raczkowski, Reyes, Reddy, Busscher, & Bauer, 2009; Stonehouse, Kay, Baffoe, & Johnston-Drury, 1988).

Moreover, mechanical tillage contributes to atmospheric carbon emissions as the practice stimulates decomposition of soil organic matter and loss of soil organic carbon (Halvorson & Jantalia, 2011; Mosier et al., 2006; Reicosky et al., 2002). These environmental implications have motivated the use of alternative tillage practices such as strip and no tillage. NT has been shown to increase soil organic matter, help conserve water, and reduce soil erosion, thereby restoring soil quality and reducing atmospheric carbon (Archer & Halvorson, 2010; Fabrizzi et al., 2005; Halvorson et al., 2001; Morgan et al., 2010; Mosier et al., 2006; Raczkowski et al., 2009; Spargo et al., 2008).

³ The ST system involves cultivation of a narrow strip in the row area while leaving the inter-row area undisturbed (Liu & Wiatrak, 2012)

The effects of alternative tillage systems on crop yields has long been studied, and evidence on whether tillage systems improve yield outcomes when contrasted to no-tillage systems is still mixed to date (Toliver et al., 2012). Examples of studies where higher corn yields have been attributed to NT include Endale et al. (2008), Smiley & Wilkins (1993), and Waggoner & Denton (1989). Other studies find NT to be associated with lower yields, including Archer, Halvorson, & Reule (2008), Busscher, Bauer, & Frederick (2006), Randall, Vetsch, & Murrell (2001), Graven & Carter (1991) and Halvorson, Mosier, Reule, & Bausch (2006).

Soil conditions—including drainage, texture, organic matter, and water holding capacity—have been found to influence yield responses to tillage practices (DeFelice et al., 2006; Licht & Al-Kaisi, 2005; Toliver et al., 2012; Wang et al., 2006). Moreover, numerous findings suggest that the appropriate tillage practice depends on location because of varying soil conditions (Al-Kaisi et al., 2015; Kalfas et al., 2011; Machado et al., 2002; Sakurai et al., 2011; Smith et al., 2007; Vyn & Raimbault, 1992).

The literature has also shown that irrigation availability plays a crucial role in determining grain yields under various tillage systems. For systems with limited irrigation, NT and ST seem to be better options for higher yields as they increase the water availability compared to CT (Archer et al., 2008). Under limited irrigation, Norwood (2000) reported higher yields for NT than CT, and likewise Hansen, Allen, Baumhardt, & Lyon (2012) and Wang et al. (2006) found higher yields for ST than for CT. For irrigated continuous corn, evidence has been mixed; Cahoon et al. (1999), and Smart & Bradford (1999) report higher yields for ST than for CT, but Díaz-Zorita (2000), Vetsch & Randall (2002), and Vyn & Raimbault (1992) reported greater yields for CT than for ST or NT.

Weather and climate variables such as temperature, precipitation, and frost-free days are also linked to differences in yields among tillage practices (DeFelice et al., 2006; Kapusta et al., 1996; Liu & Wiatrak, 2012; Manley et al., 2005). Since these variables can have significant year to year variability, the effects of tillage can be highly variable across years (Al-Kaisi et al., 2015; Endale et al., 2008; Halvorson et al., 2006; Toliver et al., 2012).

Nitrogen availability and crop nitrogen requirements are especially influenced by tillage practices, and different tillage practices require different nitrogen rates to maximize profits (Archer et al., 2008; Kwaw-Mensah & Al-Kaisi, 2006). In addition, practices such as NT reduce fuel and labor expenditures⁴. Differences in costs of inputs and machinery, combined with disparities in yields, can cause a significant impact on profits and on the attractiveness of alternative tillage practices (Archer et al., 2008; Ribera et al., 2004; Toliver et al., 2012). Various studies including Archer et al.(2008), Cahoon et al. (1999), and Smart & Bradford (1999) have reported higher economic returns associated with conservation tillage systems (NT and ST) compared to conventional systems.

Farmers in northeastern Colorado generally use conventional tillage in irrigated corn production causing serious problems of soil erosion. The use of conservation tillage systems has been proposed to mitigate the effects of conventional till, but NT irrigated corn production systems in the central Great Plains are not popular among farmers. (Archer et al., 2008)

This paper explores the interaction between tillage systems and nitrogen fertilizer requirements in northeastern Colorado and addresses how tillage and fertilization management

⁴ In the United States, continuous no-till has been adopted across only 21 percent of all cultivated cropland acres (Creech, 2017).

influence farm profits under irrigated continuous corn production. We use the linear response stochastic plateau (LRSP) model to estimate corn response to nitrogen fertilizer, as researchers have found the LRSP to best describe corn yield responses to nitrogen (Boyer, Roberts, et al., 2013; Tembo et al., 2008; Tumusiime et al., 2011).

The specific objectives of this research include (i) estimating the profit-maximizing nitrogen fertilizer rates and yields for continuous corn under different tillage systems using LRSP, and (ii) analyzing expected net returns for continuous corn under different tillage systems using the profit-maximizing nitrogen fertilizer rates and yields. We use data from a long-term study to capture year-to-year weather variability and evaluate the cumulative effects of crop management practices on profitability.

3.3. Conceptual and Empirical Models

Assuming risk neutrality, a profit-maximizing producer's objective is to maximize expected net returns from corn production:

$$(1) \quad \max_{N_{ijt}} E(\pi_{ijt}) = pE(y_{ijt}) - rN_{ijt}$$

$$(2) \quad \text{s. t.} \quad y_{ijt} = F(N_{ijt}), \quad N_{ijt} \geq 0$$

where $E(\pi_{ijt})$ is the expected net returns in \$/ha for corn grown in plot i , using tillage system j , in time t ; p is expected corn price (\$/kg), $E(y_{ijt})$ is the expected corn yield (kg/ha), r is the nitrogen fertilizer price (\$/kg), and N_{ijt} is the quantity of fertilizer applied (kg/ha).

The expected corn yields are estimated using the production function $y_{ijt} = F(N_{ijt})$.

Following Tembo et al. (2008) and Tumusiime et al. (2011) we use the linear response stochastic plateau (LRSP) with full random effects to estimate y_{ijt} under the different tillage systems. The LRSP follows von Liebig's Law of the Minimum and describes a production function where the corn yield increases in a linear fashion with the addition of nitrogen until a threshold point is reached (Tembo et al., 2008). This threshold point defines the yield plateau; beyond the threshold point additional nitrogen use will not increase the corn yield:

$$(3) \quad y_{ijt} = F(N_{ijt}) + \varepsilon_{ijt} + u_t$$

where

$$(4) \quad F(N_{ijt}) = \min\{\beta_0 + (\omega_t + \beta_1)N_{ijt}, P_m + v_t\}$$

and, $\varepsilon_{ijt} \sim N(0, \sigma_\varepsilon^2)$ is a random error term. The fixed effect parameters are the intercept β_0 , the slope β_1 , and the average plateau yield P_m . Random effects are indexed over time;

$u_t \sim N(0, \sigma_u^2)$ is an intercept year random effect, $v_t \sim N(0, \sigma_v^2)$ is a plateau year random effect

and $\omega_t \sim N(0, \sigma_\omega^2)$ is the slope year random effect. The random effect (variance) parameters ω_t , v_t , and u_t are normally distributed and allowed to be correlated, such that

$$(5) \quad \text{cov}(u_t, \omega_t, v_t) = \begin{bmatrix} \sigma_u^2 & \sigma_{u\omega} & \sigma_{uv} \\ \sigma_{u\omega} & \sigma_\omega^2 & \sigma_{\omega v} \\ \sigma_{uv} & \sigma_{\omega v} & \sigma_v^2 \end{bmatrix}$$

The addition of these random effects and their correlation helps the production function capture the influence of stochastic events on the yield response⁵. The LRSP normality assumption was tested by Boyer et al., (2015). Results showed that the LRSP has negatively skewed yields when normality of random effects is assumed, however the level of skewness is not large and the skewness approaches zero as the level of nitrogen increases.

Following Tumusiime et al. (2011), the expectation of y_{it} is estimated as:

$$(6) \quad E(y_{ijt}) = E[F(N_{ijt}) + \varepsilon_{ijt} + u_t] = E[F(N)]$$

$$(7) \quad E(y_{ijt}) = E[\min\{\beta_0 + (\beta_1 + \omega_t)N_{ijt}, P_m + v_t\}]$$

Estimation of equation (7) requires integration that must be solved numerically. Using the estimates of the parameters of the production function in equations (3) and (4), we estimate $E(y_{ijt})$ using standard methods of Monte Carlo integration.

3.4. Data

We use unique experimental data collected from a long-term, continuous corn study conducted at the Agricultural Research Development and Education Center (ARDEC) located in Fort Collins, Colorado. Tillage systems in this experiment included: No-tillage, Strip-Tillage, and Conventional-Tillage. Nitrogen fertilization treatments included a control (no nitrogen) plus eight treatment levels (34, 67, 100.8, 134.4, 168, 202, 224, and 246 kg ha⁻¹). All plots were

⁵ The intercept random effect u_t allows the production function shift up or down and represents effects from insects, diseases, poor stands, heat, freeze damage, and other weather effects. The plateau random effect v_t shifts the yield plateau potential and represent effects from other limiting inputs. The slope random effect ω_t represents effects from nitrogen productivity including losses from leaching, soil, or weather.

irrigated with a linear-move sprinkler system and water was applied as needed. The study was initiated in 2001 on a clay loam soil field, with one to two percent slope, that had previously been continuously cropped to corn for 8 years. Plots are close together and assumed to have uniform soil. Data include 16 years of crop production, from 2001 until 2017, excluding 2008 due to an unusual and severe hailstorm that decimated the corn crop. Data on No-tillage include years from 2001 to 2017, but data on Strip-tillage only include years from 2006 to 2017, and data on Conventional-tillage include only years from 2001 to 2007.

Figure 3-1 compares the tillage systems and shows average corn yield for selected nitrogen levels⁶. When comparing NT against ST, average yields are close at the different nitrogen levels. When comparing NT to CT, NT produces lower average yields for all nitrogen applications during the initial years. Average NT yields rise over time and eventually come close with those of CT after five or six years of production. NT mean yields at the different nitrogen levels from years 2006-2017 are statistically different and on average 12% larger compared to NT mean yields from years 2001-2007 (See Table A 3-1 of the Appendix). This increase in yields might be correlated with the use of improved corn varieties, but moreover it might be correlated with the benefits of the NT use over the long run, including improved soil health and productivity. This initial evidence suggests NT systems have long-term positive effects on yields, and it also hints NT profitability might compete with that of CT over the long run.

⁶ See Figures A 3-1, A 3-2, and A 3-3 of the Appendix for average yields grouped by tillage practice.

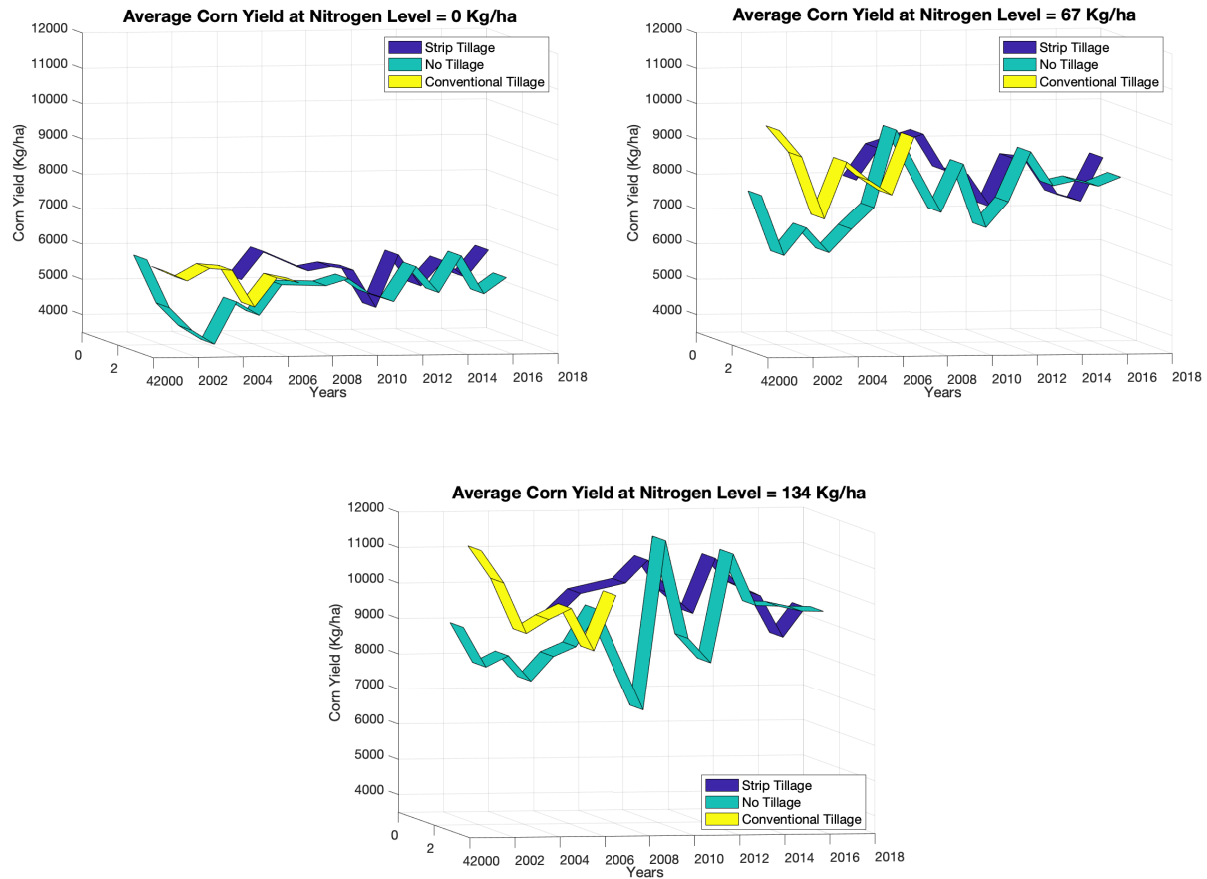


Figure 3-1. Average corn yield grouped by tillage practice and nitrogen fertilizer levels

To further analyze the rise of NT yields by year, figure 3-2 takes a closer look at the evolution of the yield response to nitrogen and presents confidence intervals for each year. The highest variation in yields occurred during year 2013 for nitrogen treatment levels 0 Kg/ha and 67 Kg/ha, while for nitrogen treatment level 134 Kg/ha happened during 2012. With the exceptions of these years, yield standard deviations for each nitrogen level took similar values across time (See Tables A 3-2, A 3-3, and A 3-4 of the Appendix). The effects of these yield variations over time are captured by the inclusion of the year random effects in our model specification, as they capture the influence of stochastic events on the yield response.

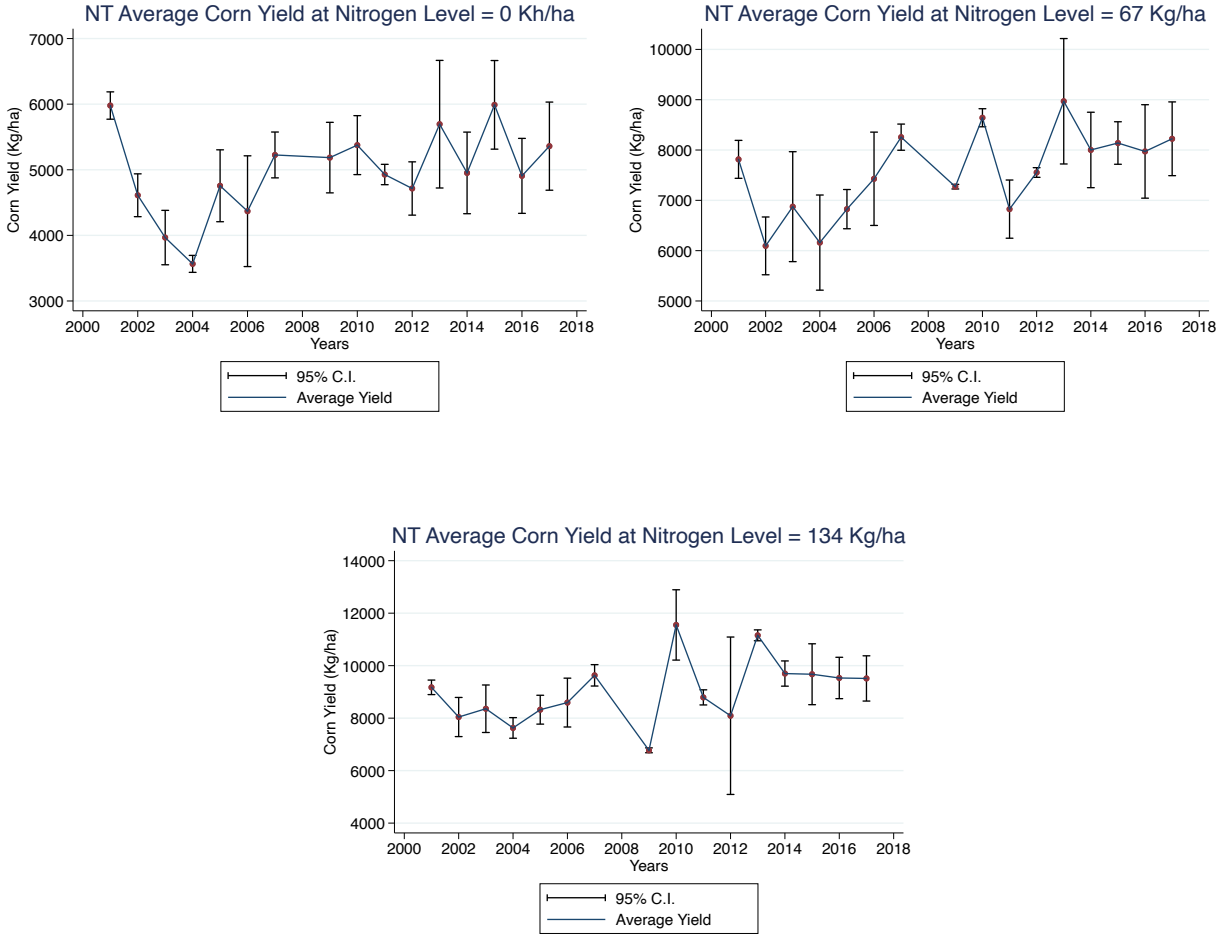


Figure 3-2. NT average corn yields grouped by nitrogen fertilizer levels with confidence intervals

3.5. Estimation

We estimate the model presented in equations (3) and (4) using MATLAB NLMEFIT: a solver for non-linear mixed effects models. To calculate expected net returns and profit maximizing nitrogen rates for the different tillage systems, we use the parameter estimates of equations (3) and (4) in combination with Monte Carlo methods. Ten thousand draws from the jointly normally distributed vector $[u_t, \omega_t, v_t] \sim N(0, \Omega)$ are generated using the respective variance/covariance estimates specified in equation (5). Ten-thousand points representing a

continuous distribution of nitrogen applications in the interval of [0, 246] are generated. Yield expectations are computed for each of the simulated nitrogen applications evaluated at the 10,000 draws of the vectors of random effects. Finally, profit maximizing nitrogen rates are calculated for each tillage system using the MATLAB nonlinear programming solver⁷ to solve the nonlinear optimization problem of equation (1)⁸.

Due to the nature and limitations of the data, and to further analyze the effect of the NT practice over time, we estimate separate regressions via partitioning the sample by the different phases of the agronomic experiment. That is, results for NT are calculated using (i) data from 2001-2017, (ii) data from 2001 to 2007 only, and (iii) data from 2006 to 2017 only. Results for CT are calculated using data from 2001 to 2007. Results for ST are calculated using data from 2006 to 2017.

A joint likelihood ratio test (McGuirk et al., 1993) was employed to determine if the yield plateau, slope, and intercept parameters were statistically different across the different tillage practices. Following (Boyer, Larson, et al., 2013), we estimate the unrestricted model as a joint response function using the data for two tillage practices, allowing the parameter estimates to be different between the tillage systems. Likewise, the restricted model is a jointly response function that constraint the parameter estimates to be equal across tillage practices. The critical value of the Likelihood ratio test is chi-squared distributed with one degree of freedom (χ_1^2) and is compared to the test statistic to decide over the statistical difference of the parameters.

⁷ MATLAB nonlinear programming solver calls the quasi-newton algorithm using the BFGS Quasi-Newton method with a cubic line search procedure.

⁸ For robustness, results are also obtained using a traditional grid search since the problem involves only one choice variable.

To compute expected returns, we use partial budgets and assume a price for nitrogen of \$0.96, per kg, which is equivalent to \$400 per ton of 46-0-0 urea fertilizer. Likewise, for corn we assume a price of \$0.20 per kg which is equivalent to \$5 per bushel. Supplementary costs incurred by the use of conventional tillage are assumed to be of \$69.68 per hectare, and of \$36.08 for the case of strip tillage. These supplementary costs include tractor, fuel, labor and depreciation on new implements, parts and repair (DeJong-Hughes & Daigh, 2018). In addition, we perform a sensitivity analysis of the profits and profit-maximizing nitrogen rates by varying the price of nitrogen over the range [0.72, 1.20] USD per kg, and the price of corn over the range [0.10, 0.30] USD per kg. We selected these prices, as they are representative of prices reported over the last decade (USDA-NASS, 2019).

3.6. Results

3.6.1. No Tillage

As discussed above, no-tillage average yields are lower during the first years of production, but then they rise and eventually match those of conventional tillage. Table 3-1 presents the regression results using all years of NT data available (2001-2017) and show this practice produces a corn yield plateau of 9,888 Kg ha⁻¹, requiring a nitrogen fertilizer rate at the plateau of 152 Kg ha⁻¹. When comparing the separate NT regressions results (2001-2007 vs. 2006-2017), Table 3-1 shows NT 2006-2017 produced a larger yield plateau, higher fertilizer productivity –as measured by the slope parameter β_1 – and required a smaller fertilizer rate to reach the plateau, in contrast to NT 2001-2007.

These results endorse a dynamic process associated to the NT practice that positively impacts the expected corn yields over time. Table 3-2 shows the Likelihood ratio test statistics

for the joint test between the two NT time periods. The slope parameters, that represent fertilizer productivity, were found to be not statistically different for the two NT time periods. This indicates that NT fertilizer productivity does not change over time. The intercepts –that represent the expected yields when no nitrogen fertilizer is applied– and the expected yield plateaus for the two NT time periods were statistically different at the 1% probability level ($\chi^2_{1,0.01} = 6.64$). NT 2006-2017 produced a corn yield plateau of 10,103 Kg ha⁻¹, that is 8% more yields at the plateau than NT 2001-2007. These results illustrate a long-term agronomic advantage of corn produced under a NT system.

3.6.2. Comparing Conventional Tillage (2001-2007) Against No Tillage

Table 1 shows conventional tillage model results produce a corn yield plateau of 10,041 Kg ha⁻¹, with a nitrogen fertilizer rate at the yield plateau of 92 Kg ha⁻¹. When compared to NT 2001-2017, CT produces a larger yield plateau and requires less nitrogen per hectare to reach this plateau. If the comparison is done against NT 2001-2007, that is using only the initial years of the NT study to match the time periods, the difference in the plateaus is of about 683 Corn Kg ha⁻¹, and fertilizer requirements to reach the plateau differ by 60 Nitrogen kg ha⁻¹. These results favor the use of CT over NT 2001-2007. The Likelihood ratio test statistics for the joint tests between them showed the intercept and slopes parameter were statistically different at the 1% probability level; likewise, the yield plateau parameters were statistically different at the 5% probability level (See Table 3-2). As discussed in the previous sections, even though NT average yields are lower than those of CT during the first years of production, they increase over time and appear to eventually match those of CT. If we compare CT results with NT 2006-2017, that is using only the last 11 years of NT study, we can observe the NT 2006-2017 corn yield plateau

is actually larger than that of CT by 62 Kg ha⁻¹. Although this last comparison is not performed over the same time period, it hints that over the long-run NT might be able to compete against CT, especially if the machinery usage involved with CT represents a significant source of costs.

3.6.3. Comparing Strip Tillage (2006-2017) Against No Tillage

Among all practices, ST produces the highest yield plateau (10,166 Kg ha⁻¹) with a corresponding nitrogen fertilizer rate of 114 Kg ha⁻¹. Like in the case of CT, ST also produces a larger yield plateau and requires less nitrogen per hectare to reach it when compared to NT 2001-2017. If the comparison is done against NT 2006-2017, that is using only the last 11 years of the NT study to match the time periods, the difference in the plateaus is of about 62 Corn Kg ha⁻¹, and fertilizer requirements to reach the plateau differ by 28 Nitrogen Kg ha⁻¹. These results favor the use of ST over NT 2006-2017. The Likelihood ratio test statistics for the joint tests between them showed the yield plateau and slopes parameter were statistically different at the 1% probability level; likewise, the intercept parameters were statistically different at the 5% probability level (See Table 3-2). Overall, as with the case of CT, these results can make NT an attractive practice to farmers if the savings associated with less machinery use can offset the differences in yields and nitrogen requirements that favor ST. This is examined in the next sections.

Table 3-1. Regression Results for the Different Tillage Systems.

Parameter	No Tillage			Conventional Tillage	Strip Tillage
	(2001-2017)	(2001-2007)	(2006-2017)	(2001-2007)	(2006-2017)
Dependent Variable: Corn Yield (kg/ha)					
Intercept β_0	5,217.07*** (160.93)	4,885.74*** (267.41)	5,384.63*** (148.56)	5,741.42*** (140.48)	5,360.71*** (140.86)
Slope β_1	30.66*** (1.94)	29.43*** (2.09)	33.20*** (3.07)	46.78*** (5.12)	42.17*** (2.50)
Nitrogen at Plateau (predicted) $\widehat{N}_p$	152.37*** (4.38)	151.95*** (6.52)	142.11*** (5.64)	91.91*** (3.79)	113.95*** (4.56)
Yield Plateau P_m	9,888.40*** (179.82)	9,358.43*** (198.73)	10,103.01*** (212.36)	10,041.17*** (320.17)	10,165.66*** (161.88)
Intercept Random Effect σ_u^2	310,455.05*** (94,043.35)	412,771.73*** (130,897.18)	126,469.36 (77,481.82)	58,094.60 (41,367.27)	113,147.53* (62,511.64)
Slope Random Effect σ_ω^2	39.87*** (12.75)	16.72* (9.69)	76.33*** (26.30)	147.22*** (45.80)	28.33 (17.71)
Yield Plateau Random Effect σ_v^2	413,413.91*** (110,322.82)	164,515.43* (86,232.06)	405,441.96*** (127,945.63)	672,719.40*** (126,950.11)	227,261.16*** (65,409.26)
MSE	442,162.07	410,809.03	459,932.70	385,169.15	481,027.47
LogLikelihood	-2,062.21	-983.56	-1,338.57	-1,211.64	-1,737.68
n (observations)	256	123	166	152	216

*** Significant at $p = 0.01$; ** significant at $p = 0.05$; * significant at $p = 0.10$.

Note: The predicted parameter $\widehat{N}_p$ is calculated using the estimation results for each model. Standard errors are in parenthesis. We used bootstrapping techniques to obtain consistent estimates of the corresponding standard errors for the random effects parameters and parameter $\widehat{N}_p$. See Appendix for a complete set of results of random effects parameters.

Table 3-2. Likelihood Ratio Test Statistics for the Estimated Intercept, Slope, and Plateau Parameters.

Parameter Estimate	Likelihood Ratio Statistic		
	No Till (2001-2007) vs. No Till (2006-2017)	No Till (2001-2007) vs. CT (2001-2007)	No Till (2006-2017) vs. ST (2006-2017)
Intercept β_0	8.90***	37.13***	5.36**
Slope β_1	0.06	23.47***	19.77***
Yield Plateau P_m	242.22***	6.61**	12.59***

*** Significant at $p = 0.01$; ** significant at $p = 0.05$; * significant at $p = 0.10$.

Note: The critical value of the test statistic are $\chi^2_{1,0.01} = 6.64$; $\chi^2_{1,0.05} = 3.84$; $\chi^2_{1,0.10} = 2.71$

3.6.4. Profit Analysis

Monte Carlo results of expected profits are shown in Figure 3-3. These are calculated using the parameter estimates from equations (3) and (4), expected yields⁹ for each tillage practice from equation (7), additional fuel and machinery costs as described in the data section, and a scenario where the price of corn is fixed at 0.20 \$/kg, and the price of nitrogen is fixed at 0.96 \$/kg.

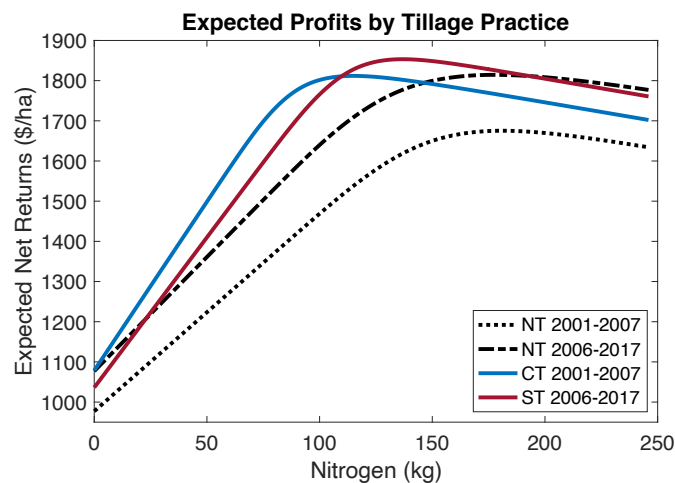


Figure 3-3. Expected profits (\$ ha⁻¹) from corn production at different nitrogen fertilizer levels.

⁹ See Figure A 3-4 of the Appendix for the results of the expected yields.

Results presented in Figure 3-3 show CT and ST profits are larger than NT 2001-2007 profits at all nitrogen levels. When comparing CT against NT 2006-2017, results show NT 2006-2017 profits are higher than CT profits at their respective profit maximizing nitrogen levels, but only by about 3 USD ha⁻¹. Moreover, NT 2006-2017 profits are larger than CT profits at levels of nitrogen fertilization higher than 146 Kg ha⁻¹. These results have important implications as farmers tend to over-fertilize the corn crops (Babcock, 1992; Sheriff, 2005; Stanger et al., 2008), hence making NT a more profitable practice at relatively large nitrogen fertilizer rates. Conversely, ST profits are larger than NT 2006-2017 profits at their respective profit maximizing nitrogen levels, but NT 2006-2017 profits become larger than ST profits at levels of nitrogen fertilization higher than 193 Kg ha⁻¹.

Table 3-3 shows the results of the nonlinear optimization problem. Profit-maximizing nitrogen rates for the different tillage practices, expected corn yields and net returns at the profit maximizing nitrogen rates were estimated. Results show CT requires the least amount of nitrogen fertilizer to maximize profits with 115 Kg ha⁻¹, followed by ST with 137 Kg ha⁻¹, and NT (2006-2017) with 177 Kg ha⁻¹. After accounting for additional costs, strip tillage produces the largest net returns. When compared to NT 2006-2017, ST was shown to be more profitable, but only by a relative small margin (1,853 USD ha⁻¹ vs. \$1,814 USD ha⁻¹). This difference of approximate 40 USD ha⁻¹ would likely get reduced in favor of NT if we account for soil implications, as ST disrupts and compact the soil more than NT (Al-Kaisi, 2001).

Table 3-3. Profit Results for the Different Tillage Practices.

Outcome	No Tillage		Conventional Tillage	Strip Tillage
	(2001-2007)	(2006-2017)	(2001-2007)	(2006-2017)
Profit Max. Nitrogen Rate (Kg ha ⁻¹) N*	180.88	177.30	114.95	136.90
Expected corn Yield at N* (Kg ha ⁻¹)	9,244.61	9,923.19	9,959.32	10,104.17
Returns (\$ ha ⁻¹)	1,675.29	1,814.43	1,881.52	1,889.43
Additional Costs (\$ ha ⁻¹) ^a	-	-	\$69.68	\$36.08
Net Returns (\$ ha ⁻¹)	1,675.29	1,814.43	1,811.84	1,853.36

^a Additional costs included tractor, fuel, labor and depreciation on new implements, parts and repair (DeJong-Hughes and Daigh, 2018).

As the comparison between NT 2006-2017 and CT occurs over different time periods, it does not account for additional confounders that could influence the variance of yields over time, primarily weather effects and the use of new corn varieties. At the assumed prices, a sensitivity analysis performed over yields showed that an increase of 1% on the expected CT yields would be sufficient to make it more profitable than NT 2006-2017 at every year, whilst an increase of 2.2% would be needed for CT to become more profitable than ST (See Table A 3-5 of the Appendix). Corn average annual productivity growth rate in the U.S. is estimated to be of 2.35% (Chavas & Mitchell, 2018), making the aforementioned growth scenario of CT yields a very likely development that happened during the last decade.

To further explore and compare the profitability of the different tillage practices, a net present value (NPV) of the yearly net returns was estimated for each practice over a period of 17 years using a 5% discount rate. For the NT practice we use our net return estimate of 1,675 USD ha⁻¹ for years 1 to 7, and our estimate of 1,814 USD ha⁻¹ for years 8 to 17. As our CT net return estimate of 1,812 USD ha⁻¹ only account for years 1 to 7, we use various scenarios of yield growth over time to analyze the CT potential profit outcomes during years 8 to 17. Likewise, given our ST net return estimate of 1,853 USD ha⁻¹ only account for years 6 to 17, we also use

counterfactual yield growth scenarios to analyze the ST potential profit outcomes during years 1 to 5.

For the case of CT, 7 different scenarios are compared. Net return outcomes for years 8 to 17 are estimated via increasing the expected yields by 0%, 0.5%, 1.0%, 1.5%, 2.0%, 2.5%, and 3.0%. Similarly, for the case of ST, as we do not have estimates for years 1 to 5, we also estimate net return outcomes for those years via decreasing the expected yields by the aforementioned percentage points.

If we assume no changes in yields for CT and ST, NPV values are 20,633 USD ha⁻¹ for NT, 21,448 USD ha⁻¹ for CT, and 21,940 USD ha⁻¹ for ST, giving ST an advantage of approximately 1,300 USD ha⁻¹ over NT, and 500 USD ha⁻¹ over CT over the 17-year period. As it is very likely that CT and ST yields would have increased over time due to, among other factors, improved seed technologies, Figure 3-4 examines the impact of expected yield changes on NPV's for the cases of CT and ST. For reference, NT NPV is also presented. Results show that a change of approximately 2.5% on expected yields –that is CT yields during years 8 to 17 are 2.5% higher than those of years 1 to 7; and ST yields during years 1 to 5 are 2.5% lower than those of years 6 to 17– will make the CT practice more profitable than ST and NT over the long run. Depending on the change of expected yields, our results estimate a loss to producers of between 815 to 1160 USD ha⁻¹ from using NT instead of CT, and a loss of between 1,039 to 1,306 USD ha⁻¹ from using NT instead of ST. These results are conservative, as there is the possibility that yields increased more than 3% over the different time periods (See also Tables A 3-6, A 3-7, and A 3-8 of the Appendix).

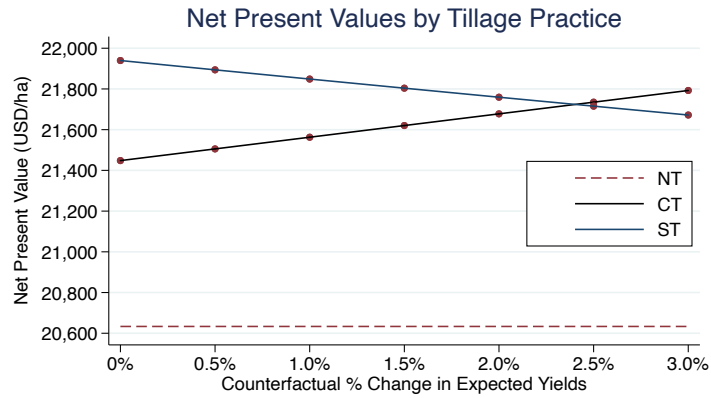


Figure 3-4. Net present values (\$ ha⁻¹) from corn production by tillage practice

3.6.5. Sensitivity Analysis to Corn and Nitrogen Price Variations

Maximum Profits

Figure 3-5 shows the maximum profits sensitivity of the different tillage practices to corn and nitrogen fertilizer price variations. As expected, and shown from all three tillage practices, maximum profits are more sensitive to changes in corn prices than to changes in nitrogen prices.

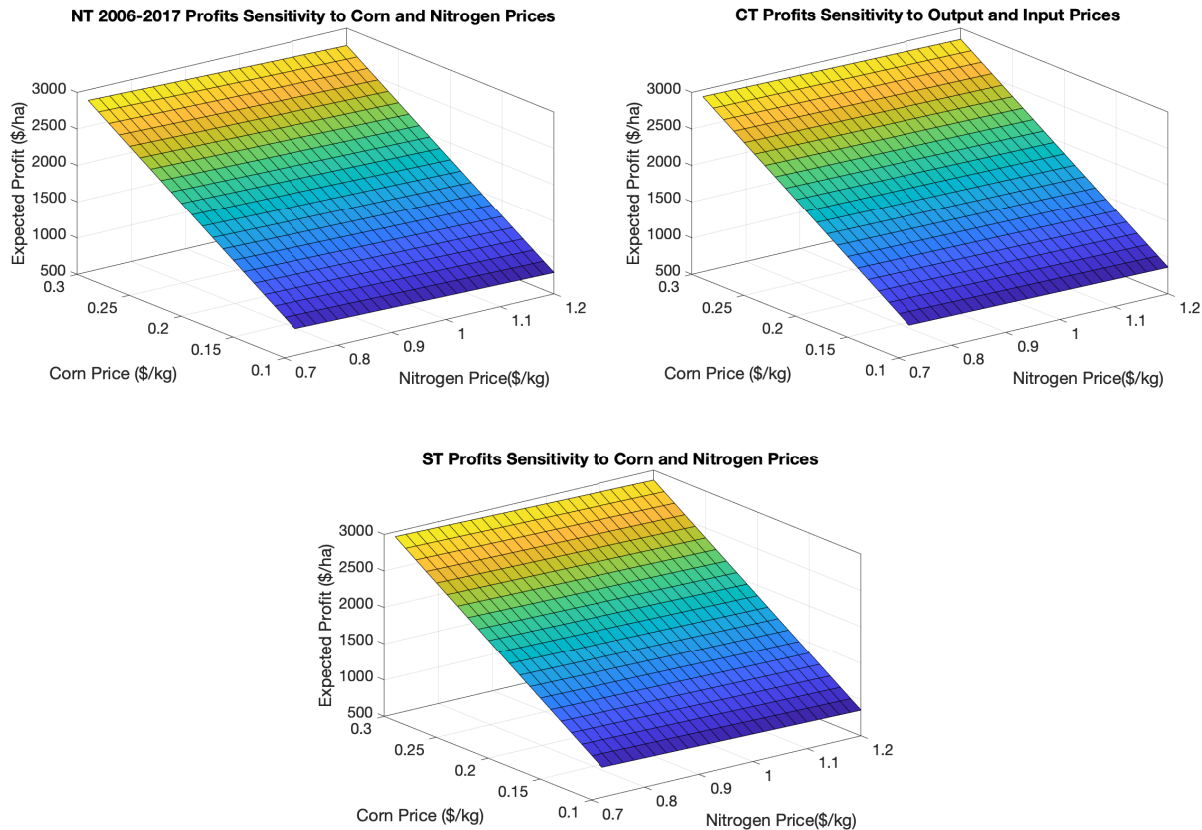


Figure 3-5. Sensitivity of maximum profits to changes in corn and nitrogen prices

Having *ceteris paribus*, table 3-4 indicates the average impact over maximum profits caused by an increase of 1 USD in the price per bushel of corn, that is an increase of 0.04 USD in the price per kg of corn. It also presents the impact of an increase of 100 USD in the price per ton of urea, that is an increase of 0.24 USD in the price per kg of nitrogen. These results show ST maximum profits are slightly more sensitive to changes in corn prices compared to the other tillage practices. Results also show NT is more sensitive to changes in nitrogen prices compared to the other tillage practices. Overall, these results indicate maximum profits of all tillage practices have similar sensitivity to changes in corn prices. However, NT is more sensitive to changes in nitrogen prices compared to the rest of tillage practices. This is due to NT requiring the largest amounts of nitrogen to maximize profits.

Table 3-4. Average Changes in Maximum Profits (USD ha⁻¹) Caused by Changes in Corn and Nitrogen Prices

Output/Input Price Change	No Tillage (2006-2017)	Conventional Tillage (2001-2007)	Strip Tillage (2006-2017)
Corn price ↑ 0.04 USD kg ⁻¹	↑ 397 USD ha ⁻¹	↑ 399 USD ha ⁻¹	↑ 404 USD ha ⁻¹
Nitrogen price ↑ 0.24 USD ⁻¹	↓ 42 USD ha ⁻¹	↓ 27 USD ha ⁻¹	↓ 32 USD ha ⁻¹

Profit Maximizing Nitrogen Rates

Changes on the profit maximizer nitrogen fertilizer rates caused by changes on the corn and nitrogen fertilizer prices were also investigated. Figure 3-6 displays this sensitivity analysis on the different tillage practices and shows relatively small sensitivity of the profit maximizing nitrogen rates to changes in corn prices and nitrogen prices.

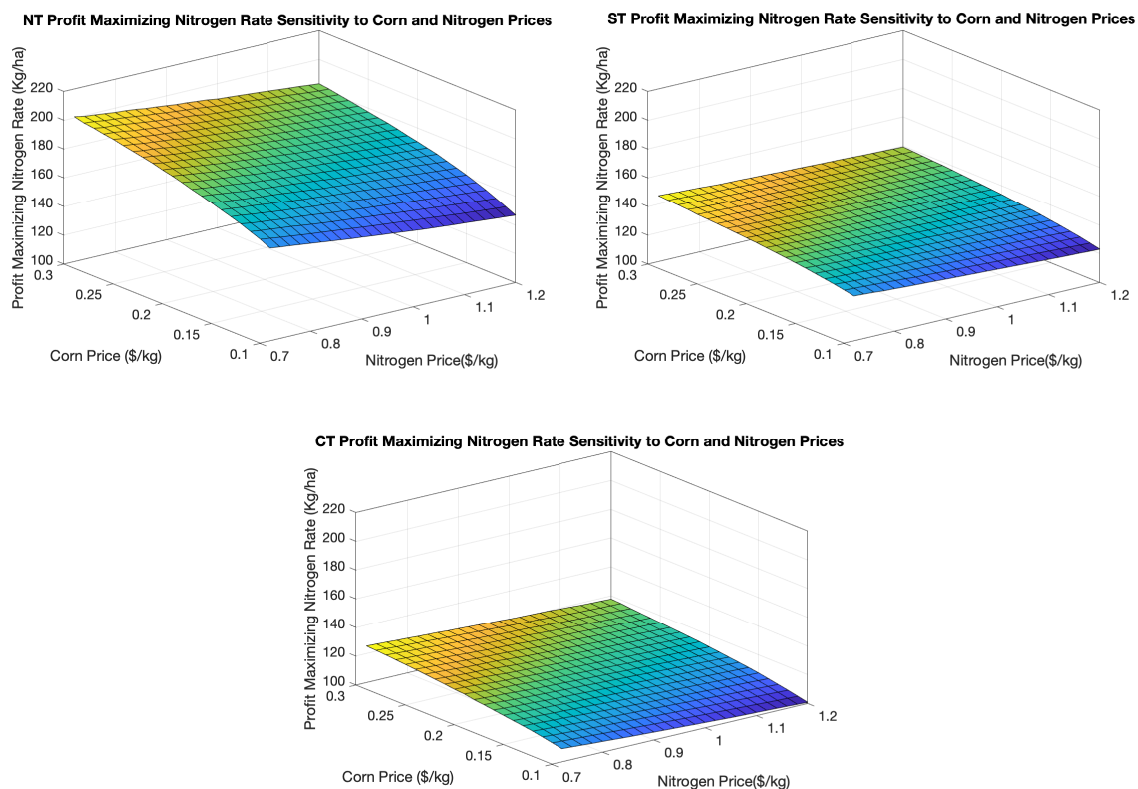


Figure 3-6. Sensitivity of profit-maximizing nitrogen fertilizer rates to changes in corn and nitrogen prices

Using the same corn and nitrogen price variations as in the previous subsection and assuming *ceteris paribus*, table 3-5 indicates the average impact of price changes over the profit maximizing nitrogen rates across the different tillage practices. Results show NT profit maximizing nitrogen rates are more sensitive to changes in both, corn prices and nitrogen prices, than the other tillage practices. Overall, these results show corn and nitrogen prices do not have substantial impacts on the use of nitrogen to maximize profits across tillage practices. Although changes on the profit maximizing nitrogen rates are relatively small, it is important to note NT is more sensitive to changes in nitrogen prices than the rest of tillage practices.

Table 3-5. Average Changes in Profit Maximizing Nitrogen Rates (kg ha⁻¹) Caused by Changes in Corn and Nitrogen Prices

Output/Input Price Change	No Tillage (2006-2017)	Conventional Tillage (2001-2007)	Strip Tillage (2006-2017)
Corn price ↑ by 0.04 USD kg ⁻¹	↑ 6.5 kg ha ⁻¹	↑ 2.9 kg ha ⁻¹	↑ 2.7 kg ha ⁻¹
Nitrogen price ↑ by 0.24 USD kg ⁻¹	↓ 8.5 kg ha ⁻¹	↓ 3.9 kg ha ⁻¹	↓ 3.5 kg ha ⁻¹

3.7. Summary and Discussion

This research determined the (i) profit maximizing nitrogen fertilizer rates, (ii) yields at the profit maximizing nitrogen rates, and (iii) expected net returns for continuous irrigated corn production under different tillage systems. Data come from the Agricultural Research Development and Education Center (ARDEC) located in the northeastern Colorado region. Analysis shows positive long-term yield effects associated with the no tillage practice. Results from separate regressions, estimated via partitioning the sample data, showed NT 2001-2007 produced lower estimates for the yield plateau compared to NT 2006-2017. Expected CT and ST

yields were higher than those of NT 2001-2007 at all nitrogen levels, but yield differences became smaller when CT and ST were compared relative to NT 2006-2017.

Using the estimated expected yields and additional machinery costs associated with the tillage practices, CT profits were found to be larger than NT 2001-2007, nonetheless, NT 2006-2017 maximum profits are slightly larger than those of CT. Given CT only occurs from 2001 to 2007, in order to compare the NPV of this practice against that of NT –which occurs over a period of 17 years– we present several scenarios for CT yield growth and analyze how they would have affected the NPV of CT. Results showed that even if CT yields would not have increased over time, producers would have experienced a loss from using NT instead of CT. These results constitute prima facie evidence showing that even though NT profits might compete with CT profits in a given year, net present values of aggregate profits over the long run will still favor the use of CT over NT among risk-neutral farmers. This is mainly caused by the relatively small initial profits obtained by the use of NT.

ST maximum profits were found to be larger than those of NT and CT practices respectively. Similarly, to compare the NPV of this practice against that of NT we present various scenarios of ST yields during the initial years and analyze how they would have affected the NPV of this practice. Results showed that even if ST yields from years 1-5 would have been 3% lower than those of years 6-17 (years actually observed), ST would still be preferred than NT. Results also showed that if (i) CT yields would have been 2.5% larger for years 8-17, and (ii) ST yields would have been 2.5% lower for years 1-5, then CT would be as profitable as the ST practice. These results make ST a very attractive tillage practice for continuous corn

production, and is mainly due to ST not having yield penalties when adopted –in contrast to NT– and the costs savings associated with less intensive machinery and labor use.

As discussed the previous sections, conservation tillage practices have various environmental benefits that CT do not provide, including reduced erosion potential, reduction of greenhouse gas emissions, and conservation of water (Archer et al., 2008). For reference, if the NT environmental benefits are assigned a value of 98 USD ha⁻¹ per year, then NT would be as profitable as CT in the long run¹⁰. This value is comparable to the typical per acre payment rates of between \$50 and \$100 that farmers of the corn belt received as part of the 2019 Market Facilitation Program (MFP) of the U.S. Department of Agriculture (Schnitkey et al., 2019). Likewise, if ST environmental benefits are assigned dollar values, this would make ST and even more attractive option over CT and NT for continuous corn production. Correspondingly, profit differences among NT and ST will get reduced if we account for the aforementioned environmental benefits.

Overall, our research results show that strip tillage is better suited for continuous corn production under the agro-climatic conditions in northeastern Colorado. Moreover, NT appears to be unable to yield competitive profits against other tillage practices over the long run, even after accounting for the significant yield increases experienced by NT. It is only by accounting for the additional environmental benefits that NT might be able to compete against NT or ST.

Government intervention through payments and extension services will be necessary to increase the adoption of conservation tillage practices, as from a social point of view they are

¹⁰ This assumes prices of \$400 per ton of urea fertilizer and \$5 per bushel of corn, as well as an increase of 3% in expected yields for the CT practice.

likely to be preferred. Extension services disseminating information about the larger profits enjoyed by the ST practice would be needed to increase the adoption of this practice, while environmental compensations in the form of subsidies could be used to increase the adoption of the NT practice.

One important finding from our research is the distinctive characteristic of the NT practice requiring significantly larger amounts of Nitrogen to maximize profits in comparison to the ST and CT practice. This particular characteristic deserves additional research, as the excessive use of nitrogen can cause further and unintended negative externalities, including the damage of water bodies. The combination of NT being the tillage practice (i) that requires the most intensive nitrogen use, and (ii) that is the most sensitive to changes in nitrogen prices, could offset the environmental benefits it creates, hence making it a very undesirable tillage practice from a producers and society point of view.

Effects of temperature changes, pests, and other weather variables are assumed to be captured by the inclusion of random effect parameters indexed over time in the main model specification. Site-specific soil effects are not controlled for, as soil uniformity is assumed across treatments. This represents a limitation of this study, as soil variability in combination with weather variables or tillage practices can have different effects on corn yields. Likewise, our analysis did not include improvements in technology that would support one tillage practice over others, including improvements in genetics, planting equipment, fertilizer applicators and pesticide sprayers. In addition, changing a tillage practice also imposes adapting current practices to new ones including different weed control and fertilizer applications, and costs related to changing equipment that are not considered in this study. This research does not address the

effect of potential losses or gains farmers may perceive by the use of crop rotations. Crop rotations have been shown to reduce plant diseases and pest problems and to increase yields. However, crop rotations have been reported to be less common in irrigated corn in Colorado, and many farms have produced continuous corn for decades in the study area as they consider other crops to be more economically risky (Bosley, 2011).

Our research results may not hold in areas with different soil types and climatic conditions, so further research in other locations is also needed to corroborate the long-term yield and profit growth effects of the NT practice presented in this study, and more importantly, to explore –if any– the profit effects of CT and ST over time.

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3.9. Appendix

Average Corn Yield Grouped by Different Tillage Practices.

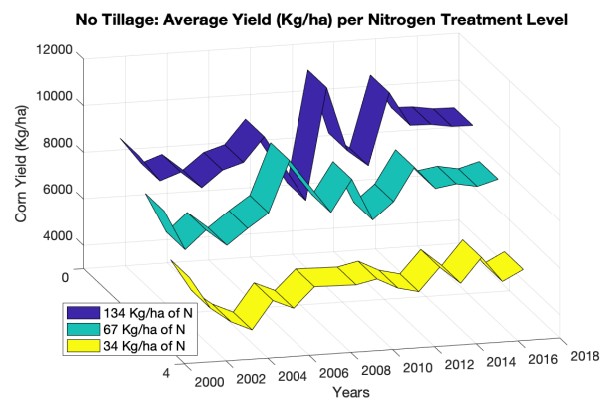


Figure A 3-1. Average corn yields for no tillage.

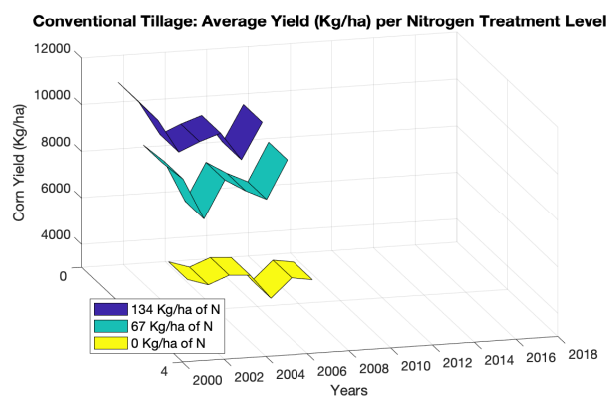


Figure A 3-2. Average corn yields for conventional tillage.

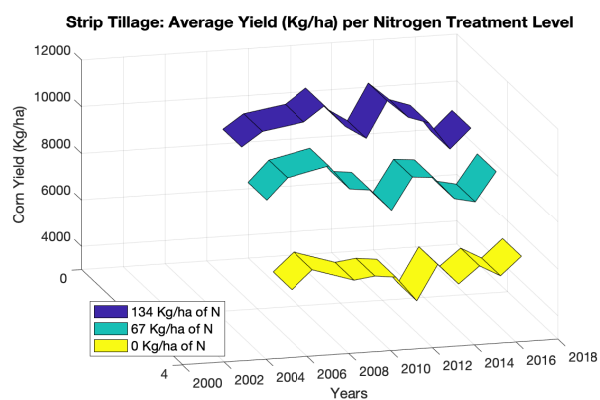


Figure A 3-3. Average corn yields for strip tillage.

Mean Values of NT Corn Yields by Year Group Periods and Nitrogen Treatments

Table A 3-1. Mean Values of NT Corn Yields by Year Group Periods and Nitrogen Treatments in kg ha⁻¹.

Nitrogen Treatment	Year Group Period		Percentage Increase	Obs.	p-Value
	2001-2007	2006-2017			
0	4638.96 [4260.88 , 5017.03]	5154.58 [4932.72 , 5376.44]	11%	54.00	0.01
67	7064.80 [6638.08 , 7491.52]	7968.33 [7677.94 , 8258.73]	13%	52.00	0.00
134	8535.30 [8170.26 , 8900.33]	9578.98 [9076.38 , 10081.58]	12%	51.00	0.00

Note: The p-value in the final column refers to the test of equality of outcomes by Year Group Period. 95% C.I. are presented in brackets.

Mean, Variance, and Standard Deviation of NT Corn Yields by Nitrogen Treatments

Table A 3-2. Mean, Variance, and Std. Dev. of NT Corn Yields for Nitrogen Treatment 0 kg ha⁻¹ by Year.

Year	Mean	Variance	Std. Dev.	95% C.I.	
				Lower Limit	Upper Limit
2017	5360.00	352440.06	593.67	4688.20	6031.80
2016	4906.93	254871.09	504.85	4335.64	5478.22
2015	5989.56	356097.53	596.74	5314.29	6664.84
2014	4952.00	302052.00	549.59	4330.08	5573.92
2013	5694.60	738615.76	859.43	4722.07	6667.14
2012	4714.58	128855.33	358.96	4308.37	5120.79
2011	4927.64	18801.35	137.12	4772.48	5082.81
2010	5375.53	157632.92	397.03	4926.25	5824.82
2009	5185.38	225653.41	475.03	4647.84	5722.93
2007	5225.77	95301.36	308.71	4876.43	5575.10
2006	4368.41	556384.19	745.91	3524.33	5212.49
2005	4755.87	234489.31	484.24	4207.90	5303.84
2004	3565.55	13028.63	114.14	3436.38	3694.71
2003	3966.69	134299.27	366.47	3551.99	4381.39
2002	4611.41	83189.39	288.43	4285.03	4937.80
2001	5979.03	33937.42	184.22	5770.57	6187.50

Table A 3-3. Mean, Variance, and Std. Dev. of NT Corn Yields for Nitrogen Treatment 67 kg ha⁻¹ by year.

Year	Mean	Variance	Std. Dev.	95% C.I.	
				Lower Limit	Upper Limit
2017	8223.36	419676.04	647.82	7490.28	8956.44
2016	7971.93	673357.00	820.58	7043.35	8900.50
2015	8139.35	139336.99	373.28	7716.94	8561.75
2014	8001.33	438980.33	662.56	7251.58	8751.09
2013	8969.09	1212935.39	1101.33	7722.81	10215.37
2012	7553.40	7166.93	84.66	7457.60	7649.20
2011	6825.51	261163.26	511.04	6247.22	7403.81
2010	8641.37	25176.96	158.67	8461.82	8820.93
2009	7271.82	1627.24	40.34	7226.17	7317.46
2007	8255.65	52798.81	229.78	7995.63	8515.67
2006	7428.37	671395.06	819.39	6501.14	8355.59
2005	6825.20	118675.09	344.49	6435.37	7215.03
2004	6160.35	698037.25	835.49	5214.91	7105.79
2003	6874.31	931932.28	965.37	5781.90	7966.73
2002	6095.11	257341.54	507.29	5521.06	6669.16
2001	7814.64	110986.79	333.15	7437.65	8191.63

Table A 3-4. Mean, Variance, and Std. Dev. of NT Corn Yields for Nitrogen Treatment 134 kg ha⁻¹ by Year.

Year	Mean	Variance	Std. Dev.	95% C.I.	
				Lower Limit	Upper Limit
2017	9513.23	580463.80	761.88	8651.08	10375.38
2016	9530.36	485148.58	696.53	8742.16	10318.55
2015	9672.86	1051500.53	1025.43	8512.48	10833.24
2014	9699.00	180379.00	424.71	9218.39	10179.61
2013	11155.47	33750.81	183.71	10947.58	11363.36
2012	8091.20	7023912.84	2650.27	5092.14	11090.26
2011	8790.90	64746.12	254.45	8502.96	9078.84
2010	11551.96	1402224.28	1184.16	10211.97	12891.96
2009	6773.81	6773.81	82.30	6680.68	6866.95
2007	9630.88	129760.96	360.22	9223.25	10038.51
2006	8593.11	675963.31	822.17	7662.73	9523.48
2005	8321.96	235979.15	485.78	7772.25	8871.66
2004	7626.89	120256.54	346.78	7234.47	8019.31
2003	8358.15	639949.72	799.97	7452.90	9263.40
2002	8042.25	434508.05	659.17	7296.33	8788.17
2001	9173.83	59741.61	244.42	8897.24	9450.42

Results of the Variance Covariance Matrix of the Random Effects Parameters.

Standard errors presented in parenthesis.

$$\text{cov}(u_t, \omega_t, v_t) = \begin{bmatrix} \sigma_u^2 & \sigma_{u\omega} & \sigma_{uv} \\ \sigma_{u\omega} & \sigma_\omega^2 & \sigma_{\omega v} \\ \sigma_{uv} & \sigma_{\omega v} & \sigma_v^2 \end{bmatrix}$$

No Tillage (2001-2017)

$$\text{cov}(u_t, \omega_t, v_t) = \begin{pmatrix} 310,455 & - & - \\ (94,043) & - & - \\ 675.76 & 39.87 & - \\ (716.52) & (12.75) & - \\ 296,931 & 1,376 & 413,414 \\ (94,295) & (1,057) & (110,323) \end{pmatrix}$$

No Tillage (2001-2007)

$$\text{cov}(u_t, \omega_t, v_t) = \begin{pmatrix} 412,771.73 & - & - \\ (130,897.18) & - & - \\ -584.88 & 16.72 & - \\ (765.59) & (9.69) & - \\ 191,586.67 & -970.01 & 164,515.43 \\ (77,599.25) & (573.28) & (86,232.06) \end{pmatrix}$$

No Tillage (2006-2017)

$$\text{cov}(u_t, \omega_t, v_t) = \begin{pmatrix} 126,469.36 & - & - \\ (77,481.82) & - & - \\ -562.51 & 76.33 & - \\ (845.13) & (26.30) & - \\ 202,857.45 & 1,528.90 & 405,441.96 \\ (84,185.88) & (1,564.61) & (127,945.63) \end{pmatrix}$$

Conventional Tillage (2001-2007)

$$\text{cov}(u_t, \omega_t, v_t) = \begin{pmatrix} 58,094.60 & - & - \\ (41,367.27) & - & - \\ -860.66 & 147.22 & - \\ (1,205.19) & (45.80) & - \\ -3,897.53 & 6,428.36 & 672,719.40 \\ (80,875.79) & (2,188.76) & (126,950.11) \end{pmatrix}$$

Strip Tillage (2006-2017)

$$\text{cov}(u_t, \omega_t, v_t) = \begin{pmatrix} 113,147.53 & - & - \\ (62,511.64) & - & - \\ 679.83 & 28.33 & - \\ (643.75) & (17.71) & - \\ 120,683.03 & -195.27 & 227,261.16 \\ (50,194.98) & (856.32) & (65,409.26) \end{pmatrix}$$

Results of Expected Yields

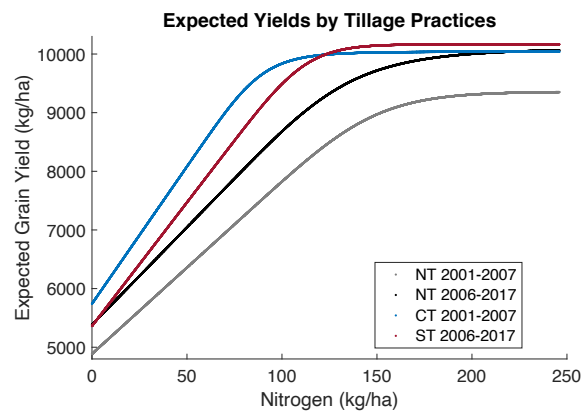


Figure A 3-4. Expected yields by tillage practices.

Sensitivity of CT Net Returns to an Increase in Expected Yields

Table A 3-5. Conventional Tillage: Sensitivity of Net Returns to an Increase in Expected Yields

	Expected Yield Increase				
	1%	2%	3%	4%	5%
Net Returns (\$ ha ⁻¹) ^a	\$ 1,831.76	\$ 1,851.68	\$ 1,871.60	\$ 1,891.52	\$ 1,911.45

^a Net returns already include additional costs related to tractor, fuel, labor and depreciation on new implements, parts and repair.

Cashflow and NPV of Different Tillage Practices Assuming Changes in CT and ST expected yields.

Table A 3-6. Cashflow and NPV of Different Tillage Practices Assuming CT and ST expected yields Increased by 0%, in USD ha-1.

Year	Tillage Practice		
	NT	CT	ST
0	1,675.29	1,811.84	1,853.36
1	1,675.29	1,811.84	1,853.36
2	1,675.29	1,811.84	1,853.36
3	1,675.29	1,811.84	1,853.36
4	1,675.29	1,811.84	1,853.36
5	1,675.29	1,811.84	1,853.36
6	1,675.29	1,811.84	1,853.36
7	1,814.43	1,811.84	1,853.36
8	1,814.43	1,811.84	1,853.36
9	1,814.43	1,811.84	1,853.36
10	1,814.43	1,811.84	1,853.36
11	1,814.43	1,811.84	1,853.36
12	1,814.43	1,811.84	1,853.36
13	1,814.43	1,811.84	1,853.36
14	1,814.43	1,811.84	1,853.36
15	1,814.43	1,811.84	1,853.36
16	1,814.43	1,811.84	1,853.36
Sum	29,871.33	30,801.20	31,507.06
Mean	1,757.14	1,811.84	1,853.36
NPV (5% discount rate)	20,633.43	21,448.09	21,939.61

Table A 3-7. Cashflow and NPV of Different Tillage Practices Assuming CT and ST expected yields Increased by 2.5%, in USD ha-1.

Year	Tillage Practice		
	NT	CT	ST
1	1,675.29	1,811.84	1,804.07
2	1,675.29	1,811.84	1,804.07
3	1,675.29	1,811.84	1,804.07
4	1,675.29	1,811.84	1,804.07
5	1,675.29	1,811.84	1,804.07
6	1,675.29	1,811.84	1,853.36
7	1,675.29	1,811.84	1,853.36
8	1,814.43	1,861.64	1,853.36
9	1,814.43	1,861.64	1,853.36
10	1,814.43	1,861.64	1,853.36
11	1,814.43	1,861.64	1,853.36
12	1,814.43	1,861.64	1,853.36
13	1,814.43	1,861.64	1,853.36
14	1,814.43	1,861.64	1,853.36
15	1,814.43	1,861.64	1,853.36
16	1,814.43	1,861.64	1,853.36
17	1,814.43	1,861.64	1,853.36
Sum	29,871.33	31,299.24	31,260.62
Mean	1,757.14	1,841.13	1,838.86
NPV (5% discount rate)	20,633.43	21,735.07	21,715.55

Table A 3-8. Cashflow and NPV of Different Tillage Practices Assuming CT and ST expected yields Increased by 3.0%, in USD ha-1.

Year	Tillage Practice		
	NT	CT	ST
1	1,675.29	1,811.84	1,794.50
2	1,675.29	1,811.84	1,794.50
3	1,675.29	1,811.84	1,794.50
4	1,675.29	1,811.84	1,794.50
5	1,675.29	1,811.84	1,794.50
6	1,675.29	1,811.84	1,853.36
7	1,675.29	1,811.84	1,853.36
8	1,814.43	1,871.60	1,853.36
9	1,814.43	1,871.60	1,853.36
10	1,814.43	1,871.60	1,853.36
11	1,814.43	1,871.60	1,853.36
12	1,814.43	1,871.60	1,853.36
13	1,814.43	1,871.60	1,853.36
14	1,814.43	1,871.60	1,853.36
15	1,814.43	1,871.60	1,853.36
16	1,814.43	1,871.60	1,853.36
17	1,814.43	1,871.60	1,853.36
Sum	29,871.33	31,398.86	31,212.78
Mean	1,757.14	1,846.99	1,836.05
NPV (5% discount rate)	20,633.43	21,792.46	21,672.05

4. Manuscript 3: Does the Use of Specialty Varieties and Post-Harvest Practices Benefit Farmers? Cocoa Value Chains in Ecuador.

4.1. Abstract

What is the impact of the use of specialty cocoa varieties on small-scale farmers' income? To what extent does performing on-farm post-harvest practices improve their situation? This article employs household data of 340 cocoa farms from 15 different villages collected in the coastal zone of Ecuador during 2018 to answer these questions. Contrary to the common belief of the international development community, we find that the use of specialty cocoa varieties –also known as fine and flavor cocoa– has in total a low impact on small-scale cocoa producers' income. This is mainly due to (i) low productivity and (ii) nonexistent price premiums. Findings presented here have implications for program interventions aimed at increasing cocoa farmer revenue and income. The Ecuadorian national cacao program promoting the specialty varieties alone is misguided and can be improved by training farmers in more modern processing techniques, regardless of the variety produced. Results suggest that recommending to farmers to perform post-harvest practices of fermentation and drying may lead to substantial price responses irrespective of the type of cocoa grown.

4.2. Introduction

Markets for specialty cocoa varieties have received substantial attention over the last decade (Gockowski et al., 2011; Daniels et al., 2012), as global demand for high-quality chocolate is on the rise. This demand influences the price of specialty cocoa varieties, as manufacturers and artisans of premium chocolate need their distinctive tastes and colors. In

international markets, specialty cocoa varieties normally receive a price premium and it is commonly believed that producers of these varieties enjoy the benefits of these higher prices (Ricketts et al., 2014).

Governments of countries where specialty varieties are produced have undertaken actions to promote and expand their cultivation (See Appendix). In 2012, the Government of Ecuador launched the Fine and Flavor Cocoa Reactivation Program (FFCRP) focused on revitalizing production among small producers. The FFCRP was intended to benefit smallholder producers and expand exports of high-valued cocoa. By using input subsidies, increasing the access to credit, the rehabilitation of older non-productive plantations, and promoting enhanced farm management, the Ecuadorian government seeks to stimulate Nacional production in approximately 284,000 hectares of current cocoa plantations¹¹. Ecuador is the world's main exporter of specialty cocoa –also known as fine and flavor cocoa– (ICCO, 2019), but currently, in addition to producing the specialty variety called Nacional, many Ecuadorian cocoa farmers produce a bulk or ordinary variety named CCN51. CCN51 does not command price premiums in international markets, but its production in Ecuador has been on the rise since the late 1990s (USDA Foreign Agricultural Service, 2015).

Increased production of the Nacional variety will benefit smallholders only if the benefits of price premiums are transmitted to producers. It is not, however, clear that this will happen, as it is well-known that distortions in commodity markets can inhibit producers of raw materials

¹¹ One of the main sub-components of this program is called La Gran Minga del Cacao, where trained teams perform specialized pruning of Nacional cocoa trees. This service is offered to small scale domestic cocoa producers who own farms smaller than 10 hectares (Minga del Cacao, 2016).

from reaping the benefits of increased quality. This question of whether benefits of quality premia are transmitted to producers is of economic interest for a number of reasons.

First, the international development community considers the “fine and flavor” cacao market as an integral development strategy for boosting the income of cocoa producers (Abbott et al., 2018). Bulk cocoa production is not widely considered to be a highly lucrative endeavor. Cocoa producers in West Africa, where most of the bulk cocoa is produced, tend to be very poor. In the Ivory Coast –the world’s largest producer of bulk cocoa– only 7% of cocoa farmers currently earn a living income (Fair Trade International, 2018), and their participation in the bulk market has not provided broad-based benefits. Higher-valued varieties might be a path toward higher earnings for many producers. Second, specialty cocoa price expectations might be based on overstated premiums that only accrue to a small share of the market. Some premium cocoa have commanded up to \$10,000 per metric ton (MT), but the high-end share of the market is less than 12,000 tons annually, less than 0.25 % of the world market (Confectionery, 2016). Third, various studies have assessed quality-related price premiums –including Fair Trade, Organic, and other sustainability certifications and standards– and their impact on smallholders in developing countries and found mixed results (e.g., Sellare et al., 2020; Meemken et al., 2019). Even though some have found positive impacts, there is growing evidence showing that transmission of price premiums to producers is marginal or non-existent (e.g., Minten et al., 2019; Van Rijsbergen et al., 2016; Waarts et al., 2016; de Janvry et al., 2015; Nelson and Martin, 2013; Cepeda et al., 2013; Melo and Hollander, 2013).

Explanations for this lack of price transmission vary depending on the country and crop context and include poor transportation infrastructure and high transportation costs, cooperatives

not distributing the benefits directly to members, market power for buyers, among others. To the best knowledge of the authors, previous studies on cocoa price transmission and their impact on farmers have not analyzed the case of specialty varieties, nor the impacts of post-harvest processing.

As in much of the developing world, farmers in Ecuador have limited access to technologies for post-harvest processing and on-farm storage; they also lack access to credit and banking services and so cannot invest in quality-enhancing technologies (Hentschel & Waters, 2002). Nonetheless, it is common for cocoa farmers in Ecuador to undertake post-harvest practices as a means of increasing value-added capture and earning additional benefits from the value chain. Varied application of post-harvest processing contributes to the heterogeneity observed in prices received by producers, and along with variable bean qualities they compound the difficulty of assessing prices received by farmers for certain cocoa varieties.

In this article, we explore what is the role of variety grown and post-harvest practices in contributing to differences in prices received by smallholder cocoa farmers. We use household survey data collected by the National Institute of Agricultural Research of Ecuador (INIAP) that included actual observations on farmer's behavior and prices received from a highly representative cocoa region in Ecuador (Barrera et al., 2018). These data allow the study of determinants of prices received by farmers, which vary by variety, degree of post-harvest processing and other factors.

With various policy implications, this research is the first empirical analysis of specialty cocoa prices received by farmers. Furthermore, we contribute to the body of literature on the impact of post-harvest practices on bulk commodity value chains in developing countries. Most

studies of post-harvest practices and food value chains in developing countries to date have been highly descriptive in nature (e.g., Swinnen & Maertens, 2007; Reardon et al., 2009; Gómez et al., 2011; Maertens et al., 2012; Reardon, 2015; Zilberman et al., 2017). To the best knowledge of the author, no previous studies have employed econometric techniques to examine the connections between specialty cocoa varieties and prices, and moreover, none have focused comprehensively on how the use of post-harvest processing affects prices received. The remainder of this article proceeds as follows. Section II describes the cocoa varieties, post-harvest practices, and price premiums in Ecuador. Section III describes the data and summary statistics. Section IV presents the empirical framework and strategy used to assess the role of varieties and post-harvest practices. Section V presents the estimation results. In section VI, we conclude with some policy recommendations for the Ecuadorian cocoa program and directions for future research.

4.3. Cocoa Production and Price Premiums

4.3.1. Varieties

World cocoa markets distinguish two cocoa beans categories: "fine or flavor" cocoa beans, also known as specialty cocoa, and "bulk" or ordinary cocoa beans. In international markets, the difference between cocoa categories is considered to reside in the flavor rather than in other quality factors, such as genetic origin, morphological characteristics, chemical characteristics, color of the beans, degree of fermentation, drying, acidity, percentage of internal mold, insect infestation, and percentage of impurities (Amores et al., 2017). This makes the assessment of the quality of fine or flavor cocoa to be subjective, and an objective procedure to

measure whether beans have fine characteristics has yet to be formulated, complicating efforts to improve the marketing position of fine or flavor cocoa.

Ecuador is the world's largest exporter of fine cocoa, accounting for around two-thirds of the global fine cocoa production. The Ecuadorean fine variety is called 'Nacional' or 'Arriba' and is used in the production of gourmet chocolate. Nacional trees are mostly cultivated by smallholder farmers (typically with less than 5 hectares). This variety needs shade for proper growth and is normally grown using agroforestry systems which impact and decrease the planting densities (Abbott et al., 2018). Ecuador also produces a bulk or ordinary variety developed during the 1960s called CCN51 (Coleccion Castro Naranjo). CCN51 is considered as a high-yielding clone, more resistant to cocoa diseases, but with lower organoleptic quality (USDA Foreign Agricultural Service, 2015). CCN51 is grown by smallholders and also by much larger farms as a monocrop with little shade and relatively high planting densities (Abbott et al., 2018).

In addition, differences in disease susceptibility of diseases and planting patterns, plantation management differs for the Nacional and CCN-51 varieties. Nacional plantations tend to be far older than CCN-51 and are less intensively managed. Few Nacional farmers use fertilizer, pesticides, or irrigation, and trees are rarely pruned. Similarly, Nacional trees are much higher (as much as 10 meters in height) and broader than CCN-51 (Alwang, 2019). Differences in age and agronomic practices cause many Nacional plantations to produce more heterogeneous bean sizes, and more variability in the percentages of fermentation and moisture, when compared to CCN-51 (personal communications, James Quiroz¹², INIAP). The combination of higher

¹² James Quiroz is a senior cocoa researcher at INIAP who was part of the committee that reviewed and updated the INEN standards.

yields, partly due to lower disease pressure, and more homogeneous beans appears to give an economic advantage to the production of CCN-51 over Nacional, at least in markets that are more focused on physical rather than organoleptic characteristics.

Despite its inferior flavor and being considered as an ordinary cocoa, CCN51 represents an attractive alternative for farmers to increase their incomes due to its high productivity. According to some authors, it yields four times as much per hectare than the *Nacional* variety (Abbott, 2018; Nieburg, 2018), but recent studies have shown that after controlling for planting densities, yield differences only occur under non-irrigated systems. When better agronomic management practices are applied, including irrigation and pest and disease control, Amores et al. (2011) found no statistical yield differences between Nacional-type clones and the CCN51 variety.

Large-scale chocolate manufacturers who dominate purchases in international markets are less concerned about flavor than are gourmet chocolate producers. This lack of concern by industrial chocolate producers for fine cocoa is explained by the processing innovations allowing companies to preserve the taste of chocolate products despite the lower quality of the cocoa beans (ICCO, 2019). For these large manufacturers, the Ecuadorian CCN51 has adequate qualities to compete with bulk beans from other countries.

4.3.2. Post-Harvest Practices

Fermentation and drying are among the most popular post-harvest practices performed, as the cocoa beans need to be fermented and dried before being sold and shipped to processing companies. Carefully controlled fermentation and drying protocols are essential to obtain the

aroma and flavor notes of the cocoa beans. These post-harvest practices are commonly performed by cocoa farmers in most cocoa producing countries such as Cote d'Ivoire, Dominican Republic, Peru, etc. (Meemken et al., 2019; Hamrick and Fernandez-Stark, 2018; Nelson and Martin, 2013). Drying and fermenting cocoa beans represents a means of increased capture of value-added. Farmers also sell their beans without them being dried or fermented. This pulp-covered condition of the bean without been dried or fermented is known in Ecuador as *en baba*. When farmers sell their beans *en baba*, normally the cooperatives, collection centers, or intermediaries do the drying and fermentation. In some cases, intermediaries or manufacturers especially concerned with quality might seek to buy the beans *en baba* in order to take control of the fermentation and drying processes. This helps them ensure these practices are well performed and obtaining a specific quality they are not sure they could get from farmers.

Good application of post-harvest practices can improve the quality of the bean, regardless of variety (Schwan & Wheals, 2004; Jespersen et al., 2005; Camu et al., 2008). Likewise, poor control of post-harvest processing can ruin the flavor of even the best beans (Daniels et al., 2012). In Ecuador, fermentation and drying have attracted considerable interest, especially from *CCN51* producers as they can improve its presumed poorer flavor and aroma (Díaz et al., 2011; Eskes et al., 2012; Jentzsch et al., 2016; Hue et al., 2016).

Fermentation can be carried out in different ways, beginning with the wet beans being removed from the pods and then piled together in heaps, boxes or trays. This process requires careful control of factors that induce chemical changes in the beans that are key to developing the chocolate flavor and color. Immediately after fermentation, the beans are dried either in the sun or in mechanical dryers until moisture is reduced to approximately 7 per cent. Like in the

fermentation process, caution must be taken during drying to ensure that beans do not develop undesirable flavors. Sun drying predominates in Ecuador, especially among small-scale producers. Producers spread the fermented beans on mats, concrete floors or even on sides of roads, which might decrease their quality, as the beans are more exposed to contamination and unpredictable rains.

4.3.3. Prices and Premiums

Cocoa beans are traded at the London (NYSE LIFFE - GBP) and New York (ICE - USD) futures markets. Cocoa futures contracts are the benchmark for setting prices worldwide (World Cocoa Foundation, 2014). Like other agricultural commodities, cocoa price variations are determined by demand and supply forces. The international demand for cocoa has experienced sustained growth during the last decade due to population and income growth mainly driven by Asia and other emerging markets. Most of the bulk cocoa supply comes from West Africa, and global price fluctuations are driven by factors affecting this region of the world, including weather, crop diseases, labor shocks, logistics, etc. Political instability has also contributed to supply fluctuations. Price volatility is also influenced by speculation in futures markets.

The Ecuadorean fine variety ‘Nacional’ or ‘Arriba’ is assumed to receive higher prices in international markets. It is common for companies that buy fine cocoa to use their own pricing models, including floor prices and premiums in different ways. Aidenvironment (2018) reported a case study showing different pricing models for various types of fine and flavor cocoa during 2015. Examples of these pricing models included (i) fixed prices, (ii) New York market price plus a fixed quality premium of 300 USD per ton, and (iii) New York market price plus a minimum quality premium of 500 USD per ton.

Nonetheless, as discussed by Martin (2017), the lack of industry standards for defining fine cacao makes the availability and verifiability of specialty pricing data a challenge. Table 4-1 shows rough estimates for market prices of specialty cocoa presented by the International Cocoa Organization (ICCO) during a forum¹³ in 2015. To this day it represents the only officially collected data by the ICCO on specialty cocoa prices (Martin, 2017), and it is widely used by the international community for discussions about price premiums of specialty cocoa. According to this data, prices for the fine category have exceeded bulk prices for up to 2,000 USD per ton (more than 60% of the base price) and this difference is even larger for the case of the ultra-premium fine category.

Table 4-1. Cocoa Production and Prices During 2015

Cacao Type	Annual Production (tons)	Market Price (USD/ton)
Ultra-Premium Fine	12,000	5,000 – 10,000+
Fine	230,000	3,700 – 5,000
Bulk Certified	600,000	3,100 – 3,700
Bulk	3,200,000	3,000 – 3,500

Note: Data for Annual Production and Market Price from Martin (2017).

Bulk cocoa price series data are available for the London and New York futures markets, and the ICCO publishes monthly averages of these daily prices for bulk cocoa futures¹⁴. Figure 4-1 displays the ICCO prices for bulk cocoa futures, and producers' price for CCN51 and Nacional varieties in Ecuador, obtained from their Ministry of Agriculture (MAGAP). These prices represent cocoa beans that have already been fermented and dried. Although local producers' prices for CCN51 and Nacional cocoa varieties are not directly comparable to the

¹³ These statistics were cited by the ICCO Executive Director at the Foro Cacao in Nicaragua in November 2015 (Martin, 2017).

¹⁴ This average represents the quotations of the nearest three active futures trading months on ICE Futures Europe (London) and ICE Futures US (New York) at the time of London close (ICCO, 2019).

ICCO bulk cocoa futures prices, Figure 1 shows producers' price in Ecuador follow the future market trend. This highlights the importance and influence of cocoa futures contracts for price determination.

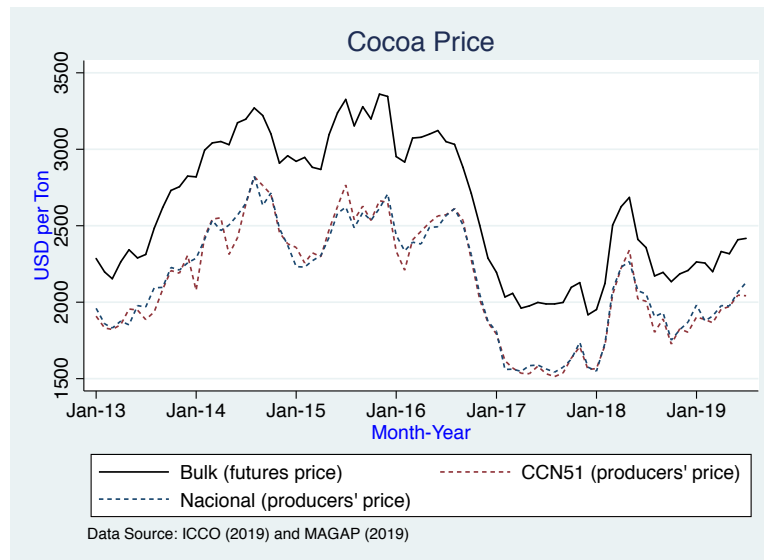


Figure 4-1. Cocoa monthly prices (Data Source: ICCO, 2019; MAGAP, 2019)

Moreover, given CCN51 is considered as a bulk type of cocoa, the gap between the producers' price of this variety and the ICCO price can be interpreted as the profit share of intermediaries and traders in the bulk cocoa value chain. Interestingly, according to this data provided by MAGAP, the differences among producers' price of CCN51 and Nacional are very small, and in some cases counterintuitive. During the last 7 years, average monthly price for Nacional has been of 2141 USD per ton, while for CCN51 it has been of 2130 USD per ton. This leaves a difference of merely 11 USD per ton (less than 1% of the price), among what are considered specialty and bulk cocoa varieties. In some months this difference increased to 210 USD per ton (about 10% of the price), but there were months where CCN51 received higher prices than Nacional by as much as 145 USD per ton. This evidence suggests specialty cocoa

price-premiums are not so evidently large among cocoa producers in Ecuador, especially when contrasted to the statistics provided by the ICCO reported in Table 4-1.

Regardless of variety, the cocoa harvest is spread over several months once or twice a year. The timing of the cocoa harvest depends on the climate and varies from country to country. The months when most of the crop is harvested are known as main-crop season, and the rest of the months are known as mid-crop season. The most pronounced differences in production between main and mid-crop harvests are found in Africa where the mid-crop accounts for about 15%-20% of the total harvest. In Ecuador, production differences between main and mid-crop harvests are not so obvious (ICCO, 2014).

Production seasonality might affect cocoa prices, especially if it comes from the largest producer countries. Nonetheless, as discussed by Bymolt et al. (2018), production seasonality does not affect international prices as no seasonal variation has been found in the reported cocoa producers' price of the main African producing countries. As Ghana and Cote d'Ivoire have marketing boards that set the producer price at the start of the season in October, seasonal variability there is nil. Ecuador has no marketing board and local prices are subject to international fluctuations (Aviles, 2017).

As Ecuadorean producers also sell unfermented and undried cocoa beans, we obtained data from MAGAP on producers' price of cocoa *en baba* according to the variety produced (Nacional and CCN51). Grouped by the type of post-harvest practice used, we estimated the difference between Nacional and CCN51 producers' price. On average, during the last 7 years, producers of the Nacional variety have received 100 USD per ton more than their CCN51 counterparts when the cocoa beans are sold *en baba*. Interestingly, this average difference gets

reduced to 11 USD per ton when the beans are sold fermented and dried (figure 4-2). It distinctly shows that when the cocoa beans are sold fermented and dried, varietal price differences are considerably reduced. Moreover, there have been periods where CCN51 prices exceed Nacional prices, particularly when sold fermented and dried. These raw estimates suggest that CCN51 producers receive larger premia than Nacional producers when performing post-harvest practices. This phenomenon raises two competing hypotheses: (i) CCN51 producers have access to better training or technologies to perform post-harvest practices and this affects the quality of the end product, or (ii) Ecuador markets are more oriented towards physical characteristics rather than organoleptic attributes.

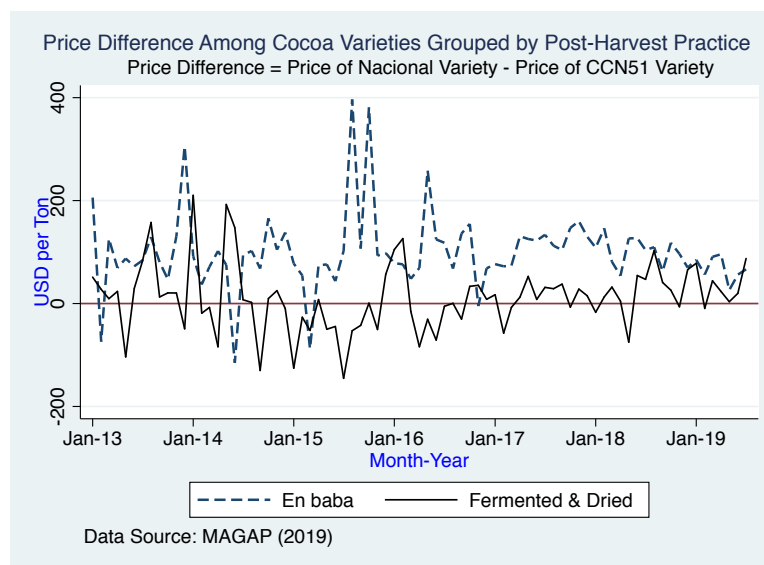


Figure 4-2. Monthly price difference of cocoa varieties (Data Source: MAGAP, 2019)

As discussed before, CCN51 trees produce more physically homogeneous beans and hence degrees of moisture and fermentation are more uniform after post-harvest practices. The extent to which this association between variety and postharvest practices influences the price is further explored in the next sections.

4.4. Data & Summary Statistics

4.4.1. Survey Description

The Department of Social and Economic Analysis of INIAP interviewed 386 cocoa farmers in 2018 from the province of Manabí, Ecuador –a highly representative cocoa region in Ecuador¹⁵. The sample was drawn to be representative of the province and the design was based on the province’s distribution of producers. The survey was enumerated in the field using tablet computers, and included questions on household demographics, farming and post-harvest practices, marketing, household borrowing, and sources of nonfarm income (Barrera et al., 2018).

Given the differences in attributes between producers of different varieties, we divide summary statistics by variety produced: (1) Farmers who produce cocoa from *Nacional* trees, and (2) Farmers who produce cocoa from *CCN51*. Data showed that 57% of the farmers in the sample were producers of *Nacional*, while 31% produced *CCN51*, and 12% grew both types of varieties¹⁶.

4.4.2. Household and Farm Characteristics

Table 2 shows producers of *Nacional* have about 10 years of additional experience producing cacao compared to those producing *CCN51*. Male household heads are more likely to be producing *CCN51*, as 92% of the *CCN51* producers are male compared to 85% of the

¹⁵ Manabí accounts for 20.8% of the national cocoa area planted, falling behind the province of Los Rios, which accounts for 21.2% (Corporación Financiera Nacional CFN, 2018).

¹⁶ In our sample, 40 farmers planted both varieties. These were dropped from the analysis as there were not enough observations for this category.

Nacional producers. About 34% of household heads who produce Nacional are members of a cacao-association while only about 5% of the CCN51 producers are members of an association. This indicate that most of the CCN51 producers market their cocoa beans individually, which might be associated with larger production volumes. As expected, more Nacional producers have received cocoa production training and have access to an extension agent when compared to CCN51 producers. This is due to the government efforts to expand Nacional production through the FFCRP.

Nacional producers have much older trees. The average Nacional tree is 23 years older than the CCN51 tree. There is no statistically significant difference in the total size of farm and the size of the cocoa lots between producers of the different varieties (Table 4-2). Average total holding size is 14 hectares, while the average size of the cacao lots is about 3.5 hectares regardless of the variety.

Typical farm cocoa beans production –already adjusted for moisture– is about 50% higher for CCN51 when compared to Nacional (2.70 tons vs 1.83 tons). When productivity is measured in a yield per hectare basis, CCN51 appears to yield twice as much as Nacional varieties (0.80 tons/ha vs 0.44 tons/ha). However, as discussed before, CCN51 is typically cultivated at higher densities. Our sample shows that on average CCN51 plantations have 25% more trees per hectare compared to Nacional plantations¹⁷. Taking into account planting densities, productivity measured in a yield per tree basis shows CCN51 trees produce only about 39% more cocoa beans than Nacional trees (0.82 kg/tree vs 0.59 kg/tree). The difference in planting densities among CCN51 and Nacional is driven by Nacional trees requiring protective

¹⁷ Average planting density of Nacional is close to a tree distance of 3m x 4m (833 trees/ha). Average planting density of CCN51 is close to a tree distance of 3m x 3m (1111 trees/ha).

shade for their correct development during the early years. This factor limits the planting density of Nacional varieties.

Other household and farm attributes do not vary significantly by variety and included household size, age of farmers, education, cellphone access, having an additional job, credit access, and time spent to arrive to the cocoa lot from the house (See Table A 4-1 of the Appendix). The non-significant difference in age of farmers across varieties accompanied by a significant difference in experience as cocoa producers, can be related to the damages caused by El Niño phenomenon at the end of the 90's. This indicates that Nacional cocoa producers turned to CCN51; producers of other popular crops grown in the coastal lowlands, including bananas and sugarcane, ventured into CCN51.

Table 4-2. Mean Values of Household and Farm Characteristics by Cocoa Variety Planted

Variable	Description of Variable	Variety		Obs.	p-Value
		Nacional	CCN51		
Household Characteristics					
Experience	Years of experience in cocoa farming	29.00	18.11	340	0.00
Gender	Gender of the head of household (Male = 1 and Female = 0)	0.85	0.92	340	0.07
Assoc. Membership	Head of HH is part of a producer's association (Yes = 1 and No = 0)	0.34	0.05	340	0.00
Cocoa Training	Household has received any cocoa production training (Yes = 1 and No = 0)	0.51	0.32	340	0.00
Access to Extension Agent	Household has access to an extension agent (Yes = 1 and No = 0)	0.32	0.21	340	0.04
Farm Characteristics					
Farm size	Total size of farm in hectares (ha)	14.40	14.53	340	0.97
Cocoa Trees Age	Age of the cocoa trees in years	29.33	6.66	340	0.00
Cocoa Area	Size of cocoa lot in hectares (ha)	3.81	3.40	340	0.49
Cocoa Production	Cocoa beans produced in tons (already adjusted for moisture) ^a	1.83	2.70	340	0.04
Planting Density	Planting density of cocoa trees (trees/ha)	814.79	1020.64	340	0.00
Production per Area	Cocoa beans produced per hectare (ton/ha)	0.44	0.80	340	0.00
Production per Tree	Cocoa beans produced per tree (kg/tree)	0.59	0.82	340	0.00

Notes: The p-value in the final column refers to the test of equality of outcomes by variety planted.

^a Cocoa production reported *en baba* was adjusted for moisture content in order to make it comparable to dried cocoa beans

4.4.3. Management and Post-Harvest Practices

Table 4-3 shows some crop management practices differs by variety planted. CCN51 producers are more likely to prune their trees and use fertilizers. The pruning result is particularly interesting since pruning is recommended as a disease-control measure for Nacional varieties, which are particularly vulnerable to the Witches broom and Frosty pod diseases. Having Manabí producers of Nacional who do not prune suggests either that the diseases are not highly prevalent in the province or that the producers are unaware of the disease-control benefits of pruning. Fertilization and pruning are generally viewed as good management practices and, as a result, yields are likely to be higher on CCN51 plantations. The higher prevalence of pruning CCN51 may be related to their smaller trees, but the difference (ten percentage points) is relatively small (Alwang, 2019).

The use of any type of certification is non-existent for CCN51 producers while 13% of Nacional farmers have some type of certification. The certification rate corresponds to higher membership in farmers' associations, some of which promote production of certified organic cocoa. Intercropping is also more common among Nacional producers (11% more), where the most common trees planted with cocoa being plantain and orange. This is related to Nacional trees requiring some protective shade for their correct development during the early years, hence motivating intercropping practices among producers of this variety. Intercropping also helps farmers with additional sources of income. In contrast, CCN51 –due to not needing shade for its development– is more densely planted, leaving little incentives for intercropping practices.

In terms of post-harvest processing, CCN51 producers are more likely to ferment and dry their cocoa beans compared to Nacional producers (80% vs 65%). Among drying technologies,

the use of concrete floors is most common for CCN51 producers. Lastly, use of other drying technologies, and the use of other farm management and post-harvest practices including irrigation, weed control, and claiming to know the factors affecting the quality of the harvested beans, does not vary significantly by variety type (See Table A 4-2 of the Appendix).

Table 4-3. Mean Values of On-Farm Management and Post-Harvest Practices by Cocoa Variety Planted.

Variable	Description of Variable	Variety		Obs.	p-Value
		Nacional	CCN51		
On-Farm Management Practices					
Pruning	Farmer prunes the cocoa plantation (Yes = 1 and No = 0)	0.71	0.81	340	0.05
Fertilization	Farmer applies fertilizers in the cocoa plantation (Yes = 1 and No = 0)	0.19	0.45	340	0.00
Any Certification	Farmer has any type of certification (Yes = 1 and No = 0)	0.13	0.00	340	0.00
Intercropping	Farmer intercroops cocoa trees (Yes = 1 and No = 0)	0.33	0.22	340	0.03
On-Farm Post-Harvest Practices					
Fermentation & Drying	Farmer ferments and dries cocoa (Yes = 1 and No = 0)	0.65	0.80	340	0.00

Notes: The p-value in the final column refers to the test of equality of outcomes by variety planted.

4.4.4. Marketing Practices

Table 4-4 shows CCN51 and Nacional farmers employ slightly different methods for marketing their products. CCN51 producers are slightly more likely to sell their beans at the farmgate (6% versus 2%) and to wholesaler warehouses (39% versus 28%) than Nacional producers. Conversely, selling the beans to associations and/or having a purchase contract is more common for Nacional producers. Nearly 26% of Nacional producers sell to associations compared to only 1% of CCN51 producers, which makes sense since few of them are members of associations. Nacional producers are much more likely to be part of cocoa associations, and these often require members to sell their production back to the association. In addition, Nacional

producers travel shorter distances to sell their beans compared to CCN51 producers (15 km vs 22 km), and this might be related to having lower transportation costs (about 50% less). Curiously, about equal percentages of Nacional and CCN51 farmers sell their beans at local markets and exporter warehouses, and also equal proportions claim to know the market price prior to selling their production (See Table A 4-3 of the Appendix).

Table 4-4. Mean Values of Marketing Practices by Cocoa Variety Produced.

Variable	Description of Variable	Variety		Obs.	p-Value
		Nacional	CCN51		
Marketing Practices					
Sell at Farmgate	Farmer sells cocoa beans at the farmgate (Yes = 1 and No = 0)	0.02	0.06	340	0.04
Sell to Assoc.	Farmer sells cocoa beans to an association (Yes = 1 and No = 0)	0.26	0.01	340	0.00
Use of Contract	Farmer sells cocoa beans under a contract (Yes = 1 and No = 0)	0.13	0.04	340	0.01
Distance to Buyer	Distance from cocoa farm to buyer in kms	14.94	21.63	340	0.07
Transportation Costs	Total transportation costs in USD	4.48	8.05	340	0.01

Notes: The p-value in the final column tests equality of outcomes by variety planted.

4.4.5. Prices Received

Respondents from 15 *cantones* (sublocations) across the province of Manabí reported the average price received for their cocoa during the time surveys were conducted (June-August of 2018). Average prices received by farmers for their cocoa beans at the different locations varied from 1,166 to 1,562 USD per ton (See Figure A 4-1 of the Appendix).

For further analysis, we also report in table 4-5 the producer's price grouped by varieties and post-harvest practices. Surprisingly, yet expected, there are not statistically significant premiums to Nacional found in the data. The average price per ton received by farmers for the CCN51 variety was 87 USD higher than that for Nacional cocoa (1485 vs 1398 USD/ton).

Average prices for the period between June to August of 2018 reported by MAGAP was of 1943 USD/ton for CCN51 and 2011 USD/ton for the case of Nacional. ICCO average price for bulk varieties was of 2313 USD/ton for that same period. Cocoa fermentation and drying adds on average 144 USD/ton to the price received. As discussed earlier, the survey data suggest that more than 2/3 of the total cocoa farmers in Manabí ferment and dry their cocoa. By type of variety, the use of fermentation and drying has a bigger impact for the price of the Nacional variety compared to CCN51 on average a premium of 156 USD/ton for Nacional producers compared to only 75 USD/ton for producers of CCN51.

Table 4-5. Mean Values of Cocoa Producers' Price (June-August 2018) Grouped by Variety and Post-harvest Practices in USD/ton.

Variety	Post-Harvest Practice		Total
	En baba	Fermented & Dried	
CCN51 (Ordinary Variety)	1425	1500	1485
Nacional (Premium Variety)	1297	1453	1398
Total	1327	1471	

Average farm gross income per hectare generated by cocoa activities is estimated to be about 1188 USD/year for CCN51 producers and 615.12 USD/year for Nacional producers. These summary statistics can be misleading in light of the many factors influencing cocoa prices received. In addition to varieties and post-harvest practices, geographic factors and farm management practices might also affect the quality and the price received by farmers, and these are explored next.

4.5. Empirical Strategy

4.5.1. Estimation of Varieties & Post-Harvest Effects on Prices Received by Farmers

To assess whether the specific variety and post-harvest practices affect the price received, we employ a set up where price outcomes are observed for the two cocoa varieties with and without the application of post-harvest practices. As discussed above, price premiums depend on the superior quality of the beans, including flavors and aromas. These flavors and aromas have been shown to be closely related to variety grown and post-harvest practices. In order to accurately estimate the effect of the variety and post-harvest practices use, additional factors influencing the price received by farmers were controlled for. With the observed cross section, the empirical model for the generic cocoa price per ton received by a farmer of any variety and post-harvest practice can be written as:

$$(1) \quad P_i = \alpha + \lambda V_j + \eta T_k + \delta(V_j \times T_k) + \gamma Q_i + \beta X_i + \psi W_i + \theta_l + \varepsilon_i$$

where P_i is the price per ton received by farmer i , producing cocoa variety j , performing post-harvest practice k . V_j is a binary variable equal to one for farmers producing Nacional cocoa. T_k is a binary variable equal to one to represent the case when a farmer ferments and dries the cocoa beans. $V_j \times T_k$ represents the interaction between the variety and post-harvest practices. The inclusion of $(V_j \times T_k)$ removes biases when comparing post-harvest practices effects between the *CCN51* and *Nacional* groups. Based on our data and given the superior flavor and aroma attributes of Nacional, we hypothesize that post-harvest practices have enhanced effects on this variety. These potential variety-specific post-harvest effects are captured by this interaction term.

The variable Q_i in equation (1) represents cocoa production, which according to respondents is equal to cocoa sales as there is no household consumption of the cocoa beans. $\mathbf{X}_i$ is the vector of farmer-level controls representing observable personal characteristics that may influence the price received by a farmer. These include age, gender, education, years of experience in cocoa farming, and ownership of a cellphone. $\mathbf{W}_i$ is a vector of farm management controls that represent observable agricultural related practices that may influence the quality of the cocoa beans and hence the price received. These include tree age, altitude of the farm, whether the farmer is aware of factors affecting quality, whether the farmer has any type of certification, whether farmer prunes, applies fertilizers, uses irrigation, or controls weeds. We also control for whether the farmer has received cocoa production training, has access to an extension agent, is part of a producer's association, and whether farmer intercropped the cocoa trees with other crops. Specifically controlling for any type of certification helps to isolate the price effect of the Nacional variety, as most producers with a certification in our sample grow Nacional trees, and the observed price might be the result of a specific variety-certification combination.

Manabí province was divided by INIAP into three major production zones: Coastal, Central, and Hillsides. The Coastal zone is comprised by the cantons (sublocations) of Jama, Pedernales, Sucre, and San Vicente. The Central zone is comprised by the cantons of Bolívar, Chone, El Carmen, Flavio Alfaro, Rocafuerte, Tosagua, and 24 de Mayo. The Hillside zone is comprised by cantons Junín, Pichincha, Portoviejo, and Santa Ana (See Figure A 4-1 of the Appendix). $\boldsymbol{\theta}_i$ is a vector of indicator variables that represent these three production zones fixed effects and ε_i is an error term with zero mean. Given we have 15 sublocations, for robustness we

report clustered standard errors at the sublocation level to account for intra-cluster correlation¹⁸ when estimating equation (1).

We also estimated an alternative specification of equation (1). Equation (2) add further variables related to the marketing practices, including: sales channels, use of contracts, whether farmer knows the market price before the sales, distance to buyer, and transportation costs:

$$(2) \quad P_i = \alpha + \lambda V_j + \eta T_k + \delta(V_j \times T_k) + \gamma Q_i + \beta \mathbf{X}_i + \psi \mathbf{W}_i + \varphi \mathbf{M}_i + \theta_l + \varepsilon_i$$

These variables are represented by vector $\mathbf{M}_i$ and might have an effect on the price received by a farmer but can also be affected by the price received. Due to the possible concerns of endogeneity, we treat this alternative regression as a robustness check, and exclude the possibly problematic regressors in equation (1) –the main regression.

4.5.2. An Instrumental Variable Approach

Including cocoa production as an independent variable in equation (1) creates problems as cocoa prices can both influence and be influenced by cocoa production. To tackle the endogeneity concern presented by this bi-directionality, we use an instrumental variable (IV) approach¹⁹. These IV approaches consist of a two-stage procedure. In the first stage, using equation (3) cocoa production Q_i is predicted by regressing the observations of this variable on all exogenous control variables and a vector of instruments $\mathbf{Z}_i$:

¹⁸ Clustering standard errors has limitations as its bias depends on the number of clusters instead of the number of observations. Other options to account for intra-cluster correlation include the Cameron, Gelbach, and Miller (2008) wild bootstrap procedure. We do not consider this method, as the number of clusters in this study is small.

¹⁹ Instrumental variable methods are generally applied in economics to address concerns related to endogeneity (Imbens and Wooldridge, 2009; Deaton, 2010)

$$(3) \quad Q_i = \alpha + \lambda V_j + \eta T_k + \delta(V_j \times T_k) + \beta X_i + \psi W_i + \tau Z_i + \theta_l + \mu_i$$

Z_i in equation (3) represents the vector of instruments that influence prices only through production, and thus can be excluded from the price equation (1). Our set of instruments included: number of days per week used to work at the cocoa farm, size of the cocoa lot in hectares, time required to get from the household to the cocoa lot in minutes, and number of people hired to work on the cocoa farm.

These variables are appropriate instruments²⁰ as their influence on the price received by cocoa farmers is assumed to come only through their effect on cocoa production. μ_i is the error term, and it is assumed to be independent and identically distributed. In the second stage, the predicted values for cocoa production $\hat{Q}_i$, obtained from the first stage are used instead of the observed values²¹ in the estimation of equation (1).

Using the estimated coefficients²² from equation (1), we can test specific hypotheses regarding cocoa price determinants, including variety types and post-harvest practices. Due to the common assumption that *Nacional* variety commands premiums in international markets, one might expect the production of this variety to positively affect the price received by local farmers. Likewise, by adding value to the raw beans, we expect the use of post-harvest practices to result in higher prices. If producing Nacional variety affects the price received by a farmer, then we will expect a significant result for λ , where $\lambda > 0$ if producing the *Nacional* variety controlling for post-harvest actions leads to higher prices, and $\lambda < 0$ if the advantage in price

²⁰ As discussed by Angrist and Krueger (2001), the ultimate choice of instruments should be based on economic intuition and theory.

²¹ This prevents the correlation of cocoa production and the error term ε_i .

²² All results were estimated using the IVREG commands and subcommands in Stata version 15.

received comes from producing *CCN51*. Likewise, if the exercise of post-harvest practices helps farmers receive better prices on average, then $\eta > 0$. Furthermore, if the combination of Nacional or CCN51 and post-harvest practices results in a price advantage, this effect will be captured by the coefficient δ . The coefficients λ and δ are of special interest for investigating how producing a specific variety and using post-harvest practices –especially fermentation to enhance the aroma and flavor– leads to better prices.

4.5.3. Identification Concerns

While we estimate the association between the type of cocoa variety produced and post-harvest practices with the price received by producers, we recognize potential sources of endogeneity that might cause our estimates to not be cleanly identified. These include simultaneity/bi-directionality, unobserved heterogeneity, and measurement error, all of which can bias our results.

As described in the previous section, simultaneity is handled using an IV approach to tackle the endogeneity concern caused by including the cacao production as a regressor in equation (1). Conditional on our identification strategy and related to this IV approach, we formally tested if the endogenous regressor Q_i is in fact exogenous²³. It can also be argued that some of the variables used as instruments can have an effect on the quality of the cocoa beans and hence on the price received by the cocoa farmers. Due to this, and given we have an overidentified model, we test the correlation between the instruments and the error term ε_i in the

²³ To test for this exogeneity assumption we used the Stata command ‘estat endogenous’. Given we clustered our standard errors, we report the Durbin (1954) and Wu–Hausman (Wu 1974; Hausman 1978) statistics. Results are shown in Table A 4-4 of the Appendix.

price regression²⁴. In the same fashion, we test for weak instruments to measure the relevance of the excluded exogenous variables as valid instruments and examined if the correlations between the endogenous variable Q_i and the instruments are not zero²⁵.

As in any empirical application, it is impossible to control for all factors and hence unobserved heterogeneity can be an important source of endogeneity in our study, creating bias in our estimates. For example, weather and geographical factors might affect the quality of the cocoa beans and hence the producer's price. For this purpose, we included indicator variables related to production zones in our main specification. These act as fixed effects, cleaning the error term of its correlation with the control variables in equation (1). We acknowledge there are various individual-level characteristics in the error term that could not be controlled for, including farmer risk preferences, bargaining power, trust, etc. These might be correlated with some of the variables of interest included in equation (1). For example, risk preferences may make farmers more willing to perform post-harvest practices, and at the same time they may also allow them to obtain better prices, which might lead to biased and inconsistent estimates of our parameter of interest.

We also argue that although measurement errors are plausible, these are minimized by the use of data collectors with expertise in the subject being studied. Data were collected by extension agents specialized in cocoa production from INIAP.

²⁴ To test for overidentifying restrictions we used the Stata command 'estat overid'. Given we clustered our standard errors, we report the Sargan's (1958) and Basman's (1960) score tests. Table A 4-4 of the Appendix.

²⁵ To test for weak instruments, we used the Stata command 'estat firststage' and reported the P-value of the F-statistic of the regression of all exogenous variables (including the instruments) on the endogenous variable (Stock et al., 2002). Results are shown in Table A 4-4 of the Appendix.

4.6. Results

4.6.1. Determinants of the Price Received by Cocoa Farmers

OLS results from the estimation of equation (1), and IV results are presented in Table 4-6. For these estimations we used the natural log of the dependent variable (price), and hence the estimated coefficients of the continuous variables can be interpreted as the percentage change in the price received by cocoa farmers caused by a one-unit change in the independent variable. In what follows, we mostly focus on our 2SLS IV specification (i.e., column 3 of Table 4-6) and on the estimated coefficients for variety, post-harvest practices, and its interaction.

Table 4-6. Regression Results: Estimates of Impacts of Varieties and Post-Harvest Practices on Mean Price Received by Cocoa Producers. Cocoa Production is an Endogenous Variable.

Variable	Model Specification		
	(1) OLS	(2) OLS†	(3) IV
Dependent Variable: Natural Log of Cocoa Price Received by Farmers (USD/Ton)			
Variety (Farmer uses Nacional = 1)	-0.067** (0.029)	-0.054* (0.028)	-0.064** (0.027)
Post-harvest Practices (Farmer ferments & dries = 1)	0.049 (0.030)	0.048 (0.029)	0.050* (0.027)
Interaction: Variety*Post-harvest Practices	0.040 (0.033)	0.032 (0.033)	0.038 (0.029)
Cocoa Production ^a (ton)	0.014*** (0.003)	0.013*** (0.003)	0.015*** (0.003)
Pruning (Farmer prunes the cocoa plantation = 1)	0.018 (0.011)	0.017* (0.008)	0.018* (0.010)
Weed Control (Farmer controls weeds in the cocoa plantation = 1)	0.030** (0.011)	0.026* (0.013)	0.029*** (0.010)
Farmer characteristics control variables	Yes	Yes	Yes
Farm management control variables	Yes	Yes	Yes
Marketing practices control variables	No	Yes	No
Production zones fixed effects	Yes	Yes	Yes
Cluster-robust standard errors	Yes	Yes	Yes
Observations	340	340	340

Notes: Asterisks *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors clustered at the canton (town/city) level in parenthesis. Complete regression results with all control variables are shown in Table A 4-4 of the Appendix. † Denotes regression in column 2 includes additional marketing practices control variables that might affect the price but also may cause endogeneity problems. ^a Denotes an instrumented value.

In line with the data shown in Figure 4-1, results in Table 4-6 show the production of the Nacional variety is associated with lower prices received. Production of the Nacional variety is associated with about a 6.6% decrease in the price received after controlling for factors such as post-harvest practices and production zones. The coefficient estimate is significant at the 5% level and shows that despite the common belief that Nacional cocoa commands higher prices than CCN51, its production is not rewarded by the market.

Controlling for the type of variety grown, producers who ferment and dry their cocoa beans receive, on average, higher prices than those who do not (about 5.1% higher), although this result is statistically significant only at the 10% level. Regarding our hypothesis of interest, these results indicate that producers of the Nacional variety do not receive price premiums when they sell their cocoa. They also hint that by fermenting and drying, farmers are able to add value and capture extra benefits from their cocoa production. Hence, by performing both practices farmers can place their cocoa beans in a better position in the value chain. Based on our sample, 30% of farmers do not perform post-harvest practices. This implies that only about two thirds of the farmers are capturing benefits from adding value in the value-chain. Overall, these patterns suggest markets in which there is a relatively weak transmission of price premiums to producers of specialty cocoa.

Turning to the next hypotheses of interest, regarding a superior price effect of post-harvest practices on the Nacional variety, we find that the estimated coefficient of the interaction term is positive, but not significant. This indicates that specific combinations of Nacional variety and post-harvest practices do not necessarily lead to higher premiums compared to their *CCN51* equivalents.

The estimated coefficient for quantity of cocoa production²⁶ is positive and statistically significant at the 1% test level. In aggregate terms, each additional ton of cocoa produced is associated with a 1.5% increase in the price received per ton of cocoa. It is widely discussed in the development literature that selling directly to formal markets is more likely to happen when the quantity sold is large and the market is close by (Fafchamps and Hill, 2005). This relation between quantity sold, distance to markets, and prices deserves further scrutiny for the case of cocoa producers.

Other statistically significant covariates included on-farm management practices of pruning and weed control, associated with an increase in the price received by farmers of 1.8% and 2.9% respectively. Pruning and weed control are essential for removing affected pods and preventing the spread of fungus related diseases including frosty pod and witch's broom. These practices improve the quality of the beans and hence the prices received by cocoa farmers. In addition, producers in the Hillside zone, receive significantly higher prices (about 3.5% higher) compared to Coastal zone producers (the omitted category) (See Table A 4-4 of the Appendix).

OLS results presented in column 1 and 2, lead to the same conclusions with regards to the use of the Nacional variety, cocoa production, and on-farm management practices. The use of post-harvest practices is not statistically significant for these model specifications. Moreover, after controlling for marketing practices, results show the use of contracts is statistically significant and positively associated with the price received by farmers. Farmers using contracts receive on average prices 3.5% higher than their counterparts without contracts. Not surprisingly, the estimated coefficient for transportation costs is positive and statistically significant, showing

²⁶ Cocoa production is an endogenous variable that was instrumented. According to respondents, cocoa production is equal to cocoa sales as there is not household consumption of the cocoa beans.

the correlation between distance traveled to market prices received (See Table A 4-4 of the Appendix).

The overall results obtained from the data are consistent with the increasing use and production of *CCN51* nationwide during the last decade as producing *Nacional* does not represent a clear advantage for the farmers. As discussed earlier, *CCN51* is more intensively managed, especially when it comes to pruning and fertilization applications. These crop management activities will likely increase the price received via yield effects, but they also increase production costs. The production costs differences among *CCN51* and *Nacional* are not explored in this article, neither the costs associated with the different post-harvest activities.

4.7. Discussion & Conclusions

The common belief that specialty cocoa varieties command price premiums in the markets, has shaped the policy choices aimed to promote the local cocoa sector in Ecuador. Efforts by the local government to promote cacao productivity have focused on the specialty variety *Nacional* and included actions to promote access to credits, inputs, and enhanced farm management practices.

Nonetheless, specialty cocoa farmers appear unable to capture the benefits of these variety-related price premiums. Using actual observations on farmer's behavior and prices received, we study the effects of producing *Nacional* and *CCN51* cocoa varieties in combination with use of the post-harvest practices fermentation and drying. We find that prices received by farmers for the specialty variety *Nacional* are not higher compared to those received by producers of the ordinary variety *CCN51*. We also find that farmers who ferment and dry their

beans after harvest, receive higher prices compared to those who do not perform post-harvest activities and sell their cocoa beans *en baba*. In line with the summary statistics of the data sample, the key coefficients in the various regression specifications are quite robust, both in terms of magnitude and statistical significance.

Our results provide evidence and contribute to understand cocoa markets in Ecuador. In the particular scenario analyzed in this article, promoting production of the *Nacional* variety based only on international and futures price premiums does not guarantee higher prices received for two main reasons summarized next. First, our results suggest that focusing on production of *Nacional* variety as means of distinguishing farmers as specialty cocoa producers ignores problems in the markets whereby price premiums fail to reach farmers. As discussed earlier, intermediaries, associations, and other buyers do not necessarily pay price premiums for the *Nacional* variety. Second, results show that only by performing fermentation and drying of the cocoa beans farmers are able to receive price premiums. As previously stated, access to technology and farmer expertise in post-harvest processes play important roles in the outcomes. These findings hint that at least some segments of the Ecuadorian cocoa market are focused on physical characteristics, rather than organoleptic attributes – the trademark of specialty cocoa varieties.

Premiums may accrue to the manufacturers or marketers of high-quality chocolate. This segment is what has been fast growing and it is probably now much bigger than the 12,000 tons stated in table 1. Nonetheless, this is still a very small share of the global cocoa market. Beyond the use of specialty varieties and good post-harvest practices, other efforts in the cocoa value chain that may earn premiums include (i) very careful chocolate manufacturing, and (ii) good

marketing strategies (that may use origin as a factor). As discussed in the introduction section, these premiums generally accrue to agents well along the value chain, and only in some instances to farmers.

This research is to our knowledge the first empirical study to directly assess the effects of variety and post-harvest practices on cocoa prices in local markets. More broadly, we contribute to the body of literature on the impact of post-harvest practices on bulk commodity value chains in developing countries. In our particular case, we showed that a combination of post-harvest practices is required if a cocoa farmer wants to receive extra benefits.

Findings presented here have implications for program interventions aimed at (i) increasing cocoa farmers revenue and income, and (ii) improving price transmission. The Ecuadorian cocoa program promoting the Nacional variety alone is misguided and can be improved by training farmers in more modern processing techniques, regardless of the variety produced. Results suggest that recommending to farmers that they perform both fermentation and drying practices may lead to substantial price responses irrespective of the variety grown. Training on post-harvest practices should complement actual program interventions, as it can help increase the impact of the FFCRP and benefit a larger segment of the cocoa farmers, not only Nacional producers. Farmers' associations can play important roles as facilitators of this training.

Farmers currently selling their beans *en baba* will likely need access to capital to invest in improved drying, and training in how to meet local moisture standards. Program interventions can also provide technical assistance to help farmers determine the most appropriate practices and factors to take into account when fermenting cocoa beans.

Because the total volume of cocoa production was significantly associated with better prices received, improvements in farm productivity will likely increase returns to cocoa farming. From a distributional point of view, if farmers receiving higher prices are large-scale producers, then policies focusing on increasing productivity, such as input subsidies, will overly benefit this group. Targeting program interventions to smaller-scale producers might reduce inequalities in the distribution of prices received by farmers.

In addition, this association between volume and better prices received might also indicate high transactions costs along the value chain, and hence buyers prioritizing and incentivizing large volume transactions. This suggests that the local markets are not competitive and that buyers may segment the market by volume. Moreover, this phenomenon raises the question of why do small-scale producers fail to associate and sell in volume? Our results suggest that association membership had a negative (but insignificant) impact on prices received (See Table A 4-4 of the Appendix). Further research on the impact of association or cooperative membership on the prices received by cocoa farmers needs to be conducted.

Regression results from equation (2) showed transaction costs incurred by farmers such as distance to buyer and transportation costs have minimal or no impact on the producers' price (See Table A 4-4 of the Appendix). Nonetheless, the research and results presented here did not address how price premiums are affected by transactions costs incurred by other members alongside the value chain. Research focusing on the effectiveness of the various links along the cocoa supply chain should complement these findings and discuss how they can contribute to raise the overall sector revenue and moreover small farmers' income. As our research focused

exclusively on producers' price received, we did not explore the possibility that premiums are diminished along the value chain by other costs including customs and logistics.

4.8. References

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4.9. Appendix

Cocoa Programs in the Dominican Republic and Perú

The Government of the Dominican Republic with the support of the United Nations Development Program (UNDP) launched in 2015 the National Cocoa Action Plan for the Sustainable Development, focused on the renovation of cocoa farms. The Government of Perú in collaboration with USAID and local private institutions, launched the Peru Cacao Alliance, focused on supporting smallholder farmers to leave illicit crops and plant cacao.

Table A 4-1. Mean Values of Household and Farm Characteristics by Cocoa Variety Planted.

Variable	Description of Variable	Variety		Obs.	p-Value
		Nacional	CCN51		
Household Characteristics					
Household Size	Total number of household members	3.68	3.50	340	0.36
Age (years)	Age of the head of the household in years	57.83	56.07	340	0.26
Education (years)	Education of the head of household in years	7.41	6.74	340	0.19
Experience (years)	Years of experience in cocoa farming	29.00	18.11	340	0.00
Gender	Gender of the head of household (Male = 1 and Female = 0)	0.85	0.92	340	0.07
Cellphone	Head of household owns cellphone (Yes = 1 and No = 0)	0.94	0.93	340	0.76
Additional Employment	Head of household has additional job outside his farm (Yes = 1 and No = 0)	0.23	0.16	340	0.15
Access to Credit	Head of household has access to credit (Yes = 1 and No = 0)	0.20	0.21	340	0.88
Association Membership	Head of household is part of a producer's association (Yes = 1 and No = 0)	0.34	0.05	340	0.00
Cocoa Training	Household has received any cocoa production training (Yes = 1 and No = 0)	0.51	0.32	340	0.00
Access to Extension Agent	Household has access to an extension agent (Yes = 1 and No = 0)	0.32	0.21	340	0.04
Farm Characteristics					
Farm size (ha)	Total size of farm in hectares	14.40	14.53	340	0.97
Time to Lot (minutes)	Time required to get from the household to the cocoa lot in minutes	7.05	4.74	340	0.37
Cocoa Trees Age (years)	Age of the cocoa trees in years	29.33	6.66	340	0.00
Cocoa Area (ha)	Size of cocoa lot in hectares	3.81	3.40	340	0.49
Cocoa Production (ton)	Cocoa beans produced in tons (already adjusted for moisture) ^a	1.83	2.70	340	0.04
Planting Density (tress/ha)	Planting density of cocoa trees in tree/ha	814.79	1020.64	340	0.00
Production per Area (ton/ha)	Cocoa beans produced per hectare (ton/ha)	0.44	0.80	340	0.00
Production per Tree (kg/tree)	Cocoa beans produced per tree (kg/tree)	0.59	0.82	340	0.00

Notes: The p-value in the final column refers to the test of equality of outcomes by variety planted. a Cocoa production reported *en baba* was adjusted for moisture content in order to make it comparable to dried cocoa beans.

Table A 4-2. Mean Values of On-Farm Management and Post-Harvest Practices by Cocoa Variety Produced.

Variable	Description of Variable	Variety		Obs.	p-Value
		Nacional	CCN51		
On-Farm Management Practices					
Pruning	Farmer prunes the cocoa plantation (Yes = 1 and No = 0)	0.71	0.81	340	0.05
Fertilization	Farmer applies fertilizers in the cocoa plantation (Yes = 1 and No = 0)	0.19	0.45	340	0.00
Irrigation	Farmer uses irrigation in the cocoa plantation (Yes = 1 and No = 0)	0.17	0.24	340	0.13
Weed Control	Farmer controls weeds in the cocoa plantation (Yes = 1 and No = 0)	0.90	0.94	340	0.25
Knowledge of Quality Factors	Farmer claims to know the factors affecting the quality of the cocoa beans (Yes = 1 and No = 0)	0.30	0.24	340	0.25
Any Certification	Farmer has any type of certification (Yes = 1 and No = 0)	0.13	0.00	340	0.00
Intercropping	Farmer intercroops the cocoa trees with other crops (Yes = 1 and No = 0)	0.33	0.22	340	0.03
On-Farm Post-Harvest Practices					
Fermentation & Drying	Farmer ferments and dries cocoa (Yes = 1 and No = 0)	0.65	0.80	340	0.00
Drying Technologies					
Wood Pallets	Farmer uses wood pallets to dry the cocoa beans (Yes = 1 and No = 0)	0.24	0.21	340	0.53
Concrete Floor	Farmer uses concrete floor to dry the cocoa beans (Yes = 1 and No = 0)	0.21	0.31	340	0.05
Roadside	Farmer uses the sides of the roads to dry the cocoa beans (Yes = 1 and No = 0)	0.02	0.03	340	0.88
Marquee	Farmer uses marquees to dry the cocoa beans (Yes = 1 and No = 0)	0.05	0.06	340	0.59
Plastic Canvas	Farmer uses plastic canvas to dry the cocoa beans (Yes = 1 and No = 0)	0.10	0.16	340	0.11

Notes: The p-value in the final column tests equality of outcomes by variety planted.

Table A 4-3. Mean Values of Marketing Practices by Cocoa Variety Produced.

Variable	Description of Variable	Variety		Obs.	p-Value
		Nacional	CCN51		
Marketing Practices					
Farmgate	Farmer sells cocoa beans at the farmgate (Yes = 1 and No = 0)	0.02	0.06	340	0.04
Local Market	Farmer sells cocoa beans at the local market (Yes = 1 and No = 0)	0.49	0.56	340	0.19
Wholesaler Warehouse	Farmer sells cocoa beans to a wholesaler warehouse (Yes = 1 and No = 0)	0.28	0.39	340	0.05
Exporter Warehouse	Farmer sells cocoa beans to an exporter warehouse (Yes = 1 and No = 0)	0.00	0.02	340	0.25
Sell to Association	Farmer sells cocoa beans to an association (Yes = 1 and No = 0)	0.26	0.01	340	0.00
Use of Contract	Farmer sells cocoa beans under a contract (Yes = 1 and No = 0)	0.13	0.04	340	0.01
Know Market Price	Farmer knows cocoa market price before sales (Yes = 1 and No = 0)	0.53	0.55	340	0.83
Distance to Buyer (km)	Distance from cocoa farm to buyer in kms	14.94	21.63	340	0.07
Transportation Costs (USD)	Total transportation costs in USD	4.48	8.05	340	0.01

Notes: The p-value in the final column tests equality of outcomes by variety planted.

Location Name	Average Price
24 de Mayo	1562
Bolívar	1354
Chone	1397
El Carmen	1473
Flavio Alfaro	1505
Jama	1452
Junín	1408
Pedernales	1326
Pichincha	1495
Portoviejo	1456
Rocafuerte	1320
San Vicente	1166
Santa Ana	1491
Sucre	1379
Tosagua	1293
Total	1428

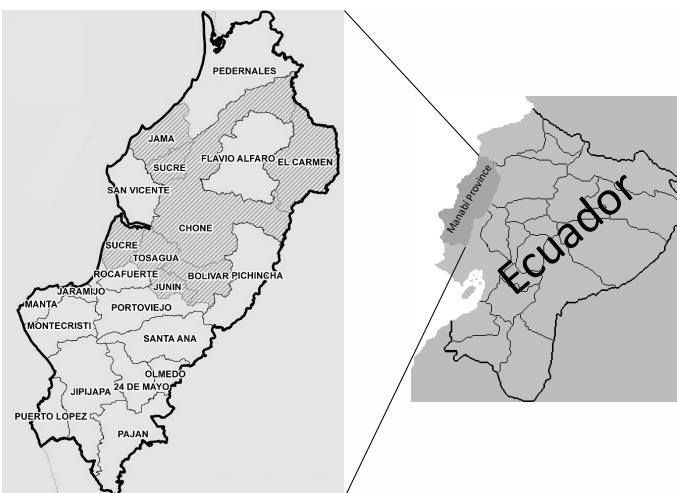


Figure A 4-1. Average price received by cocoa farmers in the province of Manabí, Ecuador (USD per Ton)

Table A 4-4. Regression Results: Estimates of Impacts of Varieties and Post-Harvest Practices on Mean Price Received by Cocoa Producers. Cocoa Production is an Endogenous Variable.

Variable	Model Specification		
	(1) OLS	(2) OLS†	(3) IV
Dependent Variable: Natural Log of Cocoa Price Received by Farmers (USD/Ton)			
Variety (Farmer uses Nacional = 1)	-0.067** (0.029)	-0.054* (0.028)	-0.064** (0.027)
Post-harvest Practices (Farmer ferments & dries = 1)	0.049 (0.030)	0.048 (0.029)	0.050* (0.027)
Interaction: Variety*Post-harvest Practices	0.040 (0.033)	0.032 (0.033)	0.038 (0.029)
Cocoa Production (ton) ^a	0.014*** (0.003)	0.013*** (0.003)	0.015*** (0.003)
Central Production Zone ^b = 1	0.012 (0.014)	0.024 (0.016)	0.011 (0.013)
Hillside Production Zone ^b = 1	0.034** (0.015)	0.049** (0.018)	0.034** (0.014)
Age (years)	-0.003 (0.002)	-0.003 (0.002)	-0.003 (0.002)
Age squared	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Gender of the Head of Household (Male = 1)	0.013 (0.014)	0.007 (0.015)	0.013 (0.012)

Notes: Asterisks *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors clustered at the canton (town/city) level in parenthesis. † Denotes regression in column 2 includes additional marketing practices control variables that might affect the price but also may cause endogeneity problems. ^a Denotes an instrumented value. ^b Coastal Production Zone is the omitted category. ^c Statistic reported is the P-value of the F-statistic of the regression of all exogenous variables on the endogenous variable.

Table A 4-4. (Continued)

Variable	Model Specification		
	(1) OLS	(2) OLS†	(3) IV
Dependent Variable: Natural Log of Cocoa Price Received by Farmers (USD/Ton)			
Education of the Head of Household in years	0.001 (0.001)	0.001 (0.001)	0.001* (0.001)
Experience (Years of experience in cocoa farming)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Cellphone (Head of household owns cellphone. Yes = 1)	0.002 (0.016)	-0.002 (0.018)	0.002 (0.015)
Knowledge of Quality Factors (Yes = 1)	-0.016 (0.018)	-0.020 (0.018)	-0.016 (0.016)
Any Certification (Farmer has any type of certification. Yes = 1)	0.017 (0.020)	0.012 (0.021)	0.017 (0.019)
Pruning (Farmer prunes the cocoa plantation. Yes = 1)	0.018 (0.011)	0.017* (0.008)	0.018* (0.010)
Fertilization (Farmer applies fertilizers in the cocoa plantation. Yes = 1)	0.012 (0.016)	0.014 (0.017)	0.011 (0.014)
Irrigation (Farmer uses irrigation in the cocoa plantation. Yes = 1)	0.000 (0.015)	-0.003 (0.013)	-0.000 (0.015)
Weed Control (Farmer controls weeds in the cocoa plantation. Yes = 1)	0.030** (0.011)	0.026* (0.013)	0.029*** (0.010)
Cocoa Trees Age (years)	0.001 (0.000)	0.001 (0.000)	0.001* (0.000)
Farm Altitude (meters)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)

Notes: Asterisks *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors clustered at the canton (town/city) level in parenthesis. † Denotes regression in column 2 includes additional marketing practices control variables that might affect the price but also may cause endogeneity problems. ^a Denotes an instrumented value. ^b Coastal Production Zone is the omitted category. ^c Statistic reported is the P-value of the F-statistic of the regression of all exogenous variables on the endogenous variable.

Table A 4-4. (Continued)

Variable	Model Specification		
	(1) OLS	(2) OLS†	(3) IV
Dependent Variable: Natural Log of Cocoa Price Received by Farmers (USD/Ton)			
Cocoa Training (Household has received any cocoa production training. Yes = 1)	0.003 (0.012)	0.000 (0.009)	0.002 (0.011)
Access to Extension Agent (Household has access to an extension agent. Yes = 1)	0.007 (0.007)	0.008 (0.007)	0.008 (0.006)
Association Membership (Head of household is part of a producer's association Yes = 1)	-0.015 (0.022)	-0.014 (0.025)	-0.016 (0.021)
Intercropping (Farmer intercroops the cocoa trees with other crops. Yes = 1)	-0.003 (0.015)	-0.006 (0.017)	-0.003 (0.014)
Farmgate (Farmer sells cocoa beans at the farmgate. Yes = 1)		-0.012 (0.037)	
Local Market (Farmer sells cocoa beans at the local market. Yes = 1)		-0.017 (0.020)	
Wholesaler Warehouse (Farmer sells cocoa beans to a wholesaler warehouse. Yes = 1)		-0.009 (0.019)	
Exporter Warehouse (Farmer sells cocoa beans to a exporter warehouse. Yes = 1)		0.019 (0.060)	
Sell to Association (Farmer sells cocoa beans to an association. Yes = 1)		-0.031 (0.022)	
Use of Contract (Farmer sells cocoa beans under a contract. Yes = 1)		0.034** (0.016)	
Know Market Price (Farmer knows cocoa market price before sales. Yes = 1)		0.015 (0.012)	

Notes: Asterisks *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors clustered at the canton (town/city) level in parenthesis. † Denotes regression in column 2 includes additional marketing practices control variables that might affect the price but also may cause endogeneity problems. ^a Denotes an instrumented value. ^b Coastal Production Zone is the omitted category. ^c Statistic reported is the P-value of the F-statistic of the regression of all exogenous variables on the endogenous variable.

Table A 4-4. (Continued)

Variable	Model Specification		
	(1) OLS	(2) OLS [†]	(3) IV
Dependent Variable: Natural Log of Cocoa Price Received by Farmers (USD/Ton)			
Distance to Buyer (km)		-0.000 (0.000)	
Transportation Costs (USD)		0.001* (0.001)	
Constant	7.211*** (0.092)	7.198*** (0.089)	7.213*** (0.084)
Observations	340	340	340
R-squared	0.421	0.442	0.420
Test of Exogeneity			
Durbin (P-value)			0.000
Wu-Hausman (P-value)			0.000
Test of Overidentifying Restrictions			
Sargan (P-value)			0.139
Basman (P-value)			0.162
Test of Weak Instruments ^c			0.000

Notes: Asterisks *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors clustered at the canton (town/city) level in parenthesis. [†] Denotes regression in column 2 includes additional marketing practices control variables that might affect the price but also may cause endogeneity problems. ^a Denotes an instrumented value. ^b Coastal Production Zone is the omitted category. ^c Statistic reported is the P-value of the F-statistic of the regression of all exogenous variables on the endogenous variable.

5. Manuscript 4: Linking Risk Preferences and Risk Perceptions of Climate Change Using Prospect Theory

5.1. Abstract

This article explores how farmers' risk preferences correlate with their risk perceptions of climate. To elicit and assess risk preferences, we use a Prospect Theory (PT) framework and a lab-in-the-field experiment with one the most vulnerable groups in the Latin American region, indigenous farmers of the Andes mountains. We find that farmers that behave in accordance to the assumptions of prospect theory, are more likely to show a greater risk perception of climate change, that is, they are more likely to perceive the risks associated with climate change as being more threatening at a personal level. Our results contribute to the understanding of farmers' behavior in developing countries. Moreover, given risk perception is a necessary prerequisite for adaptation, our results have important policy implications for the adoption process of new technologies aimed at mitigating effects of climate change (climate-smart agricultural technologies).

5.2. Introduction

The ability to categorize farmers based on behavioral attributes that have predictable technology-adoption implications is important in agricultural development. Risk preferences and risk perceptions are important examples of these behavioral attributes. Risk preferences refer to an individual's choice when faced with probabilistic events. Depending on how an individual evaluates the *riskiness* of the events, she may base her choice on the variance, the expected value, and/or the type of domain (losses or gains). These choices, in combination with an underlying utility function, will define an individual's risk attitudes i.e. risk seeking/risk averse,

loss averse, etc. Empirical studies documenting the importance of farmers' risk preferences on the technology adoption decision-making process include Feder (1980), Feder et al. (1985), Ghadim et al. (2005), Kallas et al. (2010), and Liu (2012).

Risk perceptions, defined as a decision maker's assessment of the risk inherent in a situation²⁷, are also important on the decision maker's behavior. Studies have shown that risk perceptions influence the assessment of uncertainty, and distort one's judgements, knowledge, and the ability to perform under risky conditions (Sitkin & Pablo, 1992). They are normally measured by asking about the perceived "seriousness", "concern" and/or "worry" of a situation. In the context of climate change (CC), risk perceptions have been shown to influence the adoption of new technologies. Arguing that risk perception is a necessary prerequisite for adaptation, studies have shown that farmers' CC risk perceptions influence the adoption of adaptation strategies aiming at mitigating the effects of local weather variability (Deressa et al., 2011; Hansen et al., 2004; Maddison, 2007; Mulenga et al., 2017; Silvestri et al., 2012). Thus, understanding farmers' CC risk perceptions and preferences, is of economic interest because of their implications on (i) the adoption process of new technologies aimed at mitigating effects of climate change (climate-smart agricultural technologies), and (ii) sustainable development of agriculture among smallholder farmers.

Climate change –defined as the systematic alteration of average climate conditions– is difficult for people to directly experience and perceive on a sensory level (Weber, 2010). This difficulty makes CC risk perceptions unique in the sense that not only the correct evaluation of

²⁷ This definition is consistent with previous work that has defined risk perceptions in terms of (a) the decision maker's labeling of situations, (b) probabilistic estimates of the extent and controllability of risks, and (c) confidence in those estimates (Sitkin & Pablo, 1992).

changes in long-term climate conditions plays a role on them, but also psychological related factors have been shown to influence them (van der Linden, 2017). Current research advances suggest that CC risk perceptions can be influenced by demographic, cognitive, experiential (affective), and socio-cultural characteristics (Helgeson et al., 2012; van der Linden, 2015; Xie et al., 2019).

To date, little has been researched on how risk preferences influence farmers' CC risk perceptions. Sitkin and Pablo's (1992) Model of the Determinants of Risk Behavior distinguishes between risk perceptions and risk preferences. They argue that people's inherent *risk preferences* first determine what they call the *risk propensity*, i.e., their observable level of risk aversion. Subsequently, people's *risk propensity* in combination with situational factors determines their *risk perceptions*. The objective of this paper is to explore this intersection between risk preferences and risk perceptions in the context of climate change.

Using a lab-in-the-field experiment and survey data from Ecuador, this paper elicits and assesses the risk preferences of smallholder farmers using a Prospect Theory (PT) framework. More importantly, this paper explores how elicited risk preferences correlate with climate change (i) as a perceived personal risk and (ii) as a perceived societal risk. Results show that the risk preference parameters elicited in the experiment were significantly related to the farmers' stated CC risk perceptions. Farmers that behaved in accordance to the assumptions of prospect theory were more likely to show a greater risk perception of climate change as a personal risk. In other words, these farmers were more likely to perceive the risks associated with climate change as being more threatening at a personal level.

The contribution of this paper is threefold. First, we extend the use of PT to measure farmers risk preferences to the Latin American region, by investigating one its most vulnerable groups, indigenous farmers in the Andes mountains. Previous PT studies with farmers have been mostly conducted in Asia and Africa. To the best knowledge of the authors, Galarza (2009) is the only existing study using PT with farmers in Latin America, but its target population was cotton farmers in coastal Peru. Second, we quantify the contribution that PT risk preference elements (i.e. loss aversion, and probability weighting) have to the perceived risks of climate change. Third, and perhaps most importantly, this research is among one of the first studies that examines how elicited risk preferences are related to climate change risk perceptions and weather phenomena.

Di Falco (2014) studies the impact of climatic conditions on Ethiopian farmers' risk preferences and explores if people exposed to more variable rainfall are more likely to display higher risk aversion. Using a modified version of the experimental design developed by Binswanger (1980), Di Falco estimates a binary indicator for risk aversion based on farmers choosing scenarios that qualify them as risk averse. He finds that farmer's exposure to more rainfall is negatively associated with the probability of observing risk aversion, while rainfall variability is positively correlated with this probability. Patt & Schröter (2008) studied why a program in Mozambique aimed at providing more information about climate change to farmers failed to change beliefs and adaptation practices. Using a qualitative approach, they found that farmers in the study area perceive climate-related risks to be less likely in the future than in the present. They conclude that dialog across stakeholder groups is a necessary condition for formulating policies related to adaptation to CC. Neither of these articles focuses on how risk

preferences influence risk perceptions of climate change directly, therefore, they did not attempt to address the research objective proposed in our study.

The remainder of this paper is organized as follows. Section II provides background on climate change, environmental conditions and agricultural practices found in the study area and then discusses the survey, the data and presents some descriptive statistics. Section III describes the conceptual framework and experimental design used to elicit risk parameters. It also discusses the use of Prospect Theory as a concept that helps explain farmers' CC risk perceptions. Section IV presents the empirical framework used to model the determinants of CC risk perceptions and discusses how risk preferences should influence these risk perceptions. It also discusses how we approached societal vs. personal risk judgements. Section V presents first a descriptive analysis of the results from the field experiment and examines how demographic and socio-economic characteristics are correlated with the elicited risk preferences. It then presents the estimation results of our empirical model of risk perceptions and discuss their implications. In section VI, we summarize our main findings, conclude and discuss the limitations of our approach as well as directions for future research.

5.3. Background, Data, and Descriptive Statistics

5.3.1. Ecuador and Climate Change in its Andes Region

Ecuador represents a prime location for research on adaptation to climate change by small-scale farmers as studies have shown that countries around the equator will be most severely affected by climate change (King & Harrington, 2018). The Andes Region of Ecuador is undergoing sustained increases in temperature and precipitation changes that are the results of progressing climate change (Peters et al., 2013). Recent studies using temperature time series

have shown a significant warming trend of $0.13^{\circ}\text{C}/\text{decade}$ over the past 61 years²⁸ (1950–2010). Elevation plays a significant role as higher elevations have experienced more severe temperature increases (Vuille et al., 2015). Personal exposure to temperature increases and to the occurrence of extreme weather events, play a key role in forming mental constructs. Although the impact of temperature increases on mental constructs is not directly testable, their effect on farmers' risk perceptions may vary depending on the individuals' characteristics. For example, temperature increases, which have been constant but relatively modest, might be imperceptible to relatively young farmers, who have not been exposed long enough in comparison to older farmers.

In addition, increasingly variable rainfall from 1966–2011 has been observed in the region. This variability is linked to the El Niño Southern Oscillation, which is related to climate change and other anomalies in surface air pressure over the Pacific Ocean (Morán-Tejeda et al., 2016). This increasing variability of rainfall intensifies both drought and excessive rains.

Ecuador's glaciers, all located in the Andes mountains, are uniquely threatened by the phenomena described above. Climate change is causing glaciers to recede, in turn threatening the livelihoods of Andean residents (Chevallier et al., 2011). This glacier reduction, in combination with reduced precipitation and increased evapotranspiration, will generate a decrease in the availability of water for food production and other uses in the tropical Andes. Likewise, heavy rainfall²⁹ will have negative consequences for agriculture, as it will worsen erosion, increase runoff with loss of available water, and cause damages to crop production.

²⁸ This is slightly above the global mean warming rate of $0.12^{\circ}\text{C}/\text{decade}$ between 1951 and 2012 (Stocker et al., 2013)

²⁹ Rainfall will increase by approximately 7% for each degree Celsius of temperature increase (CEPAL, 2016)

The combination of these factors has been said that will produce movements -in altitude and latitude- in the optimal areas for the cultivation of important crops including potatoes and corn, among others (CEPAL, 2016). Moreover, climate change will affect not only crop yields, but also local economies and food security in the Andean region (FAO, 2016). Weather extremes—in terms of shocks in both temperature and precipitation— can reduce crop production and exacerbate the year-to-year fluctuations of food availability. In turn, this can increase price volatility and cause adverse impacts on poor consumers. This output price volatility, that can be considered as a signal of risk to producers, can further reduce the supply of agricultural staple crops. Thus, combating climate change using mitigation and adaptation technologies is, therefore, crucial for the food security of the region (Haile et al., 2017).

Ecuador is among the countries whose agricultural sectors could suffer the greatest impacts, due to its economic dependence on agriculture, the low adaptive capacity of its population, and its geographical location. Because of these pronounced threats of climate change to the Andean region it is important to understand how Andean farmers perceive risks associated with climate change, which is the main objective of this paper.

5.3.2. Study Area and Survey

During summer 2019, we partnered with the Ecuadorian Institute of Agricultural Research (INIAP), a government research institute, to conduct our study in four indigenous villages located in the Chimborazo province. The selected villages were Balcashi, Llucud, Puculpala, and Puelazo. Farming in these villages is mostly comprised by pasture-potato-corn rotations, and dairy production. In addition to climate change, heavy erosion –caused mainly by intensive tillage– is an increasing threat to agricultural production in these areas. INIAP is

currently promoting a small pilot of an extension program in these villages that will look to encourage the adoption of conservation agriculture practices. With the aim of mitigating the effects of climate change, as well as conserving soil and improving soil health and productivity, conservation agriculture practices promoted in the zone include the use of reduced or minimum tillage, maintenance of soil cover, and adoption of improved crop rotations³⁰. This pilot program also started in summer 2019.

These villages are on average 45 minutes away from the city of Riobamba, the closest city and capital of Chimborazo Province. Populations ranged from 264 to 512 people in these villages. According to government statistics, 52% of the population are women and 48% are men (Gobierno Autónomo Descentralizado Parroquial Rural Quimiag, 2015). On average, family income in these villages is generated by two people per family. Elevation varies between 3,000 to 4,500 meters above the sea level, annual precipitation varies between 500 to 2,000 millimeters, and average temperatures over the year vary between 12 to 20 Celsius degrees.

In these villages we conducted a lab-in-the field experiment to elicit individual risk preferences of 202 farmers. Following participation in our experiment, farmers were questioned about household and individual characteristics. The study team was in charge of the administration and execution of the experiment and survey, while INIAP scientists provided organization and logistics. Experiments started approximately at 6 P.M. and lasted about two and one-half hours. Before running the experiments and surveys, we met with members and leaders of each of the villages to ask for their cooperation and help in recruiting subjects for our risk

³⁰ Results of a global meta-analysis performed by Pittelkow et al. (2015) show no-till in combination with soil cover and crop rotations significantly increases rainfed crop productivity in dry climates, suggesting conservation agriculture may become an important climate-change adaptation strategy for ever-drier regions of the world.

experiment. Meeting dates, times, and locations were announced several times by the village leaders during different days. During these announcements, farmers were summoned to attend a regular village assembly and to be part of a study conducted by INIAP. Farmers were also told they will receive a monetary compensation for their participation in the study. These announcements were done using the public communications system—village-specific megaphones.

5.3.3. Data Description

Summary statistics are shown in table 5-1 for the main variables of interest. The average participant of our study is about 44 years old, has finished elementary school, earns between 0 to 300 USD/month, and owns around 1.82 hectares of farmland. Most have access to irrigation and own dairy cattle (89% and 88% respectively). Although not tested in this study, one can argue that access to irrigation affects risk perceptions of climate change, as irrigation makes rainfalls less important for plant growth. When asked if they have heard or know about climate change, all the participants indicated that they have³¹.

The high proportion of women among our participants (55%) aligns with the demographic characteristics of the area described above³². Moreover, the high female participation in our study reflects the gender relations of indigenous farming communities in the Ecuadorean Andes. Women and men in these communities control the means and earnings of the

³¹ For a complete description of the questionnaire used in this study see Figures A 5-1 and A 5-2 of the Appendix.

³² According to Gray (2009), this gender imbalance in the Ecuadorean Andes might be explained by the fact that relative to men, women are less likely to be international migrants.

agricultural production in an egalitarian manner, and there is a balance of power between wife and husband (Hamilton, 1998).

Table 5-1. Summary Statistics: Characteristics of Participants in Risk Game

Variable	Description	Mean	Std. Dev.
Age	Age in years	43.70	16.04
Female	Gender dummy = 1 if Female, 0 otherwise	0.55	0.50
Education	Education level. Ordinal:	2.54	1.38
= 0	if never attended school	0.05	-
= 1	if attended some elementary school	0.13	-
= 2	if finished elementary school	0.46	-
= 3	if attended some high school	0.05	-
= 4	if finished high school	0.23	-
= 5	if attended some college	0.05	-
= 6	if finished college	0.03	-
Children	Number of children in the household	1.12	1.23
Household Size	Number of household members	3.80	1.72
Area	Area of total farming land (hectares)	1.82	2.08
Distance	Distance of farm to nearest commercial road (meters)	291.55	631.20
Rent	Dummy = 1 if respondent rents farming land	0.12	0.33
Nonfarm Employment	Dummy = 1 if respondent has nonfarm employment	0.25	0.44
Income	Income derived from farm and nonfarm activities. Ordinal.	1.93	1.09
= 1	if 0 - 300 USD/month	0.45	-
= 2	if 301 - 600 USD/month	0.30	-
= 3	if 601 - 900 USD/month	0.14	-
= 4	if 901 - 1,500 USD/month	0.08	-
= 5	if > 1,500 USD/month	0.03	-
Irrigation	Dummy = 1 if respondent has access to irrigation system	0.89	0.31
Extension	Dummy = 1 if respondent has been visited by extension agent during the last year	0.16	0.37
Livestock	Dummy = 1 if respondent has dairy cattle	0.88	0.32
Observations	Total number of participants	202	

5.4. Conceptual Framework

In the psychology literature, perception refers to the *process* of receiving information and stimuli from one's surroundings and converting them into psychological responses (Garner et al., 1956). The perception of risk is, therefore, a mental construct (Sjöberg, 2000) that distinguishes

between the existence of objective real-world threats, and the subjective evaluation of those threats (Rosa, 2003; van der Linden, 2017). This is why risk perceptions of climate change can vary greatly among individuals; for example, although actual changes in temperatures and rainfall patterns in some locations are inexistent, farmers in some studies report perceiving climatic change (Bryan et al., 2009; Deressa et al., 2009; Krah et al., 2019; Roco et al., 2015; Uddin et al., 2017). This subjective psychological component of risk perceptions, combined with social and cultural characteristics, contributes to the observed heterogeneity of climate change risk perceptions. Various studies have found differences between and within countries, where the perceived risk associated with climate change is greater in most of the developing world when compared to the developed world. Political, cultural, and geographic factors have been identified to shape these differences, and thus analysis of CC risk perceptions have been recommended to be conducted for each country separately (Lee et al., 2015; Leiserowitz, 2007; Tranter, 2013).

Climate change as an objective real-world threat, is learned by people through personal experience and/or statistical description³³. Personal experience refers to the assessment of stimuli from one's surroundings such as extreme weather events, increases in temperatures, flooding, etc., while statistical information is related to the assessment of information on precipitations, news reports, etc. Studies have shown that personal experiences have a stronger influence on CC perceptions compared to statistical description, even though the latter is generally more reliable (Erev & Barron, 2005; Hertwig et al., 2004). Weber (2010) argues that nonscientist and most of the population rely more on personal experience and in cases where it disagrees with statistical information, personal experience usually prevails, because it comes in faster and is more vivid.

³³ In the realm of psychology this refers as to how individuals process information, namely (a) associative processing and (b) analytic processing (Chaiken & Trope, 1999; Epstein, 1994; Sloman, 1996).

Existing models of risk perceptions of climate change are mainly defined using four key determinants: socio-demographic, cognitive, experiential and socio-cultural factors (e.g., Helgeson et al., 2012; van der Linden, 2015). While these studies combine different theoretical views into a comprehensive set of key psychological determinants, little or no attention has been given to the role of risk preferences on risk perceptions. Risk preferences are important as existing theory on risk behavior indicates that risk preferences have an effect on risk perceptions through what is called “the decision maker’s risk propensity” (Sitkin & Pablo, 1992). In their *Model of the Determinants of Risk Behavior*, Sitkin and Pablo (1992) argue that risk preferences alone do not determine specific risk behaviors, but rather they affect what is called the *risk propensity* of a person. Subsequently *risk propensity* in combination with social and other situational factors determines people’s *risk perceptions*. Ultimately, *risk propensity* and *risk perceptions* determine an individual’s risk behavior (see figure 5-1). The causal relationship between risk preferences and *risk perceptions*, operationalized through *risk propensity* in the context of climate change, is the main focus of this paper.

Risk propensity is the general likelihood or tendency of a person to i.e. either take or avoid risks. Weber and Milliman (1997), discuss that in the context of a lab experiment, the risk propensity is revealed by the shape of an underlying utility function. Moreover, Sitkin and Pablo argue that risk propensity is not conceptualized as a stable trait of an individual, but rather it is dynamic and depends not only on risk preferences, but also on the inertia of the decision maker and the outcomes of prior risky decisions (history). The use of this conceptualization of risk behavior –proposed by Sitkin and Pablo (1992)– is motivated by the observation that studies, more often than not, do not offer a causal mechanism to explain how risk preferences are

translated into risk behavior, and commonly use risk preferences as a direct determinant of risk behavior.

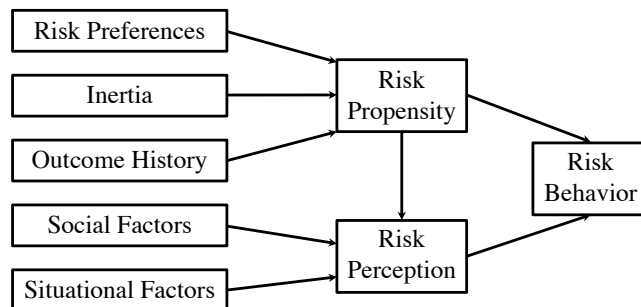


Figure 5-1. Model of the determinants of risk behavior (Sitkin and Pablo, 1992)

In the experimental literature, individual risk preferences are derived from people's choices over gambles or lotteries³⁴. In the economics literature, the most prominent framework for the conceptualization and analysis of risk preferences (i.e. the way the risk propensity is revealed) is expected utility theory (EU). In EU, the shape of the utility function describes the risk preferences of an individual, e.g., a convex utility function reflects a risk-seeking individual, while a risk-averse individual's utility function is concave. Although the use of EU is extensive in experimental studies, individual choices in conditions of low, imprecise or multiple probabilities have been shown, empirically and experimentally, to be inconsistent with a single probability distribution, as generally assumed by EU (Lange, 2003; Lange & Treich, 2008). In this context, climate change is a particular example that involves imprecise and/or low probabilities, and hence, the applicability of EU to relate to climate change phenomena could be inadequate.

³⁴ Early studies elicited these risk preferences using standard household surveys (Antle, 1987; Moscardi & de Janvry, 1977), but since the revolutionary work of Binswanger (1980), the use of experimental methods—that normally employ lotteries with different expected payoffs and variance—has become the standard practice to elicit risk preferences.

Prospect theory (PT) (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992) is an alternative paradigm used to describe risk preferences. In PT, individual risk preferences are not only described by risk aversion, but also by loss aversion, and nonlinear probability weighting. Loss aversion reflects the sensitivity of changes in well-being to loss compared to gain, or the idea the idea that people are more sensitive to losses than to gains of the same magnitude. Loss aversion is produced by making the underlying value function steeper in the region of losses than in the region of gains. Nonlinear probability weighting refers to the individual tendency of overweighting low probabilities and underweighting high probabilities. This leads to overweighting the tails of any distribution.

PT is better than EU to conceptualize risk preferences and relate them³⁵ to farmers' CC risk perceptions for two main reasons. First, in contrast to EU, PT accounts for loss aversion and its strong implications with respect to the concept of status quo bias³⁶ (Kahneman et al., 1991; Kahneman & Tversky, 1984; Samuelson & Zeckhauser, 1988; Thaler, 1980). Status quo bias in the context of climate change could offer explanations for disregarding the effects of climate change, simply because an individual has a strong tendency to remain at the status quo³⁷. Second, and more importantly, while EU weights outcomes by their objective probability, PT offers a theoretical framework that allows for probability distortion. Rare and extreme weather events – that are signals of climate change– have a low probability of occurrence. Previous studies have shown that when low-probability events do occur, they have a stronger impact on related

³⁵ In the jargon of Sitking and Pablo (1992), this would be equivalent to “reveal an individual’s risk propensity”.

³⁶ An important implication of loss aversion is that individuals have a strong tendency to remain at the status quo, because the disadvantages of leaving it loom larger than advantages (Kahneman et al., 1991).

³⁷ Jost and Hunyady (2016), argue that in addition to status quo bias, system justification theory also explains why some people also adopt motivated perceptions to view the current system as stable, fair, and/or legitimate, even when the system may be disadvantageous to others.

decisions than justified by their probability (Yechiam et al., 2005). In other words, even though frosts, flooding, or droughts are events that have an objective low probability of occurrence, if farmers experience any of these, they will likely overweight the probability of occurrence of that event after it happened. In addition, these events also lead to crop damages and therefore economic losses, which can have a further compound behavioral implication. The economic losses will reinforce the negative outcome of the low probability event, hence promoting further the probability distortion, and at the same time they will impact the sensitivity to losses of an individual. Therefore, the theoretical framework of PT could transmit and relate these behavioral phenomena to the farmers' CC risk perception.

5.4.1. Prospect Theory

Formally, prospect theory as proposed by Tversky & Kahneman (1992), is expressed in the context of a gamble:

$$(x_{-m}, p_{-m}; x_{-m+1}, p_{-m+1}; \dots; x_0, p_0; \dots; x_{n-1}, p_{n-1}; x_n, p_n) \quad (1).$$

Which is evaluated as:

$$\sum_{i=-m}^n \pi_i v(x_i) \quad (2).$$

Here x_i is a gain (or loss) that occurs with probability p_i ; outcomes are arranged in increasing order such that $x_i < x_j$ for $i < j$ and $x_0 = 0$; $v(\cdot)$ is the value function and it is an increasing function with $v(0) = 0$; π_i are decision weights.

For our study, we assume that agents behave in accordance to the assumptions of cumulative prospect theory. Therefore, a farmer's utility is defined as follows:

$$PT(x, p; y, 1 - p) = \begin{cases} v(y) + w(p)[v(x) - v(y)] & x > y > 0 \text{ or } x < y < 0 \\ w(p)v(x) + w(1 - p)v(y) & x < 0 < y \end{cases} \quad (3).$$

$PT(x, p; y, 1 - p)$ is the expected value over binary prospects $(x; y)$, with corresponding probabilities $(p; 1 - p)$. Moreover, $v(x)$ is defined as a piecewise power function that assigns different values for gains $(x > 0)$ and losses $(x < 0)$, such that:

$$v(x) = \begin{cases} x^\sigma & x \geq 0 \\ -\lambda(-x)^\sigma & x < 0 \end{cases} \quad (4).$$

σ determines the curvature or concavity of the value function for gains and losses and is the proxy for risk aversion. The individual is described as risk loving if $\sigma > 1$, risk neutral if $\sigma = 1$, and risk averse if $\sigma < 1$. λ describes the curvature below 0 relative to the curvature above 0 and reflects the degree of loss aversion. The agent is said to be more sensitive to losses than to gains when $\lambda > 1$, and respectively less sensitive to losses than to gains when $\lambda < 1$. The usual empirical finding is, $\sigma < 1$ along with $\lambda > 1$, that is the agent is risk averse and more sensitive to losses than to gains (Bocquého et al., 2014).

The function $w(\cdot)$ represents probability weighting. We use the axiomatically derived weighting function of Prelec (1998) as follows:

$$w(p) = \frac{1}{[\exp(\ln(1/p))]^\alpha} \quad (5).$$

α is the parameter that determines the curvature of the probability weighting function. If $\alpha = 1$, the probability weighting function $w(p)$ is linear and the agent has no probability distortion; that is, the agent correctly assesses given probability information. If $\alpha < 1$, $w(p)$ departs from linear probability weighting and turns to an “inverted S-shape”, that is an agent will overweight small probabilities and underweight large probabilities as shown by Tversky & Kahneman (1992). If $\alpha > 1$, $w(p)$ turns to a less conventional “S-shape”, that is an agent will underweight small probabilities and overweight large probabilities. The usual expected finding is $\alpha < 1$, that is the agent will overweight small probabilities and underweight large probabilities. This model of Prospect Theory reduces to Expected Utility when $\alpha = 1$ and $\lambda = 1$.

As previously argued, PT probability weighting and loss aversion relate closely to climate change and its behavioral implications. They account for status quo bias, the overweighting of low-probability extreme weather events, and the further behavioral implications of economic losses caused by climate-related crop damages. Therefore, although not exhaustively, PT parameters can help explain farmers’ CC risk perceptions better than EU, as EU just elicits risk aversion, the only parameter in its value function. While the roles of risk aversion, loss aversion and probability weighting on farmers’ risk perceptions of climate change have not been formally tested, many studies have explored the role of these PT risk parameters in other agricultural settings (Bocquého et al., 2014; Liebenehm & Waibel, 2014; Liu, 2012; Tanaka et al., 2010).

5.4.2. Experimental Design and Procedure

We use the experimental design of Tanaka et al. (2010) to elicit PT risk preference parameters. This design estimates three parameters of a prospect theory model³⁸ –risk aversion, loss aversion, and nonlinear probability weighting. During the last decade, this design has been tested with farmers in developing countries including Vietnam, China, Mali, and Burkina Faso.

This design consists of three independent series, each series contains a succession of paired lotteries arranged in the form of rows. Each row shows the monetary outcome for Lottery A (safe option) and Lottery B (risky option), where the probabilities of the outcomes in both lotteries are fixed throughout the series. All outcomes in the first two series are positive, and are organized such that at the beginning the expected value of lottery A is higher than that of B, but as one proceeds down the rows, eventually the expected value of lottery B exceeds that of A. In the third series, payoffs are positive and negative. Monotonic switching is enforced by asking participants at which row they would "switch" from Lottery A to Lottery B in each series, that is they cannot switch back and forth within one series³⁹. Participants, however, could switch to Lottery B at the first question or they could stay with Lottery A throughout.

To ease the understanding of these lotteries and probabilities for our participants, we adapted the lotteries to an agricultural illustration. The probabilities and payoffs were explained to participants by illustrating a farm composed of 10 lots. All lots are equally sized and a lot's particular payoff from using either Seed A or Seed B is shown. Participants were told that due to

³⁸ This design also allows to determine whether EU fits the data better, as it allows the estimation of an empirical specification of EU.

³⁹ These are adaptations of Holt & Laury's (2002) multiple price lists. See Tanaka et al. (2010) and Liu (2012) for further details of the experimental design and the game's entire payoff matrix.

climatic events, at the end of each year only one random lot out of the ten would survive. To enforce monotonic switching we asked participants at which year (row) they would "switch" from Seed A to Seed B in each series.

Figure 5-2 shows how series 1, rows 1 and 2, of table 2 in Tanaka et al. (2010) were adapted for our study and presented to participants⁴⁰. Our illustration implicitly shows that seed A in year 2020 offers a 30% chance of receiving 40 USD and a 70% chance of receiving 10 USD, while seed B in the same year offers a 10% chance of receiving 68 USD and 90% chance of receiving 5 USD. This illustration is used to tackle one of the main disadvantages of eliciting risk parameters using complex methods, which is that of subjects failing to understand the procedures and the concepts of probability (Charness et al., 2013). This disadvantage may be amplified in such field studies where subjects are farmers in a developing country with relatively low levels of education.

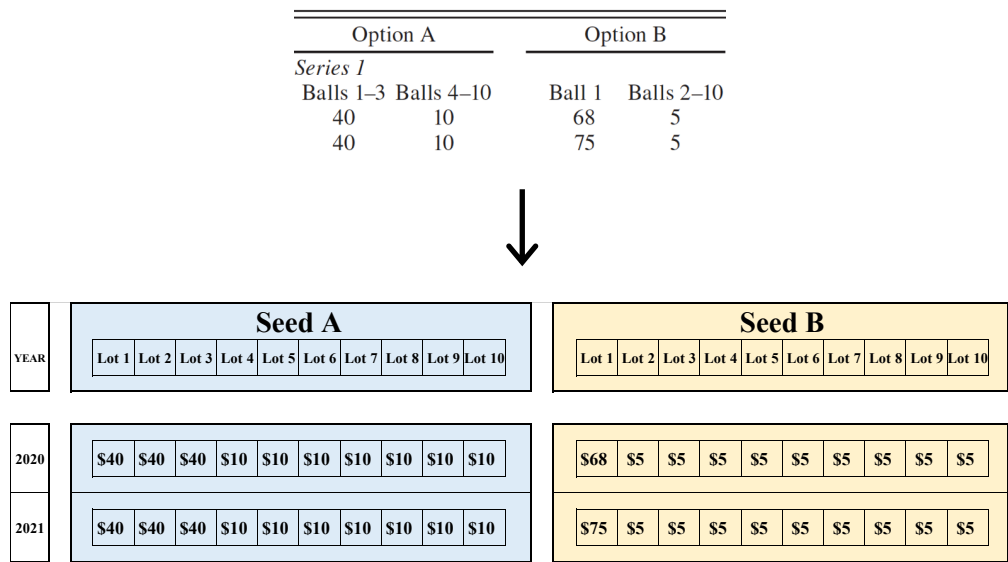


Figure 5-2. Lottery representation of the risk experiment

⁴⁰ See Figures A 5-3, A 5-4, and A 5-5 of the Appendix for the complete lotteries used in the experiment.

Participants in each experiment session were told that if they decided to choose Seed A for year 2020, and lot 3 survives at random, they would have earned 40 USD, while those who chose Seed B would have earned 5 USD. In contrast, if lot 1 survives, then those who chose Seed B would have earned 68 USD. Subjects were given printed instructions and separate printed sheets for each game (series), where they were asked to record their answers. The printed instructions contained 3 examples similar to the one above; these were explained verbally before participants played the lottery. In addition to specifying the year of the switch from seed A to seed B, participants had the option of never switching (always choosing seed A) or switching at year 1 (always choosing seed B).

Illiterate farmers were not allowed to join the experiment. Subjects who had difficulty completing record sheets by themselves were helped by research assistants who cautiously avoided recommending specific choices. Participants received 4 USD for showing up to the experiment. At the end of the experiment and survey, we drew a numbered ball from a bingo cage to randomize and determine which series, year, and lot of choice would be played for real money as a bonus. The bonus ranged from $[-3, 3]$ USD, and it was applied based on their actual experiment choices (see Liu, 2012 for a detailed discussion on payments using Tanaka's experimental design, and how for ethical reasons, studies avoid the loss of money by the farmers). The average earning for participating in the games was 6.5 USD, roughly the wage of one-half working day for agricultural labor. The monetary incentives make the experiment incentive compatible as literature shows that in games, auctions, and risky choices, incentives often reduce variance in responses and cause participants to behave more towards realistic choices (Camerer & Hogarth, 1999).

5.5. Empirical Framework

5.5.1. The Risk Perceptions Model

To examine how risk preferences influence CC risk perceptions, an ordered probit model was estimated. This model allows CC risk perceptions to be influenced by individual's risk preferences revealed by the framework of Prospect Theory. In other words, the model assumes that perceptions of risks of climate change depend on risk aversion, loss aversion, and probability distortion. The ordered probit model containing individual-specific controls and the elicited PT risk parameters is given by

$$y_i^* = \mathbf{X}_i' \boldsymbol{\beta} + \mathbf{R}_i' \boldsymbol{\psi} + u_i \quad i = 1, \dots, n \quad (6)$$
$$u_i \sim N(0,1)$$

i index participant i , $i = 1, \dots, n$, where n is the sample size; y_i^* ($-\infty < y_i^* < +\infty$) is the underlying latent variable representing respondent i 's propensity to agree with a certain risk perception; $\mathbf{X}_i$ is a vector containing individual-specific controls relevant in explaining risk perceptions of climate change and that are in accordance to the literature (cognitive, experiential, socio-demographic, and socio-cultural factors); $\mathbf{R}_i$ is a vector containing individual-specific PT risk parameters elicited in the experiment; $\boldsymbol{\beta}$ and $\boldsymbol{\psi}$ are vectors of parameters, *not* containing an intercept. y_i^* is unobserved, but the relationship between y_i^* and the observed variable y_i (individual i 's response to the survey question concerning climate change risk perceptions) is given by:

$$y_i = 1 \text{ if } -\infty < y_i^* < \kappa_1 \quad (7),$$

$$y_i = 2 \text{ if } \kappa_1 < y_i^* < \kappa_2$$

$$y_i = 3 \text{ if } \kappa_2 < y_i^* < +\infty$$

where the parameters κ_1 and κ_2 are the threshold parameters also known as “cut-points”.

Since climate change can be characterized by an individual as a distant psychological risk, i.e., happening more to “other” people and places (Gifford et al., 2009; Leiserowitz, 2005; Spence et al., 2012), recent studies of climate change have pointed out the importance of the distinction between personal (i.e., self-regarding) and societal (i.e., other-regarding) levels of risk judgments⁴¹ when assessing risk perceptions (van der Linden, 2015, 2017). In this study, we differentiate and measure farmers’ CC risk perceptions among these two dimensions. To evaluate climate change as a personal risk we asked farmers about their *Crop Management Practices, Output Prices, and Input Prices (Costs)*. Likewise, to evaluate climate change as a societal risk we asked farmers about *Geographic Location (Village)*. Participants were asked i.e. if they think that “the effects of climate change over their *Crop Management Practices*” will be *not important, slightly important, moderately important, important, or very important*. Risk perceptions take on a value of 1 for individuals who answered not important, a value of 2 for individuals who answered *slightly important, moderately important, or important*, and a value of 3 for those who answered *very important*⁴². We argue that crop management practices, output prices, and input prices (costs) relate closely to personal levels of risk judgments as farmers deal with them and experience them directly on a daily basis in the agricultural production process.

⁴¹ See Tyler and Cook (1984) for a discussion on the difference between self vs. other-regarding risk judgments.

⁴² We also ran a specification where the dependent variable took values from 1 to 5 and similar results were obtained.

On the other hand, the idea of the effect of climate change over the village implicitly involves the assessment of risk over other people⁴³ and hence it relates to societal levels of risk judgments. Based on a scale of 1-3, overall risk perceptions of climate change were reasonably high, with $\bar{y} = 2.54$ and $SD = 0.52$ for the case of crop management practices; $\bar{y} = 2.57$ and $SD = 0.54$ for case of output prices; $\bar{y} = 2.62$ and $SD = 0.50$ for case of input prices; and $\bar{y} = 2.39$ and $SD = 0.52$ for the case of the geographic location (village).

The influence of experiential factors (*personal experience*) in CC risk perceptions is assumed to be captured by the inclusion of the independent variable *Age*, as older farmers have more farming experience and have witnessed climatic phenomena for a longer period of time. Age is expected to be positively related to a farmer's CC risk perceptions, meaning higher risk perceptions for older farmers. As it can be argued that younger people are more exposed to CC through schooling and social media, we also control for this cognitive factor. The role of cognitive factors (*statistical description*) in farmers' risk perceptions of CC is thought to have two components: general knowledge, measured by inclusion of the independent variable *Education*, and additional agricultural knowledge measured by the inclusion of the independent variable *Extension*. *Education* and *Extension* are expected to increase familiarity with climate change, and consequently be positively related to the dependent variable. The role of socio-demographic factors is assumed to be mainly captured by the inclusion of the independent variable *Income*. This variable is included in the model to also test the hypothesis that concerns for the environment increases with *Income*, hence the expected sign for *Income* is positive (Tjernström & Tietenberg, 2008).

⁴³ Judging risk over others is closely related to the concept of *optimism bias* and the erroneous belief that others are more likely to be impacted by the same risk one faces (Weinstein, 1989).

Other individual/household characteristics included as controls are *Gender, Household Size, Area, Off-farm Job, Irrigation, Livestock*, and *Location fixed effects*. The inclusion of these variables is justified on the theoretical grounds that socio-demographic and socio-cultural factors (i.e., Gender, Household size, Area, Location), as well as experiential factors (i.e., Off-farm Job, Irrigation, Livestock) influence risk perceptions of climate change (van der Linden, 2015). More importantly, we include them in order to control for the variation in other subject specific characteristics. This helps when testing for the effect of risk preferences on climate change risk perceptions.

Various studies have reported interviewer effects, in both subjective and objective data collected, being the influence of interviewer's beliefs stronger in subjective questions and among female respondents (Himelein, 2016; West & Blom, 2017). Given in our study CC risk perceptions is a subjective question, and that we have a relatively high female participation in our study, we also control for *Interviewer fixed effects*⁴⁴.

The role of risk parameters in CC risk perceptions is hypothesized to emerge through the unique characteristics of PT, namely loss aversion and probability weighting. Following Liu (2012), to ease the interpretation of the coefficient on probability distortion we replace the value of α (probability distortion) with a dummy variable equal to 1 to indicate individuals who overweight low probability outcomes ($\alpha < 1$), and equal to 0 to indicate individuals who do not overweight low probability outcomes ($\alpha \geq 1$). Likewise, we replace the value of λ (loss aversion)

⁴⁴ We tested for the joint significance of the Interviewer fixed effects using a Likelihood Ratio Test. Results show Interviewer fixed effects are jointly significance at the 0.001% level in all models. (See Appendix)

with a dummy variable equal to 1 to indicate individuals who are loss averse ($\lambda > 1$), and equal to 0 otherwise ($\lambda \leq 1$).

As previously discussed, loss aversion and its relationship to status quo bias might imply that the respondent neglects the existence of climate change, hence loss aversion (λ) is expected to be negatively related to a farmer's CC risk perception. Correspondingly, the behavioral phenomenon of probability distortion can provide an explanation for the impact of extreme weather events –that occur with an objective low probability of occurrence– on CC risk perceptions. Probability distortion (α) is expected to be positively related to a farmer's CC risk perception, that is, respondents who overweight probabilities are more likely to give a higher ranking to the risk associated to climate change. Finally, we also include the level of risk aversion σ (value function curvature) and expect it to be negatively related to a farmer's CC risk perception, that is, farmers that are more risk seeking are less likely to give a higher ranking to the risk associated to climate change.

5.6. Results

A descriptive analysis of the results from the PT experiment is presented first. Then we examine how demographic and socio-economic characteristics are correlated with the elicited risk preferences. Finally, we present the estimation results of our empirical model of CC risk perceptions and discuss their implications.

5.6.1. Descriptive Analysis of PT Parameters

We follow Tanaka's et al. (2010) procedure to estimate the structural parameters of the PT utility function. This procedure provides a direct bridge between plays in the game and PT, as

every combination of the participant's choices in the three series of the experiment determine unique values of prospect theory parameters. Participant choices in series 1 and series 2 determine parameters σ and α , namely the curvature of the utility function and the curvature of the probability weighting function. Subsequently, λ –the curvature below 0 relative to the curvature above 0 –is determined using the estimated values of σ and α and the series 3 choice⁴⁵.

The average of σ is 0.66, indicating that the average participant is risk averse. The average of α is 0.80, indicating that on average, people tend to overweight low probabilities. These results are close to the findings in the farmer's subsample of Tanaka et al. (2010). The average of λ in our sample is 4.64, indicating that people are more sensitive to losses than to gains, at a magnitude of 4 to 1. This latter result is close to the finding of Liu (2012).

In figure 5-3(a) we present the simulated PT value function $v(x)$ (Eq.(4)) for gains and losses using our average estimates of σ and λ . As expected, the shape of the PT utility in the gain domain is concave, while in the loss domain is convex. In addition, over the loss domain the slope of the PT value function is steeper than in the gain domain, reflecting the original findings of Tversky and Kahneman (1992). For reference, we also plot in the loss region the value function using $\lambda=1$, as this represents the case of an individual that would behave in accordance to EU. In figure 5-3(b) we present the PT weighting function $w(p)$ (Eq.(5)) using our average estimate of α . It shows individuals overestimate probabilities approximately under 0.35, and this overestimation increases as probabilities approach zero. Likewise, individuals underestimate

⁴⁵ I follow the conventional approximation of σ , α , and λ and use the midpoint of their interval solution as their respective point estimate. See Tanaka et al. (2010) and Liu (2012) for more details about the estimation method of the structural parameters of prospect theory.

probabilities above 0.35, and most of the underestimation happens around 0.8. For reference, we also plot the objective probability weighting assumed by EU.

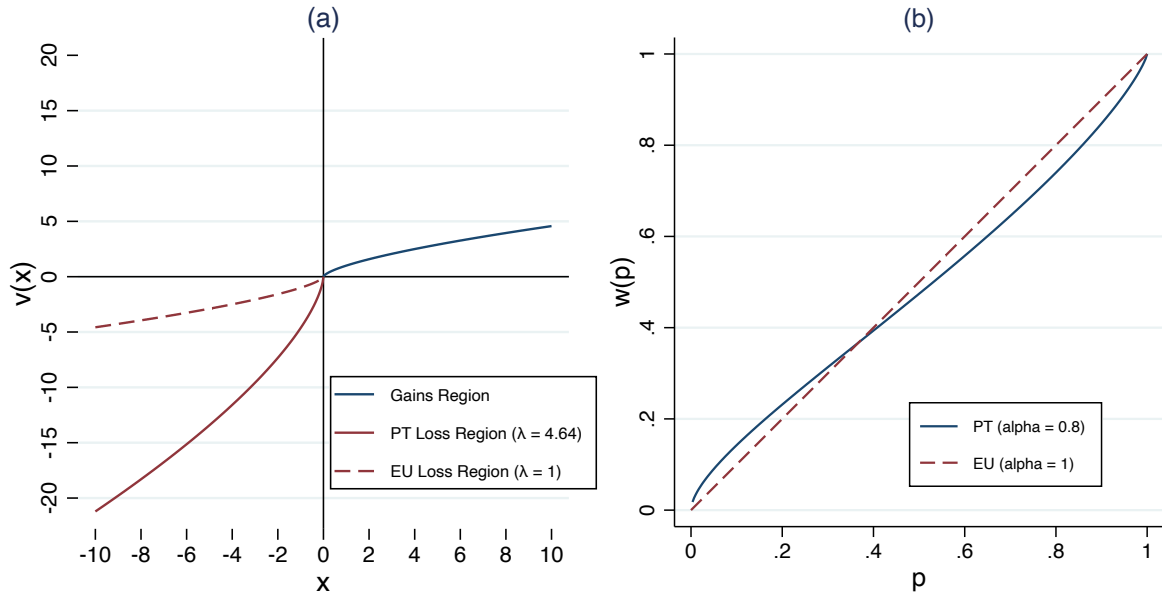


Figure 5-3. PT value function (a) and weighting function (b)

The distributions of σ , α , and λ parameters are shown in figure 5-4. Results show the estimated mean values of α and λ are significantly different from one at the 0.01 percent significance level by t -test, rejecting EU in favor of the “inverted-S shaped” probability weighting. This suggests the PT utility function specification, along with the experimental design, describes the choices better than the standard EU function.

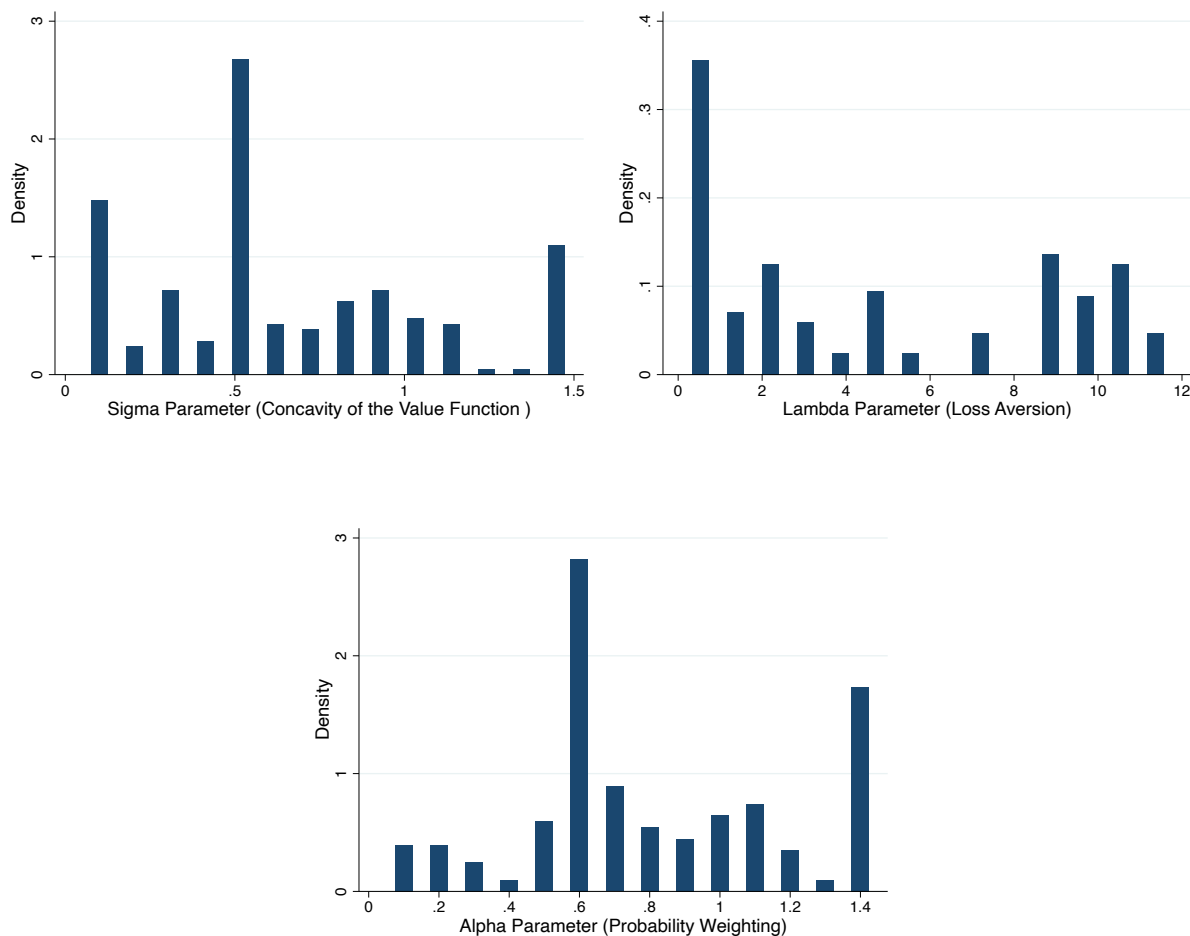


Figure 5-4. Distribution of risk preference parameters

5.6.2. Determinants of Preference Parameters

Table 5-2 reports results of OLS regressions using the curvature of the utility function (σ), probability weighting (α), and loss aversion (λ) as dependent variables. Controls included age, gender, education, rent, income, area, distance, nonfarm job, irrigation, extension, livestock, location fixed effects, and interviewer fixed effects. A dummy variable was included which was equal to 1 when a participant chose only seed A or only seed B through all three series. Choosing either seed A or seed B all of the time might signal lack of understanding of the experiment

instructions. This dummy variable was also used as a control and included in our OLS regressions.

Columns 1, 2, and 3 show the OLS results with σ , α , and λ , respectively, as the dependent variables. The results show a positive effect of age over the value of σ (curvature of the value function) and agrees with previous findings in the literature (Campos-Vazquez & Cuilty, 2014; Donkers et al., 2001; Halek & Eisenhauer, 2001; Harrison & Elisabet Rutström, 2008). This positive effect decreases the curvature in the value function which (i) in the gains domain is interpreted as a decrease in the level of risk aversion (increase in the level of risk willingness), and (ii) in the loss domain is interpreted as an increase in the level of risk aversion (decrease in the level of risk willingness). Such behavior could be explained by the idea that older people have more experience farming, and hence they are willing to take more risks when there is an opportunity to win. Experience also conveys to them it is safer to lose a little when encountered with the possibility of losing a lot.

Education at the level of some high school (level = 3) has a similar effect and interpretation over the value of σ , and agrees with the finding of Liebenehm & Waibel (2014) with farmers in Mali and Burkina Faso. In addition, education at the level of some college (level = 5) is negatively related to λ (loss aversion). This signals that the more educated the farmer, the lower the loss aversion. Similar findings of the effect of education on loss aversion have been reported with French farmers and Vietnamese fishermen (Bocquého et al., 2014; Nguyen & Leung, 2009). In addition, participating in extension programs is negatively related to λ (loss aversion). This signals that farmers that have received assistance and additional agricultural knowledge have lower levels of loss aversion.

Results also show a positive relationship between renting land and the value of α (probability weighting), suggesting that farmers who rent land for farming have a more accurate assessment of probability information. Finally, there was no significant correlation between income⁴⁶ and σ , α , and λ respectively. No significant gender effect⁴⁷ was detected.

Table 5-2. Estimates of Individual Characteristics and their Relationship to Risk Preference Parameters

Variable	Dependent Variables		
	(1) σ (Value function curvature)	(2) α (Probability weighting)	(3) λ (Loss aversion)
Age	0.005*** (0.00)	-0.003 (0.00)	-0.025 (0.01)
Female	0.036 (0.05)	0.105 (0.06)	0.755 (0.47)
Education = 1	0.132 (0.27)	-0.016 (0.22)	-0.075 (2.68)
Education = 2	0.114 (0.20)	-0.028 (0.13)	-0.707 (1.81)
Education = 3	0.464* (0.18)	-0.25 (0.16)	-0.441 (2.56)
Education = 4	0.336 (0.15)	-0.099 (0.20)	-2.719 (1.85)
Education = 5	0.131 (0.26)	-0.143 (0.11)	-4.166* (1.55)
Education = 6	0.248 (0.19)	0.078 (0.11)	-0.34 (1.87)
Rent	-0.081 (0.07)	0.094*** (0.02)	0.546 (0.81)
Extension	-0.015 (0.09)	-0.014 (0.04)	-1.676** (0.30)
Income	0.027 (0.06)	-0.021 (0.05)	0.364 (0.46)
Constant	0.205 (0.35)	1.023*** (0.07)	4.967** (1.53)
Observations	202	202	202
R-squared	0.156	0.163	0.2

Notes: Asterisks *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors clustered at the village level are in parenthesis. All regressions include village fixed effects and interviewer fixed effects. Complete regression results with all control variables are shown in Table A 5-1 of the Appendix.

⁴⁶ Literature findings about the wealth effects on risk preferences are mixed to date. See Cardenas & Carpenter (2008) and Lybbert & Just (2007) for a discussion on this.

⁴⁷ Studies reporting gender differences in risk aversion include Croson & Gneezy (2009); Eckel & Grossman (2008); and Liu (2012).

5.6.3. Empirical Model Estimates

Recalling from above –that participants choosing either seed A or seed B all of the time might have not understood the experiment– the main model specifications omit these observations⁴⁸. Results for the full sample were estimated as a robustness check. Interval-censored regression was also used to estimate the risk perception models. Results are qualitatively robust to these alternative model specifications (See Table A 5-2 and A 5-3 of the Appendix). The main results of this paper are reported in tables 5-3 and 5-4. Given the interpretation of coefficients from an ordered probit model can be difficult (Greene, 2017), marginal effects are also reported. Table 5-3 reports estimates from two models for each of the dependent variables defined and discussed in the previous section. Given current related studies do not have any control for individual risk preferences, regression results in model 1 exclude the PT risk parameters as a comparison, while they are included in model 2. Since model 1 is a nested version of the full specification model 2, the two competing specifications were tested using a Likelihood Ratio Test (Greene, 2017).

Results indicate that the PT risk preference parameters are jointly significant at the 0.06% and 3.3% level for the models of crop management practices and output prices respectively. For the models of input prices and geographic location (village) the PT risk preference parameters are jointly significant only at the at the 19% and 12% level respectively⁴⁹. Estimation results in table 5-3 show Probability Distortion significantly influenced CC risk perceptions over all the dependent variables, implying this distinctive feature of PT helps explain CC risk perceptions

⁴⁸ 12% of our participants exhibited this type of responses. In Liu (2012), this proportion was of 7.6%.

⁴⁹ To run the Likelihood Ratio Tests for all the models, the standard errors from the estimated regressions cannot be robust standard errors. See Appendix.

over both risk dimensions, individual and societal. Although, it is important to note that the impact of Probability Distortion is the smallest on Village (0.376), our proxy for societal evaluation of risk, and it is significant only at the 10% level. The impact of Education is somewhat heterogeneous over the different dependent variables, and it only appears to be consistently significant over Crop Management Practices.

Table 5-3. Determinants of Climate Change Risk Perceptions: Ordered Probit Estimates

Independent Variables	Dependent Variables: Risk Perceptions of the Effect of Climate Change On:							
	Crop Mngt. Practices		Output Prices		Input Prices		Village	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
σ (Value fun. curvature)		-0.996*** (0.33)		-0.535* (0.31)		-0.107 (0.30)		-0.271 (0.28)
$\lambda > 1$ dummy (Loss avers.)		0.285 (0.25)		0.187 (0.24)		0.043 (0.23)		0.371* (0.21)
$\alpha < 1$ dummy (Prob. distort)		0.851*** (0.24)		0.631*** (0.24)		0.519** (0.21)		0.376* (0.22)
Age	0.013 (0.01)	0.017 (0.01)	0.004 (0.01)	0.005 (0.01)	0.002 (0.01)	0.001 (0.01)	0.014 (0.01)	0.014 (0.01)
Income	-0.188 (0.14)	-0.117 (0.16)	0.141 (0.15)	0.208 (0.16)	0.107 (0.15)	0.128 (0.15)	-0.247* (0.14)	-0.237 (0.15)
Extension	-0.253 (0.37)	-0.348 (0.37)	-0.137 (0.28)	-0.14 (0.29)	0.419 (0.29)	0.429 (0.30)	-0.261 (0.39)	-0.25 (0.39)
Education = 1	0.216 (0.60)	0.283 (0.63)	-0.745 (0.65)	-0.881 (0.63)	-0.922 (0.58)	-1.112* (0.60)	-0.111 (0.52)	-0.115 (0.53)
Education = 2	0.81 (0.56)	0.803 (0.60)	-0.591 (0.62)	-0.843 (0.60)	-0.549 (0.54)	-0.792 (0.56)	-0.151 (0.47)	-0.264 (0.47)
Education = 3	1.255* (0.73)	1.431* (0.78)	-0.097 (0.76)	-0.364 (0.76)	-0.277 (0.86)	-0.625 (0.88)	-0.111 (0.69)	-0.277 (0.71)
Education = 4	1.253* (0.66)	1.319* (0.69)	0.084 (0.71)	-0.142 (0.70)	-0.112 (0.62)	-0.374 (0.63)	0.269 (0.55)	0.156 (0.56)
Education = 5	1.219 (0.74)	1.19 (0.80)	0.881 (0.82)	0.59 (0.81)	0.899 (0.76)	0.638 (0.75)	0.602 (0.61)	0.542 (0.65)
Education = 6	1.742** (0.75)	2.159** (0.84)	0.436 (0.96)	0.468 (1.01)	0.688 (0.78)	0.626 (0.78)	1.286* (0.77)	1.318 (0.81)
Observations	177	177	177	177	177	177	177	177

Notes: Asterisks *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Heteroscedasticity-robust standard errors in parenthesis. All regressions included village and interviewers fixed effects. Threshold parameters and control variables not reported.

Table 5-4 reports the marginal effects for the ordered probit estimates of model 2 presented in table 5-3. Results show that individuals who distort probability information stated a higher CC risk perception over all the dependent variables. For example, the phenomenon of distorting probability information is associated with being 23.1% less likely to perceive the risks of climate change over output prices as *important*, and being 23.5% more likely to perceive them as *very important*. In practical terms, these results suggest that the incorrect assessment of probability information lead farmers to perceive the risk associated with climatic phenomena as more threatening. This phenomenon of probability distortion has a larger impact on the CC risk perceptions over crop management practices (31.4%), and a relative smaller impact over the geographic location/village (14.1%).

Individuals with higher values of σ (curvature of the value function), that is, are less risk averse⁵⁰, stated a lower risk perception of climate change over crop management practices. A one-unit increase in the σ scale (a decrease in the level of risk aversion), is associated with being 36.7% more likely to perceive the risk of CC over crop management practices as *important*, and being 36.7% less likely to perceive it as *very important*. This result suggests that risk-seeking farmers perceive climate change risk to be less threatening toward agricultural practices. Literature suggests that less risk averse farmers are more willing to adopt new agricultural technologies (e.g., Feder, 1980; Feder et al., 1985), hence they might adapt and mitigate the effects of climate change more quickly. A similar but lesser pronounced effect of σ is also observed for the case of the perceived risks of climate change over output prices.

⁵⁰ Similarly, being less risk averse can also be interpreted as being more risk loving. This analysis corresponds to the gains domain. In the loss domain, higher values of σ are interpreted as being more risk averse (less risk willing).

Furthermore, and contrary to the starting hypothesis, loss averse individuals stated a higher risk perception of climate change over their geographic location (village). Results show loss averse individuals are associated with being 13.9% less likely to perceive the risks of climate change over their village as *important*, and being 14.2% more likely to perceive it as very *important*. One possible explanation for this result is that people might feel a close affinity for their village, and this is reflected in their measure of loss aversion.

In addition, education was significantly associated with the perceived risks of CC over crop management practices. More educated individuals stated a higher risk perception of climate change over this dependent variable. We also found no statistical significance for Age and Income. Being older, and with a higher income does not necessarily translates into a greater perception of the risks associated with climate change in our study area. Surprisingly, the variable Extension did not produce statistically significant results in our study. This may be caused by the fact that INIAP just began the extension program in our study area at the time of our experiments. In addition, only a small proportion of farmers in our sample (16%) claimed to have been visited by extension agents recently. This may have caused this parameter to be poorly identified.

Table 5-4. Marginal Effects of the Determinants of Risk Perceptions of Climate Change

	Crop Mngt. Practices	Output Prices	Input Prices	Geo. Location
Marginal effect on Prob. (Y =2)				
σ (Value function curvature)	0.367***	0.196*	0.039	0.102
$\lambda > 1$ (Loss aversion)	-0.105	-0.068	-0.016	-0.139*
$\alpha < 1$ (Probability distortion)	-0.314***	-0.231***	-0.192**	-0.141*
Age	-0.006	-0.002	-0.001	-0.005
Education = 3	-0.518**	0.114	0.203	0.099
Education = 4	-0.486**	0.041	0.112	-0.061
Education = 5	-0.446*	-0.121	-0.117	-0.212
Education = 6	-0.651***	-0.102	-0.116	-0.453**
Marginal effect on Prob. (Y =3)				
σ (Value function curvature)	-0.367***	-0.199*	-0.039	-0.104
$\lambda > 1$ (Loss aversion)	0.105	0.069	0.016	0.142*
$\alpha < 1$ (Probability distortion)	0.314***	0.235***	0.193**	0.144*
Age	0.006	0.002	0.001	0.005
Education = 3	0.519**	-0.115	-0.204	-0.102
Education = 4	0.487**	-0.041	-0.113	0.061
Education = 5	0.448*	0.121	0.117	0.213
Education = 6	0.653***	0.103	0.116	0.456**

Notes: Marginal effects calculated at mean values of independent variables. Asterisks *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Marginal effects on Prob. (Y =1) not shown as none of the variables was statistically significant for this category.

Behavior elicited from our PT experiment was statistically significant in every model 2 reported in table 5-3. In general terms, results indicate that individuals who distort probabilities – as determined from the lottery game via the coefficient of probability weighting α – were more likely to give higher rankings to CC risk perceptions over personal risk judgments—crop management practices output prices, input prices. This impact of probability distortion is less pronounced on the perceived risks of climate change over the geographic location or village—the variable considered as a proxy for societal risk judgments. A plausible explanation for these results is that the impact of extreme weather events is more tangible in the farmers’ crops and agricultural prices rather than in the physical appearance or characteristics of the village. Risk loving individuals were less likely to give higher rankings to CC risk perceptions over crop management practices. Status quo bias, as represented by the variable λ (Loss aversion), does not appear to explain risk perceptions of climate change. Nonetheless, our findings suggest that

farmers that perceive prospective losses greater than equivalent prospective gains, are more likely to perceive risks of climate change over their villages. Lastly, none of our control variables were consistently significant across the models. This pattern of results deserves further scrutiny, but it presents evidence suggesting PT parameters help with the distinction between societal and personal risk judgements when it comes to the evaluation of CC risk perceptions performed by farmers. This evidence agrees with the findings of van der Linden (2015).

5.7. Discussion and Conclusions

This article explores how elicited farmers' risk preferences using a lab-in-the-field experiment, correlate with the farmers' climate change risk perceptions. This research varies from previous papers in that it is the first empirical study that offers evidence showing that Prospect Theory can be used as a mediating mechanism to explain the role of risk preferences on risk perceptions, whereas at the same time contributing to existing literature on climate change

By relating the risk parameters elicited from our lab-in-the-field experiment with the Ecuadorian farmers' risk perceptions of CC, we find that those who distort probability information are more likely to state higher climate change risk perceptions. Education was also found to be significantly related to the farmers' CC risk perceptions, specifically, over crop management practices. This relationship between education and CC risk perceptions highlights the importance of the role of *cognitive* factors and confirm the findings of Maddison (2007), Nyanga et al. (2011), O'Connor et al. (1999), Roco et al. (2015) and Shi et al. (2016).

Our findings constitute *prima facie* evidence suggesting risk preferences, as measured in this study, have an important influence over risk perceptions of climate change. As extensively

argued in the literature, it may be most effective to change risky choice behavior by affecting individuals' perception of the riskiness of a situation (Cooper et al., 1988; Sitkin & Weingart, 1995; Weber & Milliman, 1997). Therefore, identifying the extent to which climate change risk perceptions can be influenced is of importance for designing and executing policies aiming at mitigating the effects of climate change. In these terms, policy interventions focused on improving farmers' access to information and education would do most to affect CC risk perceptions, and therefore, hasten the adoption of adaptation strategies. Thus, the current and future provision of free extension services play a key role in the process of agricultural development of our study region. INIAP interventions aiming at promoting adaptation practices, should consider the parallel facilitation of accurate weather information and additional advice specifically related to climate change. Although extension services are somewhat limited in Ecuador and the Latin American region, these can be effective facilitators for nudging farmers' behavior.

An important caveat of this paper is that the findings presented here do not look to challenge the importance of cognitive, experiential, socio-demographic, and socio-cultural factors, and how they influence climate change risk perceptions. Instead, results highlight the role of individual risk preferences in forming risk perceptions, as theorized by Sitkin and Pablo (1992). A limitation of our study is that it did not control for the "recency effect" i.e., the recent happening of a rare weather event, as it can also influence climate change risk perceptions (Li et al., 2011; Marx et al., 2007; Weber & Stern, 2011). It also did not explore the role of time preferences and how they might impact risk perceptions. As discussed in the literature, temporal discounting influence how people evaluate future risks against present risks (Trope & Liberman,

2010). Future research should examine these factors as they likely influence how farmers perceive and evaluate climate-related phenomena.

Although the external validity of our results needs to be verified, our results show that risk preferences are correlated with risk perceptions in the context of climate change. Hence, the findings presented here can also have important implications for empirical studies that uses both, risk preferences and perceptions, to predict certain behaviors in the context of climate change, including adoption decisions (see for example Krah et al., 2019). Causal inference and identification strategies would need to account for this correlation as described in the next directed acyclic graph (DAG), which is nothing but the representation of the relationship between risk preferences, risk perceptions, and risk behavior described in Sitkin and Pablo (1992). In it, risk preferences, R , is a common cause affecting both risk perceptions, P , and the observed behavior, B .

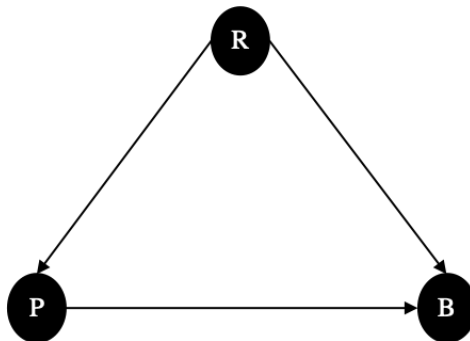


Figure 5-5. DAG showing the role of a confounding variable

5.8. References

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5.9. Appendix

Survey Questionnaire

Survey No:	_____
Interviewer:	_____
Date:	_____ Time: _____

SURVEY QUESTIONNAIRE

1. What is your age?
_____ (years)
2. What is your gender?
__ Male __ Female __ Other. Specify: _____
3. What is your education level?
__ Never attended school.
__ Attended elementary school but did not finish.
__ Elementary school graduate.
__ Attended high school but did not finish.
__ High school graduate.
__ Attended college but did not finish.
__ College graduate.
4. How many children are there in your household?

5. How many adults, including yourself, are there in your household?

6. Do you rent land for farming?
__ Yes __ No.
7. What is your total farm size (if you rent land, please include it here)?
_____ (hectares)
8. How many of your household members work on the farm?

9. What is the distance between your farm and the nearest road?
_____ (meters)
10. Do you have access to an irrigation system?
__ Yes __ No.
11. Has an extension agent visited your farm in the past year?
__ Yes __ No.
12. Do you have livestock?
__ Yes __ No.

Figure A 5-1 Survey questionnaire part 1.

13. What is your approximate monthly income from farming activities?

- ☐ \$0 - \$300
- ☐ \$300 - \$600
- ☐ \$600 - \$1000
- ☐ \$1,000 - \$1,500
- ☐ \$1,500 - \$3,000
- ☐ more than \$3,000

14. Do you receive income from non-farming activities? (If not, move to question 16)

- ☐ Yes ☐ No.

15. What is your approximate monthly income from non-farming activities?

- ☐ \$0 - \$300
- ☐ \$300 - \$600
- ☐ \$600 - \$1000
- ☐ \$1,000 - \$1,500
- ☐ \$1,500 - \$3,000
- ☐ more than \$3,000

FARMERS' PERCEPTION OF THEIR EXPOSURE TO CLIMATE CHANGE

16. How important do you think will be the effect of climate change on your crop prices?

- ☐ Not important.
- ☐ Slightly important.
- ☐ Fairly important.
- ☐ Important.
- ☐ Very important.

17. How important do you think will be the effect of climate change on your production costs?

- ☐ Not important.
- ☐ Slightly important.
- ☐ Fairly important.
- ☐ Important.
- ☐ Very important.

18. How important do you think will be the effect of climate change on your area?

- ☐ Not important.
- ☐ Slightly important.
- ☐ Fairly important.
- ☐ Important.
- ☐ Very important.

19. How important do you think will be the effect of climate change on your crop management practices?

- ☐ Not important.
- ☐ Slightly important.
- ☐ Fairly important.
- ☐ Important.
- ☐ Very important.

Figure A 5-2 Survey questionnaire part 2.

Lotteries Used in the Experiment.

		ESCENARIO 1																			
		Semilla A										Semilla B									
		Late 1 Late 2 Late 3 Late 4 Late 5 Late 6 Late 7 Late 8 Late 9 Late 10										Late 1 Late 2 Late 3 Late 4 Late 5 Late 6 Late 7 Late 8 Late 9 Late 10									
2020		\$40 \$40 \$40 \$10 \$10 \$10 \$10 \$10 \$10 \$10										\$68 \$5 \$5 \$5 \$5 \$5 \$5 \$5 \$5 \$5									
2021		\$40 \$40 \$40 \$10 \$10 \$10 \$10 \$10 \$10 \$10										\$75 \$5 \$5 \$5 \$5 \$5 \$5 \$5 \$5 \$5									
2022		\$40 \$40 \$40 \$10 \$10 \$10 \$10 \$10 \$10 \$10										\$83 \$5 \$5 \$5 \$5 \$5 \$5 \$5 \$5 \$5									
2023		\$40 \$40 \$40 \$10 \$10 \$10 \$10 \$10 \$10 \$10										\$93 \$5 \$5 \$5 \$5 \$5 \$5 \$5 \$5 \$5									
2024		\$40 \$40 \$40 \$10 \$10 \$10 \$10 \$10 \$10 \$10										\$106 \$5 \$5 \$5 \$5 \$5 \$5 \$5 \$5 \$5									
2025		\$40 \$40 \$40 \$10 \$10 \$10 \$10 \$10 \$10 \$10										\$125 \$5 \$5 \$5 \$5 \$5 \$5 \$5 \$5 \$5									
2026		\$40 \$40 \$40 \$10 \$10 \$10 \$10 \$10 \$10 \$10										\$150 \$5 \$5 \$5 \$5 \$5 \$5 \$5 \$5 \$5									
2027		\$40 \$40 \$40 \$10 \$10 \$10 \$10 \$10 \$10 \$10										\$185 \$5 \$5 \$5 \$5 \$5 \$5 \$5 \$5 \$5									
2028		\$40 \$40 \$40 \$10 \$10 \$10 \$10 \$10 \$10 \$10										\$220 \$5 \$5 \$5 \$5 \$5 \$5 \$5 \$5 \$5									
2029		\$40 \$40 \$40 \$10 \$10 \$10 \$10 \$10 \$10 \$10										\$300 \$5 \$5 \$5 \$5 \$5 \$5 \$5 \$5 \$5									
2030		\$40 \$40 \$40 \$10 \$10 \$10 \$10 \$10 \$10 \$10										\$400 \$5 \$5 \$5 \$5 \$5 \$5 \$5 \$5 \$5									
2031		\$40 \$40 \$40 \$10 \$10 \$10 \$10 \$10 \$10 \$10										\$600 \$5 \$5 \$5 \$5 \$5 \$5 \$5 \$5 \$5									
2032		\$40 \$40 \$40 \$10 \$10 \$10 \$10 \$10 \$10 \$10										\$1,000 \$5 \$5 \$5 \$5 \$5 \$5 \$5 \$5 \$5									
2033		\$40 \$40 \$40 \$10 \$10 \$10 \$10 \$10 \$10 \$10										\$1,700 \$5 \$5 \$5 \$5 \$5 \$5 \$5 \$5 \$5									

☐
Usaré la semilla A para todos los años

☐
Usaré la semilla B para todos los años

☐
Usaré la semilla A desde el año 2020 hasta el año _____ ; y la semilla B desde el año _____ hasta el año 2033

Figure A 5-3. Series 1 of lottery game

ESCENARIO 2

AÑO	Semilla A										Semilla B									
	Lote 1	Lote 2	Lote 3	Lote 4	Lote 5	Lote 6	Lote 7	Lote 8	Lote 9	Lote 10	Lote 1	Lote 2	Lote 3	Lote 4	Lote 5	Lote 6	Lote 7	Lote 8	Lote 9	Lote 10
2020	\$30	\$40	\$40	\$40	\$40	\$40	\$40	\$40	\$40	\$40	\$5	\$5	\$5	\$54	\$54	\$54	\$54	\$54	\$54	\$54
2021	\$30	\$40	\$40	\$40	\$40	\$40	\$40	\$40	\$40	\$40	\$5	\$5	\$5	\$56	\$56	\$56	\$56	\$56	\$56	\$56
2022	\$30	\$40	\$40	\$40	\$40	\$40	\$40	\$40	\$40	\$40	\$5	\$5	\$5	\$58	\$58	\$58	\$58	\$58	\$58	\$58
2023	\$30	\$40	\$40	\$40	\$40	\$40	\$40	\$40	\$40	\$40	\$5	\$5	\$5	\$60	\$60	\$60	\$60	\$60	\$60	\$60
2024	\$30	\$40	\$40	\$40	\$40	\$40	\$40	\$40	\$40	\$40	\$5	\$5	\$5	\$62	\$62	\$62	\$62	\$62	\$62	\$62
2025	\$30	\$40	\$40	\$40	\$40	\$40	\$40	\$40	\$40	\$40	\$5	\$5	\$5	\$65	\$65	\$65	\$65	\$65	\$65	\$65
2026	\$30	\$40	\$40	\$40	\$40	\$40	\$40	\$40	\$40	\$40	\$5	\$5	\$5	\$68	\$68	\$68	\$68	\$68	\$68	\$68
2027	\$30	\$40	\$40	\$40	\$40	\$40	\$40	\$40	\$40	\$40	\$5	\$5	\$5	\$72	\$72	\$72	\$72	\$72	\$72	\$72
2028	\$30	\$40	\$40	\$40	\$40	\$40	\$40	\$40	\$40	\$40	\$5	\$5	\$5	\$77	\$77	\$77	\$77	\$77	\$77	\$77
2029	\$30	\$40	\$40	\$40	\$40	\$40	\$40	\$40	\$40	\$40	\$5	\$5	\$5	\$83	\$83	\$83	\$83	\$83	\$83	\$83
2030	\$30	\$40	\$40	\$40	\$40	\$40	\$40	\$40	\$40	\$40	\$5	\$5	\$5	\$90	\$90	\$90	\$90	\$90	\$90	\$90
2031	\$30	\$40	\$40	\$40	\$40	\$40	\$40	\$40	\$40	\$40	\$5	\$5	\$5	\$100	\$100	\$100	\$100	\$100	\$100	\$100
2032	\$30	\$40	\$40	\$40	\$40	\$40	\$40	\$40	\$40	\$40	\$5	\$5	\$5	\$110	\$110	\$110	\$110	\$110	\$110	\$110
2033	\$30	\$40	\$40	\$40	\$40	\$40	\$40	\$40	\$40	\$40	\$5	\$5	\$5	\$130	\$130	\$130	\$130	\$130	\$130	\$130

☐ Usaré la semilla A para todos los años

☐ Usaré la semilla B para todos los años

☐ Usaré la semilla A desde el año 2020 hasta el año ____ ; y la semilla B desde el año ____ hasta el año 2033

3

Figure A 5-4. Series 2 of lottery game

ESCENARIO 3

AÑO	Semilla A										Semilla B									
	Lote 1	Lote 2	Lote 3	Lote 4	Lote 5	Lote 6	Lote 7	Lote 8	Lote 9	Lote 10	Lote 1	Lote 2	Lote 3	Lote 4	Lote 5	Lote 6	Lote 7	Lote 8	Lote 9	Lote 10
2020	\$25	\$25	\$25	\$25	\$25	-\$4	-\$4	-\$4	-\$4	-\$4	\$30	\$30	\$30	\$30	\$30	-\$21	-\$21	-\$21	-\$21	-\$21
2021	\$4	\$4	\$4	\$4	\$4	-\$4	-\$4	-\$4	-\$4	-\$4	\$30	\$30	\$30	\$30	\$30	-\$21	-\$21	-\$21	-\$21	-\$21
2022	\$1	\$1	\$1	\$1	\$1	-\$4	-\$4	-\$4	-\$4	-\$4	\$30	\$30	\$30	\$30	\$30	-\$21	-\$21	-\$21	-\$21	-\$21
2023	\$1	\$1	\$1	\$1	\$1	-\$4	-\$4	-\$4	-\$4	-\$4	\$30	\$30	\$30	\$30	\$30	-\$16	-\$16	-\$16	-\$16	-\$16
2024	\$1	\$1	\$1	\$1	\$1	-\$8	-\$8	-\$8	-\$8	-\$8	\$30	\$30	\$30	\$30	\$30	-\$16	-\$16	-\$16	-\$16	-\$16
2025	\$1	\$1	\$1	\$1	\$1	-\$8	-\$8	-\$8	-\$8	-\$8	\$30	\$30	\$30	\$30	\$30	-\$14	-\$14	-\$14	-\$14	-\$14
2026	\$1	\$1	\$1	\$1	\$1	-\$8	-\$8	-\$8	-\$8	-\$8	\$30	\$30	\$30	\$30	\$30	-\$11	-\$11	-\$11	-\$11	-\$11

☐ Usaré la semilla A para todos los años

☐ Usaré la semilla B para todos los años

☐ Usaré la semilla A desde el año 2020 hasta el año _____; y la semilla B desde el año _____ hasta el año 2026

4

Figure A 5-5. Series 3 of lottery game

Likelihood-ratio test for the jointly significance of the Interviewer fixed effects

- Model 1: Crop Management Practices LR $\chi^2(7) = 52.75$; Prob > $\chi^2 = 0.0000$
- Model 2: Output Prices LR $\chi^2(7) = 40.77$; Prob > $\chi^2 = 0.0000$
- Model 3: Input Prices LR $\chi^2(7) = 32.61$; Prob > $\chi^2 = 0.0000$
- Model 4: Geographic Location (Village) LR $\chi^2(7) = 44.75$; Prob > $\chi^2 = 0.0000$

Notes: These models refer to Equation (6). In all these tests, the unconstrained (full) model contains Interviewer fixed effects, while the constrained model does not.

Table A 5-1. Estimates of Individual Characteristics and their Relationship to Risk Preference Parameters

Variable	Dependent Variables		
	(1) σ (Value function curvature)	(2) α (Probability weighting)	(3) λ (Loss aversion)
Age	0.005*** (0.00)	0.00 (0.00)	-0.03 (0.01)
Female	0.04 (0.05)	0.11 (0.06)	0.76 (0.47)
1.EdLevel	0.13 (0.27)	-0.02 (0.22)	-0.08 (2.68)
2.EdLevel	0.11 (0.20)	-0.03 (0.13)	-0.71 (1.81)
3.EdLevel	0.464* (0.18)	-0.25 (0.16)	-0.44 (2.56)
4.EdLevel	0.34 (0.15)	-0.10 (0.20)	-2.72 (1.85)
5.EdLevel	0.13 (0.26)	-0.14 (0.11)	-4.166* (1.55)
6.EdLevel	0.25 (0.19)	0.08 (0.11)	-0.34 (1.87)
HHSize	0.01 (0.02)	-0.02 (0.01)	-0.04 (0.20)
Area	-0.01 (0.02)	0.02 (0.03)	0.14 (0.24)
Distance	0.00 (0.00)	-0.000** (0.00)	0.00 (0.00)
Rent	-0.08 (0.07)	0.094*** (0.02)	0.55 (0.81)
NFJob	-0.07 (0.10)	-0.11 (0.08)	-1.96 (1.53)
TotIncome	0.03 (0.06)	-0.02 (0.05)	0.36 (0.46)
Liu1	-0.06 (0.23)	-0.284** (0.09)	1.82 (1.07)
IrrigAccess	-0.09 (0.07)	0.06 (0.07)	0.34 (1.16)
ExtAccess	-0.02 (0.09)	-0.01 (0.04)	-1.676** (0.30)
OwnLivestock	0.08 (0.09)	-0.03 (0.08)	0.21 (0.69)

Notes: Asterisks *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors clustered at the village level in parenthesis. All regressions include village fixed effects and interviewer fixed effects.

Table A 5-1 (Continued)

Variable	Dependent Variables		
	(1) σ (Value function curvature)	(2) α (Probability weighting)	(3) λ (Loss aversion)
2.Location	0.066** (0.02)	-0.068** (0.02)	0.18 (0.38)
3.Location	0.09 (0.05)	0.00 (0.06)	0.20 (0.46)
4.Location	0.281** (0.07)	-0.07 (0.05)	0.52 (0.56)
2.Interviewer	-0.02 (0.15)	0.12 (0.19)	-0.23 (2.22)
3.Interviewer	-0.19 (0.09)	0.06 (0.19)	0.58 (0.95)
4.Interviewer	-0.387** (0.07)	-0.06 (0.10)	-1.30 (0.67)
5.Interviewer	-0.08 (0.10)	0.03 (0.19)	2.26 (1.05)
6.Interviewer	-0.08 (0.09)	-0.05 (0.13)	1.52 (1.05)
7.Interviewer	0.05 (0.15)	0.08 (0.14)	-0.09 (1.01)
8.Interviewer	-0.01 (0.19)	0.10 (0.27)	0.70 (0.73)
Constant	0.21 (0.35)	1.023*** (0.07)	4.967** (1.53)
Observations	202	202	202
R-squared	0.156	0.163	0.20

Notes: Asterisks *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors clustered at the village level in parenthesis. All regressions include village fixed effects and interviewer fixed effects.

Likelihood-ratio test for the jointly significance of the Interviewer fixed effects:

- Model 1: σ (Value function curvature): LR $\chi^2(7) = 10.82$; Prob > $\chi^2 = 0.1467$
- Model 2: α (Probability weighting): LR $\chi^2(7) = 4.22$; Prob > $\chi^2 = 0.7541$
- Model 3: λ (Loss aversion): LR $\chi^2(7) = 11.59$; Prob > $\chi^2 = 0.1148$

Notes: In all these tests, the unconstrained (full) model contains Interviewer fixed effects, while the constrained model does not.

Table A 5-2. Determinants of Risk Perceptions of Climate Change: Ordered Probit Estimates (Model 2 - Full Sample).

Independent Variables	Dependent Variables: Risk Perceptions of the Effect of Climate Change On:			
	Crop Mngt. Practices	Output Prices	Input Prices	Geo. Location
σ (Value fun. curvature)	-0.147 (0.26)	-0.176 (0.26)	0.022 (0.25)	0.106 (0.23)
$\lambda > 1$ dummy (Loss avers.)	0.143 (0.22)	0.165 (0.23)	-0.004 (0.22)	0.350* (0.20)
$\alpha < 1$ dummy (Prob. distort)	0.469** (0.22)	0.451** (0.23)	0.439** (0.20)	0.19 (0.22)
Age	0.01 (0.01)	0.006 (0.01)	0.004 (0.01)	0.014* (0.01)
Income	-0.241* (0.14)	0.177 (0.13)	0.089 (0.14)	-0.250* (0.13)
Extension	-0.167 (0.33)	-0.072 (0.25)	0.161 (0.29)	-0.313 (0.35)
Education = 1	0.178 (0.50)	-1.153** (0.56)	-0.427 (0.54)	-0.078 (0.51)
Education = 2	0.581 (0.49)	-0.823 (0.55)	-0.397 (0.51)	-0.044 (0.48)
Education = 3	0.718 (0.73)	-0.714 (0.72)	-0.503 (0.76)	-0.23 (0.68)
Education = 4	1.018* (0.57)	-0.204 (0.63)	-0.061 (0.56)	0.417 (0.54)
Education = 5	0.997 (0.67)	0.441 (0.73)	0.904 (0.71)	0.848 (0.62)
Education = 6	1.810*** (0.68)	0.38 (0.89)	0.959 (0.74)	1.409* (0.76)
Observations	202	202	202	202

Notes: Asterisks *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Heteroscedasticity-robust standard errors in parenthesis. All regressions included village and enumerators fixed effects. Threshold parameters and control variables not reported.

Table A 5-3. Determinants of Risk Perceptions of Climate Change: Interval-Censored Regression Estimates (Model 2).

Independent Variables	Dependent Variables: Risk Perceptions of the Effect of Climate Change On:			
	Crop Mngt. Practices	Output Prices	Input Prices	Geo. Location
σ (Value fun. curvature)	-0.250*** (0.09)	-0.138 (0.09)	-0.028 (0.09)	-0.078 (0.09)
$\lambda > 1$ dummy (Loss avers.)	0.068 (0.07)	0.072 (0.07)	0.025 (0.07)	0.115* (0.07)
$\alpha < 1$ dummy (Prob. distort)	0.216*** (0.06)	0.194*** (0.08)	0.142** (0.06)	0.11 (0.07)
Age	0.004 (0.00)	0.001 (0.00)	0 (0.00)	0.004 (0.00)
Income	-0.039 (0.04)	0.077 (0.05)	0.036 (0.05)	-0.074* (0.04)
Extension	-0.088 (0.11)	-0.044 (0.10)	0.14 (0.09)	-0.085 (0.12)
Education = 1	0.056 (0.17)	-0.222 (0.15)	-0.330* (0.17)	-0.024 (0.16)
Education = 2	0.179 (0.15)	-0.203 (0.13)	-0.224 (0.15)	-0.075 (0.14)
Education = 3	0.311 (0.19)	-0.069 (0.18)	-0.177 (0.26)	-0.07 (0.22)
Education = 4	0.318* (0.18)	0.024 (0.16)	-0.093 (0.18)	0.06 (0.17)
Education = 5	0.285 (0.21)	0.177 (0.18)	0.184 (0.20)	0.161 (0.19)
Education = 6	0.458** (0.18)	0.129 (0.21)	0.102 (0.20)	0.388* (0.22)
Observations	177	177	177	177

Notes: Asterisks *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Heteroscedasticity-robust standard errors in parenthesis. All regressions included village and enumerators fixed effects. Threshold parameters and control variables not reported.

Likelihood-ratio test for the jointly significance of the PT Risk Parameters:

- Model 1: Crop Management Practices LR $\chi^2(7) = 17.38$; Prob > $\chi^2 = 0.0006$
- Model 2: Output Prices LR $\chi^2(7) = 8.75$; Prob > $\chi^2 = 0.0328$
- Model 3: Input Prices LR $\chi^2(7) = 4.68$; Prob > $\chi^2 = 0.1968$
- Model 4: Geographic Location (Village) LR $\chi^2(7) = 5.78$; Prob > $\chi^2 = 0.1229$

Notes: In all these tests, the unconstrained (full) model contains the PT Risk Parameters, while the constrained model does not.