Three Essays on the Interactions between Agriculture and the Environment

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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
Economics, Agriculture and Life Sciences

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February 18, 2016
Blacksburg, VA

Keywords: Technology Adoption, Willingness to Pay, Climate Change, Agriculture

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ABSTRACT

This dissertation consists of three essays studying two aspects of the interactions between agriculture and the environment: agricultural technology adoption and its environmental impacts (in the first essay), and weather shocks and their impacts on rural households in developing countries (in the second and third essays).

The first essay proposes a multimarket equilibrium approach to estimating the consumer surplus for environmentally-friendly technologies adopted by farmers. Compared to conventional non-market valuation techniques based on single-market equilibrium, this new method allows for farmers' price feedback effects on consumers' willingness to pay (WTP) for those technologies. Results from an application indicate that consumers are willing to pay a premium for environmentally-friendly technologies adopted by farmers, and that the multimarket equilibrium WTP is smaller in magnitude than its single-market equilibrium counterpart.

In the second essay, I develop a unitary agricultural household model to examine the impacts of rainfall variability on migration, off-farm employment and transfers in rural Ethiopia. Empirical results show that the share of out-migrated household members and per capita off-farm labor supply decrease with average rainfall in the main growing

seasons, and increase with the standard deviation of average rainfall in the five main growing seasons prior to the survey. The level and standard deviation of rainfall are found to have indeterminate effects on the amount of transfers that households receive from the extended family or informal social safety nets.

The third essay evaluates the effectiveness of different diversification strategies in smoothing consumption. Results suggest that adverse rainfall shock (below average rainfall) and temperature shock (above average extreme heat degree days) both negatively impact consumption. Receiving public transfers is effective in smoothing consumption against adverse rainfall shock, and participating in off-farm employment is effective against adverse temperature shock. Sending migrants to urban areas and receiving transfers from former household members or informal social safety nets are not effective against any weather shock.

DEDICATION

I dedicate this dissertation to the three most important women in my life:

my mother who firmly believes that

knowledge is power;

my wife who empirically demonstrates that

love is unconditional;

and

my daughter who unconsciously teaches me that

parenting is learning.

ACKNOWLEDGEMENTS

I am deeply indebted to my advisor, Dr. George Norton, for his guidance, mentorship, encouragement and support throughout my study at Virginia Tech. Dr. Norton means everything a student can rely on, and it's always a great pleasure to work with him.

My sincere gratitude goes to my co-advisor, Dr. Bradford Mills, without whose guidance this dissertation would not have been finished. His thought-provoking comments, constructive suggestions, and timely feedback have greatly shaped my research.

I would also like to thank all other members on my committee. Dr. Klaus Moeltner's lectures offered me essential training on econometrics and environmental economics, and his incisive remarks on my papers pushed me forward with my research. Dr. Kevin Boyle provided invaluable, insightful, and inspiring comments on my dissertation. Dr. Mary Marchant has been a dedicated committee member and I have benefited tremendously from her advice on effective writing and style.

I want to extend my gratitude to Drs. Wen You, Jeffrey Alwang, Everett Peterson, and Eric Bahel, whose classes were especially enlightening and helpful. Discussions with my fellow students, Xiaojin Sun, Di Zeng, Tiefeng Qian, Clara Yuan, Chaoping Xie, Yanliang Yang, and Yu Sun, was truly enjoyable and stimulating. I am also deeply thankful to Professor Xiao Zhang for introducing me to the field of environmental economics and inspiring me to continue my academic journey, Drs. Shaochuan Cheng, Fan He and Linyan

Yang for their encouragement and support, and Li Chen, Qiang He and Lianke Zhan for their friendship and help.

Finally, I am very grateful to my big extended family, including my brothers and my sisters-in-law, for their continuing love and support. I owe special thanks to my wife, Yuhong, without whose sacrifice and support my pursuit of a doctoral degree would never have been possible; my daughter, Manyi, who has been my sunshine since her birth; and my parents-in-law and parents for helping take care of my daughter while I was busy with my study and research.

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Chapter 1 Introduction

This dissertation consists of three essays studying two aspects of the interactions between agriculture and the environment: agricultural technology adoption and its environmental impacts, and weather shocks and their impacts on rural households in developing countries where *rainfed agriculture* (i.e., agricultural production relies heavily on rainfall for water) remains the dominant source of livelihood.

The adoption of new technologies can change farmers' optimal use of synthetic chemicals, which in turn may affect consumer welfare. This impact pathway is well-documented in the literature, but few studies have evaluated the size of the impact – consumers' willingness to pay (WTP) for environmentally-friendly technologies adopted by farmers. The main challenge is that many technologies adopted in agricultural production are not easily observed in the final products, therefore it is difficult to gauge consumers' preference for these technologies.

The first essay is devoted to this topic by proposing a multimarket equilibrium approach to estimating the consumer surplus for environmentally-friendly technologies adopted by farmers. Compared to conventional non-market valuation techniques based on single-market equilibrium, this new method allows for farmers' price feedback effects on consumers' WTP for those technologies, thus can more accurately estimate that WTP. As an illustration, this approach is applied to a sample of 219 tomato farms and a sample of 498 consumers in Maryland, New York, and Ohio. The results indicate that consumers are willing to pay a premium for environmentally-friendly technologies adopted by farmers, and that the multimarket equilibrium WTP is smaller in magnitude than its conventional single-market equilibrium counterpart due to producer price feedback effects. Given the consumers' WTP for a higher retail price, the farm price is likely to be raised, encouraging the farmers to apply the synthetic chemicals at a higher rate in order to increase their yields. This higher rate results in the producers' applying a little higher amount of the input than in single-market equilibrium, and therefore the consumer is willing to pay a little lower retail price than in single-market equilibrium. This interactive process keeps going, back and forth, until the multimarket equilibrium WTP is reached, and in the end, the magnitude of multimarket equilibrium WTP is smaller than the single-market equilibrium WTP. The results imply that the conventional choice experiment approach based on single-market equilibrium tends to overestimate the environmental benefits of an environmentally friendly technology adoption.

The second and third essays examine weather shocks and their impacts on rural households' well-being and responses. Numerous previous studies have shown adverse (poor or variable) weather conditions tend to reduce the mean yields of agricultural products and increase the output variance in developing countries. When households rely heavily on *rainfed agriculture*, the induced production shock is often transformed into an income shock and, in turn, into a negative consumption shock. To mitigate the adverse impact of these shocks, rural households adopt three major coping strategies, namely farming, diversification, and asset smoothing. Farming strategies are adopted to stabilize or boost agricultural income, including adopting drought resistant varieties, changing planting and harvesting dates, or investing in irrigation infrastructure. Diversification strategies reinvest household resource to increase income flows from nonagricultural activities and transfers by engaging in off-farm activities or non-agricultural small businesses, participating in formal and informal social safety networks (ISSN) to receive various transfers as needed, or sending household members to urban areas to receive remittances from them. Asset smoothing strategies seek an intertemporal equilibrium by reallocating the stream of assets over time more efficiently. For example, households can accumulate livestock assets during good times and sell livestock during hard times. The two essays focus on diversification strategies in the Ethiopian context, which have never been systematically investigated in the literature.

The second essay addresses a research question: are these diversification strategies responsive to weather shocks? A unitary agricultural household model is developed in which migration, (on-farm, off-farm, and urban) labor supplies and transfers are jointly determined. Hypotheses about the partial effects of rainfall shocks on household decisions are derived from the theoretical framework and are tested using a multi-wave household survey combined with measures of village-level rainfall shocks from a high resolution, historical rainfall dataset. The results show that the share of out-migrated household members and per capita off-farm labor supply decrease with positive changes in rainfall in the main growing seasons, and increase with the standard deviation of rainfall in the main seasons in the five years prior to the survey. The level and standard deviation of rainfall are found to have indeterminate effects on the amount of transfers that households receive from the extended family or informal social safety nets.

Overall, this essay presents a coherent picture on the responsiveness of different coping strategies to rainfall shocks in rural Ethiopia: migration and off-farm labor supply do respond to rainfall level and variability, whereas transfers from family and other ISSN do not. This information will improve Sub-Saharan Africa countries' abilities to adapt to and cope with climatic change. For example, policy makers are advised to support investments in interventions that facilitate rural households' migration and urban employment, as well as off-farm activities.

The third essay answers another research question: can these diversification strategies, once adopted, help rural households smooth consumption against weather shocks? It first examines the net impact of weather shocks on consumption in rural Ethiopia, and then evaluates the effectiveness of different diversification strategies in smoothing consumption against these shocks. The results suggest that adverse rainfall shock (below average rainfall) and temperature shock (above average extreme heat degree days) both negatively impact real consumption per adult equivalent. Receiving public transfers is effective in smoothing consumption against adverse rainfall shock, and participating in off-farm employment is effective against adverse temperature shock. Sending migrants to urban areas for labor market reasons and receiving transfers from former household members or informal social safety nets are not effective against any weather shock.

Findings from the second and third essays suggest that policy makers in Ethiopia should (1) free up rural labor market for local employment by removing barriers to off-farm activities, opening off-farm activities for more households, and supporting more rapid off-farm employment growth; (2) reform public social protection programs and make them more adaptive and more responsive to weather shocks so as to increase their adoption rate when weather shocks hit; and (3) encourage the adoption of other coping strategies since these diversification strategies are not able to fully buffer against weather shocks.

Chapter 2 Consumer Willingness to Pay for Environmentally Friendly Technology with Producer Price Feedback*

2.1 Introduction

The adoption of new technologies can change farmers' optimal use of synthetic chemicals, which in turn may affect consumer welfare. This impact pathway has been well-documented in the literature. For example, many studies have shown that the adoption of integrated pest management (IPM) programs effectively reduce the use of chemically-based pesticides such as herbicides, insecticides, and fungicides (Burrows 1983; Fernandez-cornejo 1996; Mariyono 2008, to name a few). Wu and Babcock (1998) suggest that the adoption of crop rotation and conservation tillage can reduce nitrogen fertilizer rates. Chintawar, Gabrielyan, and Westra (2011) find that adopters of cover crops tend to apply less nitrogen fertilizer than non-adopters. On the other hand, previous studies also demonstrate that consumers care about chemical use in the production of goods they consume (Roosen et al. 1998; Boccaletti and Nardella 2000; Cranfield and Magnusson 2003; McCluskey, Durham, and Horn 2009; Combris et al. 2012).

When the adopted technologies can be directly observed by consumers, through certified or voluntary labels such as USDA Organic, Cage-free, Locally Grown, Non-GMO, and Grass-fed, researchers can estimate consumers' willingness to pay (WTP) for these technologies (Loureiro and Hine 2002; Loureiro, McCluskey, and Mittelhammer 2002; Bashir 2012; Michaud, Llerena, and Joly 2013). It becomes more difficult for

* I am grateful to the United States Department of Agriculture's National Agricultural Statistics Service Ohio Field Office for implementing the farmer survey. Funding for this research was provided by the National Institute of Food and Agriculture of the United States Department of Agriculture under grant number 2009-51300-05512.

environmental valuation when the technologies adopted are not easily observable in the final products, because the consumers are usually unaware of, unfamiliar with, or uninterested in them, not to mention placing monetary values on changes in environmental quality resulting from the technologies.

A handful of studies have attempted to gauge consumers' preference for technologies adopted by farmers. Mullen, Norton, and Reaves (1997) and Cuyno, Norton, and Rola (2001) assess the economic value of environmental benefits of IPM adoption by farmers, but their approach relies heavily on scientific, experimental, aggregate, or forecasting data on the supply side; without the data, it may not be generalized. Moreover, it largely ignores the producers' price feedback effects on consumers' welfare; thus may lead to incorrect estimates of the benefits.

In the present study a novel multimarket equilibrium framework is proposed to take into account the price feedback effects while estimating the consumers' WTP for unobserved technology adoption by farmers. In a competitive economy of heterogeneous farmers and consumers, an agricultural good is produced by each farmer using an environmentally harmful input, fixed land, and an exogenous farming technology. Profit maximization leads to the optimal demand for the input, and hence the supply of many distinct types of the agricultural good. These types are differentiated by two attributes: farm (retail) price, and the amount of the environmentally harmful input applied in the production. Facing a differentiated goods market, each consumer makes a purely discrete choice among the types of the good.[1] The consumers' utility maximization results in the demand for the good types, as well as their indirect utility functions of attributes. In

[1] We deliberately use "type" rather than "variety" to avoid confusing with "new varieties" which itself is a common technology adopted by many agricultural households in development context.

multimarket equilibrium, changes in retail price of the agricultural good have feedback effects on farm price, and both the agricultural good market and the input market must be cleared to determine the equilibrium farm and retail prices. In contrast, in single-market equilibrium, the farm and retail prices are independent and only the agricultural good market is cleared to determine the equilibrium retail price. Finally, the input demand functions substitutes for the input attributes in the indirect utility function, giving the new utility as function of technology adoption. Then the multimarket and single-market equilibrium WTPs for the adoption of the farming technology are derived and compared.

We apply this framework to the production and consumption of vine-ripened tomatoes in the Northeastern United States. Estimation results from a grower dataset and a consumer dataset show that the magnitude of WTP becomes smaller when we consider producer price feedback.

Our study contributes to the existing literature in several aspects. First, it is the first study to allow for producer price feedback effects in a choice experiment setting. Multimarket or general equilibrium WTP is not new to environmental valuation; multiple studies have estimated the general equilibrium WTP for large environmental improvements using spatial sorting models (Sieg et al. 2004; Smith et al. 2004; Tra 2010; Tra 2013). To the best of my knowledge, however, no research has incorporated producer price feedback effects into environmental valuation using choice experiments.

Second, a novel theoretical model is developed to show how technology adoption and supply side environmental impacts can be integrated into consumer welfare analysis, how the consumers’ WTP for farmers’ unobserved (by consumers) technology adoption can be derived, and how the single-market and multimarket equilibrium WTP could be different.

Third, the study proposes a general, applicable approach to estimating the consumers' WTP for unobserved technology adoption on the supply side, thus extending the boundaries of environmental valuation. In the literature of non-market valuation of technology adoption, most studies focus on the extreme cases: organic, pesticide-free, or non-GM modified. Many farmers, however, are in-between organic and conventional farming. In fact, there is a wide spectrum of farming systems that are more environmentally friendly than conventional farming but less than organic farming – from low-input farming to community-supported agriculture, and from transitional organic farming to non-certified organic farming. These farming systems are differentiated by their choices over technologies such as crop rotation, green manure and irrigation structures. Different technologies can yield distinct economic, environmental and consequently welfare outcomes. It is of empirical importance to assess consumers' WTP for transforming from one type of organic certification system to another, or for transforming from one production technology to another. With few data restrictions, our generalized approach provides a tool to meet this need.

Fourth, we highlight the difference between single-market and multimarket equilibrium WTP in environmental valuation using choice experiments. The supply of an agricultural good is affected by its farm price, and its demand is affected by the retail price. The two prices, however, often differ significantly (this difference is the so-called "farm to retail price spread" or "price spread from farm to consumer"). When farmers adopt an environmentally-friendly technology, their demand for chemicals decreases and the supply of more eco-friendly types of the agricultural good increases. In single-market equilibrium, the retail price and farm price are independent, and the retail price is adjusted to clear the agricultural good market. In multimarket equilibrium, the two prices are dependent, and the farm price changes with retail price. The demand for chemicals changes too with the farm price, thus in equilibrium both the good market and input market must be cleared. This paper shows that the multimarket equilibrium WTP for an environmentally friendly technology adoption is smaller than its single-market equilibrium counterpart. Therefore, the current choice experiment approach based on a single-market equilibrium tends to overestimate the environmental benefits of an environmentally friendly technology adoption.

Finally, the proposed framework can isolate the supply-side environmental benefits from health, and nutritional benefits. Consider the traditional method that uses an organic label to elicit consumer preferences for organic foods. The label contains a lot of information besides supply-side environmental impacts, including less pesticide residues, more nutritive components, and better taste. Therefore the estimated WTP is a combination of all these benefits, not just supply side environmental benefits.

The rest of the paper is organized as follows: Section 2 presents the theoretical and empirical framework proposed to estimate consumers' WTP for farmers' technology adoption. The survey and data are described in Section 3 while the empirical results are analyzed in Section 4. Section 5 summarizes and concludes the paper.

2.2 A Multimarket Equilibrium Framework

Consider a competitive economy consisting of J farms and N consumers where $N \gg J$. Farm j produces Y_j units of agricultural good Y using two primary inputs, an environmentally harmful input X_j and fixed land A_j, and one farming technology T_j

which is treated exogenous in the following analysis. The production function $F_j : \mathbb{R}_+^2 \times [0,1] \to \mathbb{R}_+$,[2] defined as

$$Y_j = F_j(X_j, A_j, T_j),$$

is continuous, twice differentiable, and exhibit positive and diminishing marginal products as well as constant returns to scale in X_j and A_j:

$$\left.\begin{aligned}
&F'_{jX}(X_j, A_j, T_j) = \frac{\partial F_j(.)}{\partial X_j} > 0, \quad F'_{jA}(X_j, A_j, T_j) = \frac{\partial F_j(.)}{\partial A_j} > 0, \\
&F''_{jXX}(X_j, A_j, T_j) = \frac{\partial^2 F_j(.)}{\partial X_j^2} < 0, \quad F''_{jA}(X_j, A_j, T_j) = \frac{\partial^2 F_j(.)}{\partial A_j^2} < 0, \\
&F_j(X_j, A_j, T_j) = A_j F_j(\frac{X_j}{A_j}, 1, T_j) \triangleq A_j f_j(x_j, T_j), \quad \forall j = 1, ..., J
\end{aligned}\right\} \tag{2.1}$$

where $x_j \triangleq X_j / A_j$ is the quantity of the environmentally harmful input used per acre, and $y_j = f_j \triangleq F_j / A_j \triangleq F_j(X_j / A_j, 1, T_j)$ is a yield function.

Moreover, we assume that the technology T_j is environmentally friendly such that the marginal product of X_j decreases with technology T_j:

$$F''_{jXT}(X_j, A_j, T_j) = \frac{\partial^2 F_j(.)}{\partial X_j \partial T_j} < 0. \tag{2.2}$$

This assumption implies that the two inputs, X_j and T_j, are technically competitive: with an exogenous increase in the technology adoption rate T_j, the marginal product of X_j declines, and as a result the farm tends to use less of environmentally harmful input X_j to

[2] Here the variable T_j is continuous, and can be interpreted as the share of cropland on which the technology has been adopted by the farm. Empirically, T_j may be a discrete variable, e.g. a dummy indicating whether the technology has been adopted by the farm. Although the analyses in this section are based on the continuous nature of T_j for mathematical convenience, they can be easily adapted to their discrete analogs.

equalize the marginal revenue and cost of this input.

Following Lancaster (1966), we assume that consumers care about not the good Y as a whole, but its characteristics, especially the quantities of the input X that farms use in the production of Y. Suppose that the J farms supply J distinct combinations of farm price (p_{f_j}) and per acre demand of the environmentally harmful input (x_j), as a result of either different forms of the production function, different farm prices, or different levels of technology adoption. Each combination consists of a type of the good Y, denoted as C_j, and each consumer chooses one and only one type when facing a total of J types. Consumer n has a continuous, differentiable, and quasi-concave utility function defined over the quantity of the types consumed, their input demands, a numeraire z, and her characteristics L as $U_n = U_n(C_1,...,C_J, x_1,...,x_J, z_n, L_n)$, with the following assumptions:

$$\left.\begin{aligned} &\frac{\partial U_n}{\partial C_j} > 0, \forall j = 1,..., J, \\ &\frac{\partial U_n}{\partial z_n} > 0, \\ &\frac{\partial U_n}{\partial x_j} < 0, \forall j = 1,..., J, \end{aligned}\right\} \tag{2.3}$$

where T_j's are not included because they are not labeled on the good and thus not observed by the consumer.

To concentrate on the product markets rather than factor markets of the economy, we further assume that the prices of the two inputs are fixed at (w, r). Denoting the farm price of C_j as p_{f_j}, and the retail price of C_j as p_{r_j}, our main objective is to determine the equilibrium farm and retail prices in the J type/product markets (p_{f_j}, p_{r_j}), and the supply of and demand for each type.

2.2.1 The supply of types

The producer j solves the following profit maximization problem

$$\max_{x_j} A_j[p_{f_j} f_j(x_j,\ T_j) - wx_j - r],$$

and derives the per acre input demand function $x_j^* = x_j^*(p_{f_j}, w, r, T_j)$. Then the supply of type j is given by

$$S_j(A_j, p_{f_j}, w, r, T_j) = A_j f_j(x_j^*,\ T_j). \tag{2.4}$$

It follows from assumptions (1) and (2) that

$$\frac{\partial f_j(.)}{\partial x_j} > 0, \frac{\partial^2 f_j(.)}{\partial x_j^2} < 0, \frac{\partial^2 f_j(.)}{\partial x_j \partial T_j} < 0.$$

Combining these conditions with the first order condition of the problem, we have

$$\frac{\partial x_j^*}{\partial p_{f_j}} > 0, \frac{\partial x_j^*}{\partial T_j} < 0, \tag{2.5}$$

$$\frac{\partial S_j}{\partial p_{f_j}} > 0. \tag{2.6}$$

Now each farm supplies S_j units of type j, which is characterized by the farm price p_{f_j} and the per acre application of the environmentally harmful input x_j^*. Assuming the one-to-one correspondence between the set of p_{f_j} and that of p_{r_j}, i.e. $p_{r_j} = r(p_{f_j})$ where r is invertible, the type is translated to the combination of p_{r_j} and x_j^* for the consumers.

2.2.2 The demand for types: deterministic utility

Facing J types of the same good (or J differentiated goods), consumer n is essentially making a discrete choice by selecting either one type or none. Her utility maximization problem can be written as (Hanemann 1984; Alpizar, Carlsson, and Martinsson 2003; Hanemann 1999)

$$\begin{aligned}
&\underset{\{C_{nj}\}}{Max}\ U_n(C_{n1},...,C_{nJ},x_1,...,x_J,z_n,L_n) \\
&s.t.\quad (i)\ y_n = \sum_{j=1}^{J} p_{r_j} C_{nj} + z_n \\
&\qquad (ii)\ \mathrm{C}_{ni} C_{nj} = 0,\ \forall i \neq j; \mathrm{C}_{nj} \in \{0, \mathrm{c}\}, \forall j \\
&\qquad (iii)\ \mathrm{C}_{nj} = 0 \Rightarrow \frac{\partial U_n}{\partial x_j} = 0, \forall j \\
&\qquad (iv)\ z_n \geq 0
\end{aligned}$$

where y_n is the consumer's income.

Constraint (ii) specifies that the consumer can choose at most one type at a time, and once she chooses a particular type she can only buy it with an exogenously fixed quantity c. This assumption is made to isolate the discrete choice with the continuous choice, leaving a purely discrete choice for the consumer. In (iii) we further assume weak complementarity (Mäler 1974; Hanemann 1984), i.e. the attributes of type j do not matter unless that type is actually consumed.

Given assumptions (2.3), the consumer would prefer consuming c units of the good with a certain type to consuming none of the good. Now suppose that the consumer has decided to consume c units of good of variety j. Conditional on this decision, her indirect utility function, by constraint (ii), can be written as

$$V_{nj}(\mathrm{x}_j, p_{r_j}, \mathrm{y}_n, L_n) = U_n(0,...,0,\mathrm{c},0,...,0,x_1,...,x_J,z_n,L_n) \triangleq U_{nj}(\mathrm{x}_j, \mathrm{y}_n - cp_{r_j}, L_n)$$

where the last equality follows from constraints (i) and (iii).

The consumer will choose type j if and only if

$$V_{nj}(\mathrm{x}_j, p_{r_j}, \mathrm{y}_n, L_n) \geq V_{nk}(\mathrm{x}_k, p_{r_k}, \mathrm{y}_n, L_n), \forall\, \mathrm{k} \neq \mathrm{j},$$

and the solution to the problem is given by

$$C_{nj}^{*} = \begin{cases} c, & \text{if } V_{nj}(\mathrm{x}_j, p_{r_j}, \mathrm{y}_n, L_n) \geq V_{nk}(\mathrm{x}_k, p_{r_k}, \mathrm{y}_n, L_n), \forall\, \mathrm{k} \neq \mathrm{j}, \\ 0, & \text{otherwise.} \end{cases}$$

2.2.3 The demand for types: random utility

Although the above decision-making is deterministic in nature for the consumer herself, it contains some elements that are not observable to the researcher. The unobservable elements could be unobserved characteristics of the consumer, excluded attributes of the types, and/or heterogeneity of consumers' tastes. Taking these elements into account leads to the use of a random utility model (McFadden 1974), in which an error term ε enters into the utility function, and the new random utility function is written as $U_n(C_{n1},...,C_{nJ}, x_1,...,x_J, z_n, L_n, \boldsymbol{\varepsilon}_n)$.

Following the same procedure as in section 2.2.2, consumer $n's$ conditional indirect utility function becomes $V_{nj}(\mathrm{x}_j, p_{r_j}, \mathrm{y}_n, L_n, \varepsilon_{nj})$, and the solution to her utility maximization problem is

$$C_{nj}^{*} = \begin{cases} c, & \text{if } V_{nj}(\mathrm{x}_j, p_{r_j}, \mathrm{y}_n, L_n, \varepsilon_{nj}) \geq V_{nk}(\mathrm{x}_k, p_{r_k}, \mathrm{y}_n, L_n, \varepsilon_{nk}), \forall\, \mathrm{k} \neq \mathrm{j}, \\ 0, & \text{otherwise.} \end{cases} \quad (2.7)$$

Due to the introduction of the error term, C_{nj}^{*} is a random variable with a mean given by

$$E(C_{nj}^{*}) = \pi_{nj} \cdot \text{c}, \tag{2.8}$$

where $\pi_{nj} = \Pr\{V_{nj}(x_j, p_{r_j}, y_n, L_n, \varepsilon_{nj}) \geq V_{nk}(x_k, p_{r_k}, y_n, L_n, \varepsilon_{nk}), \forall k \neq j\}$ is the probability that the consumer n will choose type j.

Then the expectation of the total demand for type j is

$$E(D_j)(x_1, ..., \text{x}_J, p_{r_1}, ...p_{r_J}, y_n, L_n) = \sum_{n=1}^{N} E(C_{nj}^{*}) = c\sum_{n=1}^{N} \pi_{nj}. \tag{2.9}$$

2.2.4 Characterizing the multimarket equilibrium

In multimarket equilibrium, the supply of each type is equal to the demand for it:

$$S_j(A_j, p_{f_j}, w, r, T_j) = E(D_j)(x_1, ..., \text{x}_J, p_{r_1}, ...p_{r_J}, y_n, L_n), \forall j. \tag{2.10}$$

In addition, the input demand functions are given by

$$x_j = x_j^{*}(p_{f_j}, w, r, T_j), \forall j, \tag{2.11}$$

and the transition between farm price and retail price is defined as

$$p_{r_j} = r(p_{f_j}), \forall j. \tag{2.12}$$

Given exogenous variables $(A_j, w, r, T_j, y_n, L_n)$, conditions (2.10)-(2.12) determine market clearing prices $(p_{f_1}, ...p_{f_J})$ and $(p_{r_1}, ...p_{r_J})$, and the equilibrium supply and demand (expected) of each type $(S_1, ..., S_J)$ and $(E(D_1), ..., E(S_J))$.

2.2.5 Welfare computation

Define the unconditional indirect utility function as

$$V_n(x_1,...,x_J, p_{r_1},...p_{r_J}, y_n, L_n, \boldsymbol{\varepsilon}_n)$$
$$= \max[V_{n1}(x_1, p_{r_1}, y_n, L_n, \varepsilon_{n1}),...,V_{nJ}(x_J, p_{r_J}, y_n, L_n, \varepsilon_{nJ})] \qquad (2.13)$$

Plugging the input demand function into equation (2.13) yields

$$V_n(p_{f_1},...p_{f_J}, p_{r_1},...p_{r_J}, T_1,...,T_J, w, r, y_n, L_n, \varepsilon_n)$$
$$= \max[V_{n1}(x_1(p_{f_1}, w, r, T_1), p_{r_1}, y_n, L_n, \varepsilon_{n1}),...,V_{nJ}(x_J(p_{f_J}, w, r, T_J), p_{r_J}, y_n, L_n, \varepsilon_{nJ})] \qquad (2.14)$$

Multimarket Equilibrium

Now consider an exogenous shock in T_j initiated by the policy maker to affect type j only. In the context of multimarket equilibrium, we assume that the farm price is responsive to the changes in the retail price and vise visa. Therefore in the long term p_{f_j} is dependent on p_{r_j}, i.e. $p_{r_j} = r(p_{f_j})$. In this case, the multimarket equilibrium WTP for the adoption of T_j is defined as

$$V_n(r(p_{r_1}),...,r(p_{r_J}), p_{r_1},...p_{r_J}, T_j = 0, T_{-j}, w, r, y_n, L_n, \varepsilon_n)$$
$$= V_n(r(p_{r_j} + \mathrm{WTP}_{ME}), r_{-j}(p_{r_{-j}}), p_{r_j} + \mathrm{WTP}_{ME}, p_{r_{-j}}, T_j = 1, T_{-jJ}, w, r, y_n, L_n, \varepsilon_n). \qquad (2.15)$$

Single-market Equilibrium

In the context of single market partial equilibrium, we assume that the farm price is fixed by the contracts between growers and retailers, and therefore in the short term p_{f_j} is independent of p_{r_j}. In this case, the single-market equilibrium WTP for the adoption of T_j is defined as

$$
\begin{aligned}
&V_n(p_{f_1},\dots p_{f_J}, p_{r_1},\dots p_{r_J}, T_j=0, T_{-j}, w, r, y_n, L_n, \varepsilon_n) \\
&= V_n(p_{f_1},\dots p_{f_J}, p_{r_j}+\mathrm{WTP}_{SE}, p_{r_{-j}}, T_j=1, T_{-jJ}, w, r, y_n, L_n, \varepsilon_n).
\end{aligned} \tag{2.16}
$$

Note that given the assumptions of the production function and the utility function, the magnitude of single-market equilibrium WTP for an exogenous shock in T_j is greater than that of multimarket equilibrium WTP. In single-market equilibrium, an exogenous shock in T_j leads to reduced demand for the environmentally harmful input, and hence the consumer is willing to pay a higher retail price for the agricultural good. In equation (2.16) the retail price of type j changes from p_{r_j} to $p_{r_j}+\mathrm{WTP}_{SE}$, and the *jth* technology changes from 0 to 1, keeping everything else constant. In contrast, the impact mechanism continues in multimarket equilibrium since the consumption side also has a feedback effect on the production side. In equation (2.15), when the retail price of type j changes from p_{r_j} to $p_{r_j}+\mathrm{WTP}_{ME}$, its farm price changes accordingly from $r(p_{r_j})$ to $r(p_{r_j}+\mathrm{WTP}_{ME})$. Intuitively, given the consumers' willingness to pay for a higher retail price, the farm price is likely to be raised, encouraging the farmers to apply the input at a higher rate in order to increase their yields. This higher rate results in the producers' applying a little higher amount of the input than in single-market equilibrium, and therefore the consumer is willing to pay a little lower retail price than in single-market equilibrium. This interactive process keeps going, back and forth, until the multimarket equilibrium WTP is reached. From the above reasoning the WTP in multimarket equilibrium has a smaller magnitude than the WTP in single-market equilibrium.

2.3 Surveys and Data

2.3.1 Background

The United States is the world's second largest producer of tomatoes, just behind China. In 2012, the United States produced 27.59 million hundredweight of fresh tomatoes on 94,700 acres of harvested land, accounting for $864 million in total market value (ERS 2013).

While the U.S. fresh field-grown tomato production has increased over the past decades, the application rate of chemicals has generally declined. In 2010, nitrogen, phosphate, potash and sulfur were applied at an average rate of 142, 111, 182 and 47 pounds per acre, dropping 34%, 16%, 36% and 64% from the rate in 2006, respectively. In the meanwhile, fungicides, herbicides, insecticides and other pesticides were applied at an average rate of 17.07, 0.68, 2.26 and 25.70 pounds of active ingredient per acre, all less than to the corresponding rate in 2006 except herbicides which have risen by 25% (NASS 2007, 2011).

2.3.2 The grower survey and data

The grower survey questionnaire is composed of three parts: the first part asks about the technologies that tomato growers used in 2011; the second is about the application of pesticides and fertilizers; and the third requests demographic information.

The survey was conducted by the United States Department of Agriculture's National Agricultural Statistics Service (NASS) Ohio Field Office from March to May 2012, and was distributed to all tomato growers in Maryland, New York, and Ohio on the NASS' list. A total of 305 questionnaires were returned. After dropping those with incomplete responses or severe missing data, 219 valid questionnaires were obtained. Two observations are recorded if a farmer grows both organic and conventional fresh tomatoes, making the number of total valid observations equal to 222. Among them, 91 are organic growers and 131 are conventional ones. Descriptive statistics are provided in Table 2.1. [3]

The average amount of active ingredient of chemical pesticides applied on conventional tomato farms is 5.89 pounds per acre per year, and of chemical fertilizers is 88.83 pounds per acre per year. For organic tomato farms, the application of chemical pesticides or fertilizers is zero, in accordance with the USDA national organic standards for certified organic farms. On average conventional tomato farms have 4.25 acres of tomatoes, whereas organic farms only have 0.72 tomato acres. The average output price received by conventional farms is \$1.41/lb, and by organic farms is \$2.32/lb. Among the conventional farms, 41.2%, 8.4%, 12.2% and 9.2% adopt a cover crop, mixed-species cover crop, high tunnel, and greenhouses, respectively. For organic farms, the corresponding percentages are 48.4%, 28.6%, 19.8% and 8.8%.

2.3.3 The consumer survey and data

The consumer data come from a choice experiment via an online survey conducted in May 2013 by QSample. The sampled individuals were recruited by QSample through email and online marketing, which targeted all residents in Maryland, New York, and Ohio who usually shop for fresh tomatoes. A total of 498 valid responses were obtained[4], with each respondent answering four choice questions, or 1992 total observations.

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[3] All figures and tables are placed separately at the end of the chapter.

[4] Among the 692 consumers who responded to the survey, 70 did not complete the survey, 72 indicated that they don't usually eat fresh tomatoes, and 7 are not from our research states. In addition, 17 of them spent less than 120 seconds in completing the survey, and 27 always chose the same alternative in the four choice sets, both highlighting the probability of attribute non-attendance, which occurs when a respondent ignores some attributes while performing a choice task. See

Table 2.2 provides the descriptive statistics for the sample characteristics. Among the 498 consumers in the sample, 43.9% are male, and 45.7% are married. The average age, years of education, and household size are 41.7 years, 14.9 years and 2.8, respectively. More than half of the consumers in the sample have an annual household income under $60,000, and about 18% of them report a household income more than $100,000 per year. Caucasians account for 78.0% of the sample, the largest share. Next come African Americans (11.4%), Asian Americans (6.6%) and Latino Americans (5.4%). 45.5% of the consumers have full time jobs, 17.0% have part time jobs, and 9.6% are unemployed. Most consumers in the sample are from New York (55.1%), and the rest are from Ohio (32.5%), and from Maryland (12.4%).

During the experimental design, a draft questionnaire was sent to a group of people for pilot testing, and their responses were used to estimate the prior value for the coefficients of a simple conditional logit model. The prior information is used to increase the utility balance in efficient choice design – the utility of each alternative in the same choice set should be set equal to make sure no alternative will become dominant. An experimental design was conducted using the software Ngene11 (ChoiceMetrics 2012). Finally, the design results were employed to create the final choice questions and questionnaire. Comments and suggestions from the pilot testing also helped improve the final questionnaire.

The questionnaire has three sections. The first section asks about the consumers' attitudes toward the environment and their perception of chemicals in their consumption of

Scarpa et al. (2009) for more details.

fresh tomatoes. The second asks consumers to make four hypothetical choices, and the third requests demographic information.

Because our research objective is to estimate the consumers' willingness to pay for reduction in the applications of chemicals, especially pesticides and fertilizers, we used the application of pesticides, the application of fertilizers and the price of tomato as the attributes of alternatives in any choice sets. In addition, to simplify the choice tasks, only the above three attributes were selected. The questionnaire has four choice sets in which the respondents are asked to choose the one they prefer among three alternatives. Figure 2.1 presents an example choice question.

The levels of the attributes were selected based on two status quo alternatives: conventional and organic tomatoes. According to NASS (2011), the average application of chemical fertilizers (active ingredients) in conventional fresh tomato production in Ohio[5] is 197.45 lb/acre, and that of pesticides is 27.26 lb/acre. The applications of chemical fertilizers and pesticides are zero for organic tomato production. USDA Agricultural Marketing Service's Fruit and Vegetable Programs regularly monitor the retail price of fresh tomatoes. Between April to May 2013, the retail price of conventional vine-ripened tomatoes is around $1.99/lb, and that of organic vine-ripened tomatoes is about $3.99/lb. Based on these benchmarks, we set the price of conventional and organic tomatoes as $1.9/lb and $4/lb, the application of pesticides as 27 lb/acre/year and 0, the application of fertilizers as 200 lb/acre/year and 0, respectively. Different combinations of pesticides and

[5] The NASS Agricultural Chemical Use Program provides USDA's official statistics about on-farm chemical use and pest management practices. Since 1990, NASS has surveyed U.S. farmers to collect information on the chemical ingredients they apply to agricultural commodities through fertilizers and pesticides. The program conducts survey on certain commodities on a rotating basis, and has surveyed fresh tomato farmers in selected states and in certain years. The most recent survey on chemical use in fresh tomato production was in 2010, and only included farmers in California, Florida, Georgia, New Jersey, North Carolina, Ohio and Tennessee. Since the main focus of our application is for consumers in Maryland, New York and Ohio, we choose the Ohio aggregate data in 2010 as a benchmark.

fertilizers levels, for example 0 in pesticide application and 200 lb/acre/year in fertilizer application, should correspond to a different level of price rather than 1.9 $/lb or 4 $/lb to make sure the utility is balanced. Therefore, we finally determined the levels of the three attributes as shown in Table 2.3.

Note that the alternatives differ in price and total amount of chemical fertilizer and pesticides applied in their production, and other characteristics, e.g. taste, appearance, nutritional contents and chemical residue, are the same. As shown in Figure 2.1, each type of tomato is described by application of chemical pesticide and fertilizer as well as price, all in a row. Two numbers are given for the application of pesticides or fertilizer: one for the percent reduction from the current situation, and the other for the total amount of application in pounds per acre per year.

2.4 Empirical Strategies and Results

2.4.1 The growers' demand for pesticides and fertilizers[6]

In our sample, the applications of pesticides and fertilizers for organic growers are both zero. In other words, if grower i adopts a technology called organic farming, her expected level of chemical inputs will be zero, or will be reduced by 100%.

For conventional growers in our sample, Figure 2.2 depicts the Kernel density of their pesticide and fertilizer applications. It shows a clear pattern of notable zero observations and a heavy right-hand tail, similar to health care expenditure data described by Manning and Mullahy (2001). Santos Silva, Tenreyro, and Windmeijer (2015) present four "corner solution" models that are widely employed for such non-negative data with many zeros:

[6] One limitation of this study is the poor quality of our grower survey dataset. Missing values greatly reduced the sample size, and the absence of some input prices reduces the reliability of our estimation results of input demand functions.

(1) the exponential conditional expectation (ECE); (2) the two-part model (2PM) of Duan et al. (1983); (3) Mullahy's (1998) modified two-part model (M-2PM), and (4) the sample selection model in logs. The specification of each model and the expectation of the dependent variable are summarized in Table 2.4.

We first estimate the conventional farmers' demand functions for pesticides and fertilizers using these four models, and present the results in Tables 2.5 and 2.7. The four models are then tested against each other using the HPC specification test (Santos Silva, Tenreyro, and Windmeijer 2015). Tables 2.6 and 2.8 summarizes the testing results, which clearly reject the ECE model for pesticide demand but fail to reject any of the four models for fertilizer demand. The final choice of model is based on two criteria: (1) consistency with economic theory, i.e., the demand function for one input is increasing with output price and the price of its substitute inputs, and decreasing in own price; (2) simplicity for computations, which implies that the ECE model is always preferable to two-part models and the sample selection model. According to these criteria, we choose the modified two-part model and the ECE model as the most suitable model for the pesticide and fertilizer demand functions, respectively.

2.4.2 The consumers' preference for pesticides and fertilizers

We consider the following three representative types of discrete choice models:

(1) Conditional Logit Model (CL Model) (McFadden 1974)

The utility consumer n obtains from alternative j is specified as

$$U_{nj} = \varphi_0 + \varphi_1 pest_{nj} + \varphi_2 fert_{nj} + \varphi_3 p_{r_{nj}} + \varepsilon_{nj}, \tag{2.17}$$

where the coefficients φ 's are constant, and ε_{nj} 's follow independent and identically distributed (i.i.d.) Gumbel distribution. An alternative specification is

$$U_{nj} = \varphi_0 + \varphi_1 pest_{nj} + \varphi_2 fert_{nj} + \varphi_4 pest_{nj} \cdot fert_{nj} + \varphi_3 p_{r_{nj}} + \varepsilon_{nj}, \qquad (2.17')$$

(2) Mixed Logit Model with Uncorrelated Coefficients (MXL-UC Model) (McFadden and Train 2000)

The utility consumer n obtains from alternative j is specified as

$$\begin{aligned} U_{nj} &= \varphi_{n0} + \varphi_{n1} pest_{nj} + \varphi_{n2} fert_{nj} + \varphi_3 p_{r_{nj}} + \varepsilon_{nj}, \\ \varphi_{nk} &\triangleq \varphi + \eta_{nk}, k = 0,1,2,3 \end{aligned} \qquad (2.18)$$

$$U_{nj} = \varphi_{n0} + \varphi_{n1} pest_{nj} + \varphi_{n2} fert_{nj} + \varphi_{n4} pest_{nj} \cdot fert_{nj} + \varphi_3 p_{r_{nj}} + \varepsilon_{nj}, \qquad (2.18')$$

where the φ_n 's are random coefficients that are not correlated with each other, and ε_{nj} 's follow i.i.d. Gumbel distribution.

(3) Mixed Logit Model with Correlated Coefficients (MXL-C Model)

The utility consumer n obtains from alternative j is specified the same as in equation (2.18), but now the coefficients φ 's are random coefficients that are correlated with each other.

The above models are estimated using maximum simulated likelihood method (Hole 2007), and the results are presented in Table 2.9. Since the models include the interaction term, the marginal WTP (MWTP) for a one pound reduction in the application of active ingredients of chemical pesticides (fertilizers) depends on the total application of active ingredients of chemical fertilizers (pesticides). The three models give slightly different results. At the grower sample mean, The Conditional Logit model shows that the consumers' MWTP for a one pound reduction in the application of active ingredients of chemical pesticides is 11.8 cents, and for chemical fertilizers it is 1.8 cents. The mixed logit model with uncorrelated coefficients indicates that the consumers' MWTP for a one pound reduction in the application of active ingredients of chemical pesticides is 9.8 cents, and for chemical fertilizers it is 2.2 cents. The mixed logit model with correlated coefficients suggests that the MWTP for a one pound reduction in the application of active ingredient of chemical pesticides is 3.2 cents, and for chemical fertilizers it is 1.7 cents.

According to the information criteria such as AIC and BIC, the mixed logit model with correlated coefficient is the best fit among the three models. However, for comparison purposes all three models are used to measure welfare changes.

2.4.3 Relationship between farm and retail prices

Using 22 years of data on the farm and retail prices of field grown fresh tomatoes, we estimate two simple relationships between farm and retail prices in Table 2.10: one is fixed farm share and the other is a linear relationship with constant term.[7] The results can be summarized as

$$\begin{aligned}
&(1)\, p_r = r(p_f) = 3.7037 * p_f \Leftrightarrow p_f = r^{-1}(p_r) = 1/3.7037 * p_r; \\
&(2)\, p_r = r(p_f) = 2.0532 * p_f + 0.6543 \\
&\Leftrightarrow p_f = r^{-1}(p_r) = 1/2.0532 * p_r - 0.6543/2.0532.
\end{aligned} \tag{2.19}$$

[7] The data are from the Economic Research Service (ERS) at the United States Department of Agriculture (USDA), available at: http://www.ers.usda.gov/data-products/price-spreads-from-farm-to-consumer.aspx.

2.4.4 Welfare measurement

Following the framework developed in section 2.2.3, the consumers' MWTP is estimated for adoption of technologies such as organic farming, mixed-species cover crop, and greenhouses.[8] The MWTP for the adoption of one technology is a function of grower characteristics and other technology adoption variables. To ensure easy comparison, a status quo baseline scenario is established (Table 2.11), in which the grower characteristics variables are assumed to take the conventional grower sample mean values, and currently all technologies are not adopted.

The consumers' MWTP for the adoption of organic farming, mixed-species cover crops and greenhouses are summarized in Tables 2.12 under different utility functions and different assumptions about the relationship between farm price and retail price. In case that equations (2.15) and (2.16) do not have closed-form solutions, the WTPs are calculated by numerical approximation, and as a result their distributions are unknown.[9] The results show that in our sample the consumers' average single-market and multimarket equilibrium marginal WTP for the environmental benefits from the tomato growers' adoption of organic farming technology is between \$2.09 and \$3.03 per pound, compared to the baseline scenario.

Compared to baseline scenario, in our sample the consumers' average single-market equilibrium marginal WTP for the environmental benefits from the tomato growers'

[8] When predicting the expected demands for fertilizers and pesticides, we follow Gelman and Hill's (2007, pp. 69) suggestion that: (a) If a predictor is not statistically significant and has the expected sign, it is generally fine to keep it in. It may not help predictions dramatically but is also probably not hurting them. (b) If a predictor is not statistically significant and does not have the expected sign (for example, incumbency having a negative effect on vote share), consider removing it from the model (that is, setting its coefficient to zero). (c) If a predictor is statistically significant and does not have the expected sign, then think hard if it makes sense. (For example, perhaps this is a country such as India in which incumbents are generally unpopular; see Linden, 2006.) Try to gather data on potential lurking variables and include them in the analysis. (d) If a predictor is statistically significant and has the expected sign, then by all means keep it in the model.

[9] Standard deviations may be simulated using bootstrapping, and these will be done in future research.

adoption of mixed-species cover crops is between $0.72 and $0.91 per pound, whereas the average multimarket equilibrium marginal WTP is from $0.44 to $0.80 per pound. The consumers' average single-market equilibrium marginal WTP for the environmental benefits from the tomato growers' adoption of greenhouses is between $1.07 and $1.52 per pound, whereas the average multimarket equilibrium marginal WTP is from $0.95 to $1.20 per pound.

These results confirm that the average multimarket equilibrium marginal WTP is smaller in magnitude than the average single-market equilibrium WTP for all cases. The difference between them are smaller if the average farm share is smaller and thus the farm price is less responsive to retail price. These results imply that the conventional choice experiment approach based on a single-market equilibrium tends to overestimate the environmental benefits of an environmentally friendly technology adoption, and the size of the bias depends on the sensitiveness of the farm price to retail price – the more sensitive, the larger the bias is.

2.5 Conclusion

The adoption of new technologies can change farmers' optimal use of synthetic chemicals, which in turn may affect consumer welfare. This impact pathway is well-documented in the literature, but few studies have evaluate the size of the impact – consumers' willingness to pay (WTP) for environmentally-friendly technologies adopted by farmers. The main challenge is that many technologies adopted in agricultural production are not easily observable in the final products, therefore it is difficult to gauge consumers' preference for these technologies.

This study proposes a novel multimarket equilibrium framework for more accurately estimating the consumer surplus for environmentally-friendly technologies adopted by farmers. In a competitive economy of heterogeneous farmers and consumers, an agricultural good is produced by each farmer using an environmentally harmful input, fixed land, and an exogenous farming technology. Profit maximization leads to the optimal demand for the input, and hence the supply of many distinct types of the agricultural good. These types are differentiated by two attributes: farm (retail) price, and the amount of the environmentally harmful input applied in the production. Facing a differentiated goods market, each consumer makes a purely discrete choice among the types good. The consumers' utility maximization results in the demand for the good types, as well as their indirect utility functions. In multimarket equilibrium, changes in retail price of the agricultural good have feedback effects on farm price, and both the agricultural good market and the input market must be cleared to determine the equilibrium farm and retail prices. In contrast, in single-market equilibrium, the farm and retail prices are independent and only the agricultural good market is cleared to determine the equilibrium retail price. Finally, the input demand functions substitutes for the input attributes in the indirect utility function, giving the new utility as function of technology adoption. Then the multimarket and single-market equilibrium WTPs for the adoption of the farming technology are derived and compared.

We conduct two surveys on the production and consumption of vine-ripened tomatoes in the Northeastern United States, and apply the above framework to the survey data. Estimation results show that in our sample the multi-market equilibrium WTP is smaller in magnitude than the conventional single-market equilibrium WTP, implying that the conventional choice experiment approach based on a single-market equilibrium tends to overestimate the environmental benefits of an environmentally friendly technology adoption.

Some may argue that our framework has not solved the latent attributes problem: the consumers cannot directly observe the total amount of pesticides and fertilizers applied in the production of a box of fresh tomatoes in the grocery store. While the tomato consumers may not know the exact amount of pesticides and fertilizers applications, they are most likely to be aware of, familiar with, or interested in these applications, making the elicitation of their preferences for pesticide and fertilizer applications possible. Since the choice experiments are hypothetical, we can create labels in a form similar to energy labels, displaying the percentage of reduction in pesticide and fertilizer applications as well as the projected amount of absolute applications. If we label the tomato products, then the consumers can observe that label in the same way they observe the USDA Organic label. In this way, the total amounts of pesticides and fertilizers become an observed attribute of tomatoes. In the consumer survey, we create such labels and present them to our sample, and the respondents seemed to accept and understand them. What the consumers do not know is the relationship between technologies adopted and the application of pesticides and fertilizers, but we establish the linkage through estimation of the grower survey data.

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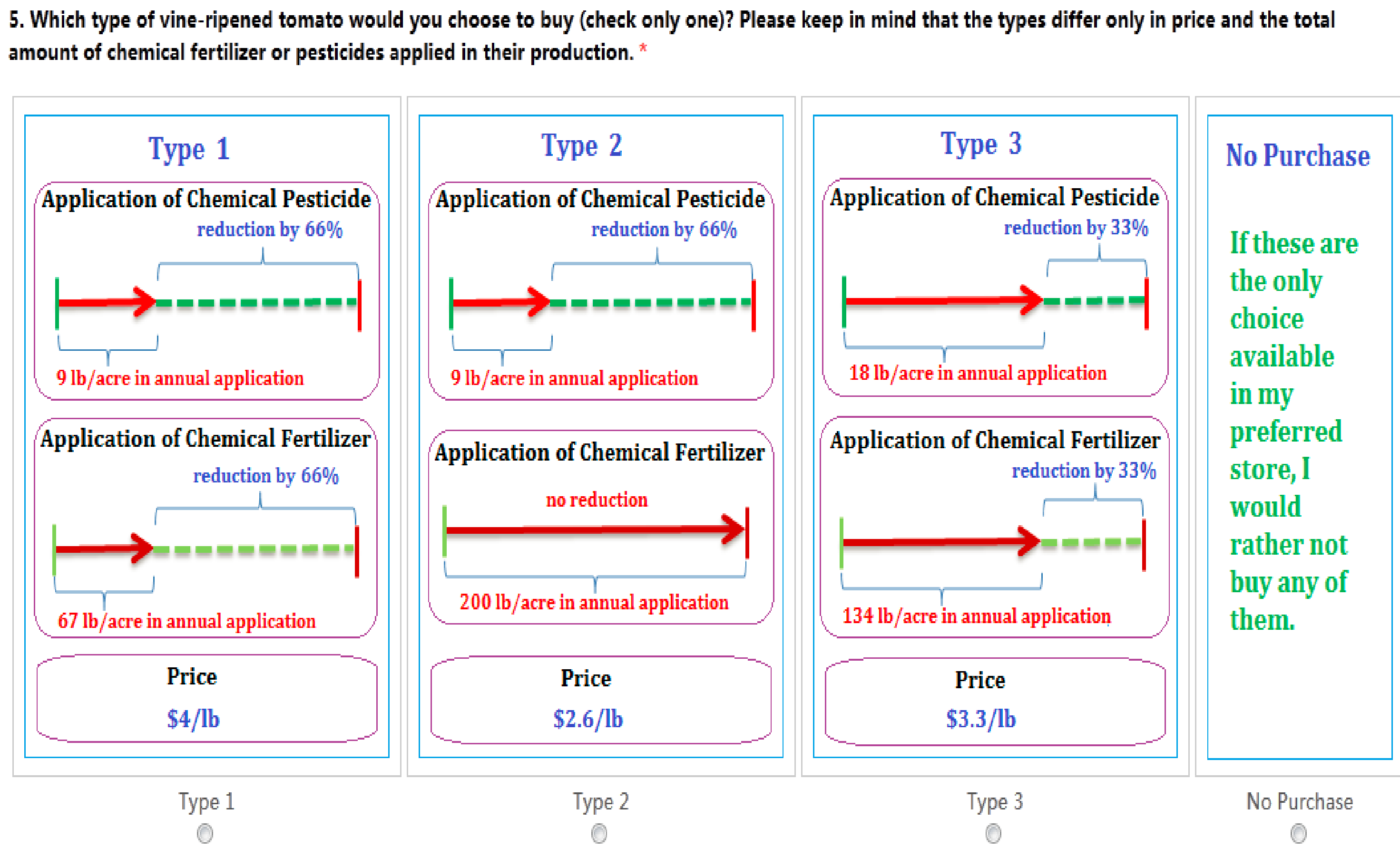

Figure 2.1 Example choice question

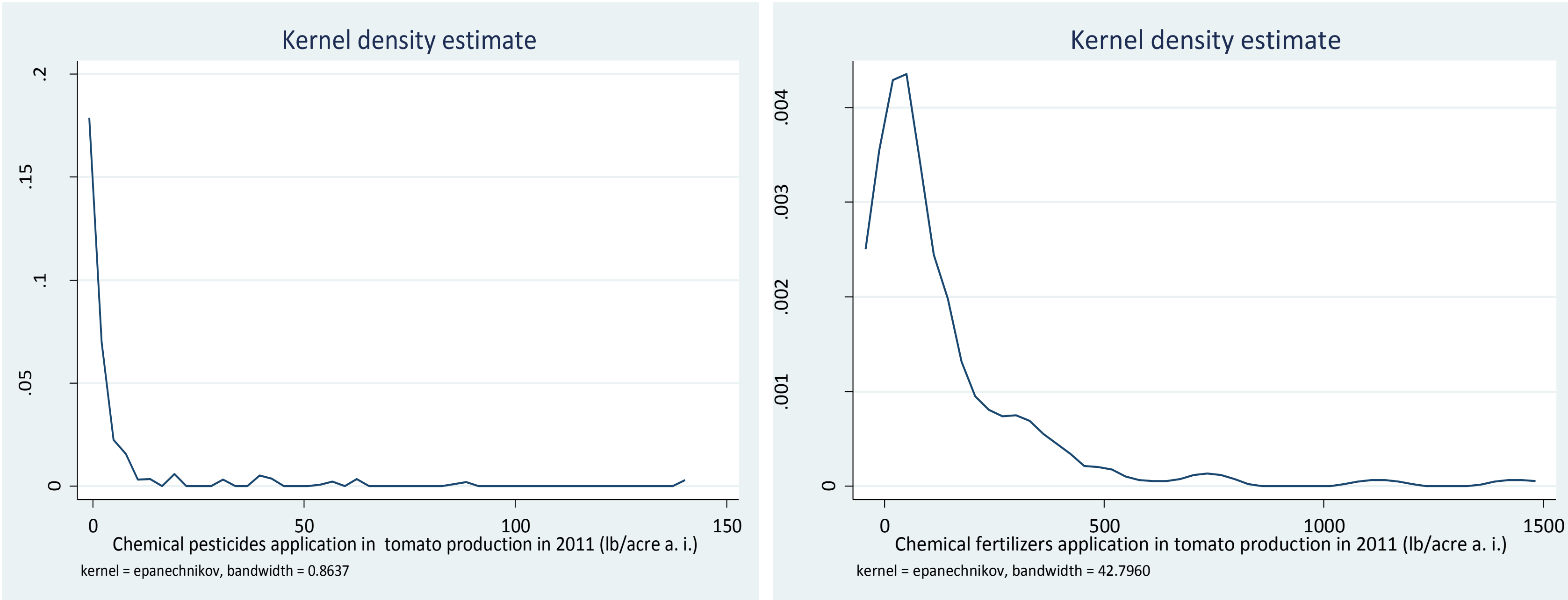

Figure 2.2 Kernel density of pesticides and fertilizers application in conventional tomato production

Table 2.1 Descriptive statistics for conventional and organic farmers

	Conventional farms			Organic farms			All farms		
Variable	count	mean	sd	count	mean	sd	count	mean	sd
Production									
Application of active ingredient of chemical pesticides (lb/acre/year)	106	5.890	18.570	72	0	0	178	3.508	14.590
Application of active ingredient of chemical fertilizers (lb/acre/year)	116	88.830	120.800	86	0	0	202	51.010	101.400
Acreage of farmland for fresh tomatoes (acre)	131	4.253	21.170	91	0.724	1.571	222	2.806	16.360
Farm price ($/lb)	101	1.413	0.825	66	2.315	1.132	167	1.769	1.053
Technology Adopted									
Use of cover crop (1=yes, 0=no)	131	0.412	0.494	91	0.484	0.502	222	0.441	0.498
Use of mixed-species cover crop (1=yes, 0=no)	131	0.084	0.278	91	0.286	0.454	222	0.167	0.374
Use of high tunnel (1=yes, 0=no)	131	0.122	0.329	91	0.198	0.401	222	0.153	0.361
Use of greenhouses (1=yes, 0=no)	131	0.092	0.290	91	0.088	0.285	222	0.090	0.287
Farmer Characteristics									
Farmer is male (1=yes, 0=no)	124	0.790	0.409	91	0.670	0.473	215	0.740	0.440
Farmer’s age (years)	124	59.480	12.790	90	55.880	13.020	214	57.970	12.980
Farmer’s education (years)	124	14.160	2.892	90	16.180	3.189	214	15.010	3.174

Table 2.2 Descriptive statistics for consumer characteristics

Variable	N	Mean/Percentage	Standard Deviation	Min	Max
Male	5988	43.89%			
Married	5988	45.69%			
Age (years)	5988	41.70	13.88	18	72
Education (years)	5988	14.91	2.85	8	22
Household size	5988	2.79	1.337	1	8
Annual Household Income					
Below $20,000	5988	17.64%			
$20,000 - $39,999	5988	20.44%			
$40,000 - $59,999	5988	15.03%			
$60,000 - $99,999	5988	23.44%			
$100,000 - $159,999	5988	14.03%			
Above $159,999	5988	4.01%			
Prefer not to disclose	5988	5.41%			
Race & Ethnicity					
Asian	5988	6.61%			
Black	5988	11.42%			
Latino	5988	5.41%			
White	5988	77.96%			
Employment					
Full time	5988	45.49%			
Part time	5988	17.03%			
Unemployed	5988	9.62%			
Residence					
MD	5988	12.42%			

NY	5988	55.11%
OH	5988	32.46%

Table 2.3 Attributes and levels of alternatives

Attribute	Level	Description
Application of Chemical Pesticides (lb/acre/year)	0, 9, 18, 27 (100%, 67%, 33%, 0 in reduction)	Set average application rates for organic and conventional tomato production as benchmarks and produce evenly spaced levels. 27 lb/acre/year represents status quo level of pesticide application
Application of Chemical Fertilizers (lb/acre/year)	0, 67, 134, 200 (100%, 67%, 33%, 0 in reduction)	Set average application rates for organic and conventional tomato production as benchmarks and produce evenly spaced levels. 200 lb/acre/year represents status quo level of fertilizer application
Price ($/lb)	1.9, 2.6, 3.3, 4	Set average application rates for organic and conventional tomato production as benchmarks and produce evenly spaced levels. $1.9/lb represents status quo level of price

Table 2.4 Some models for corner solution data

Model	Specification	$E(y\mid x)$
ECE	$E(y\mid x)=\exp(x'\beta)$	$\exp(x'\beta)$
2PM	$\Pr(y>0\mid x)=\Phi(x'\gamma)$, $\ln(y)=x'\beta+e, \forall y>0$ $e\mid x\sim N(0,\sigma^2)$	$\exp(x'\beta+\frac{\sigma^2}{2})\Phi(x'\gamma)$
M-2PM	$\Pr(y>0\mid x)=\Phi(x'\gamma)$, $\mathrm{E(y\mid x, y>0)}=\exp(x'\beta)$	$\exp(x'\beta)\Phi(x'\gamma)$
Sample selection	$\Pr(y>0\mid x)=\Pr(x'\gamma+e_1>0\mid x)$, $\ln(y)=x'\beta+e_2, \forall y>0$ $\left.\begin{bmatrix} e_1 \\ e_2 \end{bmatrix}\right\| x\sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{pmatrix} 1 & \rho\sigma \\ \rho\sigma & \sigma^2 \end{pmatrix}\right)$.	$\exp(x'\beta+\frac{\sigma^2}{2})\Phi(x'\gamma+\rho\sigma)$

Notes: ECE is exponential conditional expectation; 2PM is two-part model; M-2PM is modified two-part model. $\Phi(.)$ is the cumulative density function of standard normal distribution.
Source: Santos Silva, Tenreyro, and Windmeijer (2015).

Table 2.5 Demand for pesticides

Pesticide	(1) ECE	(2) 2PM 1st Part	(2) 2PM 2nd Part	(3) M-2PM 1st Part	(3) M-2PM 2nd Part	(4) Selection 1st Part	(4) Selection 2nd Part
Output price (farm price)	0.44913****	-0.07564	0.66199**	-0.07564	0.68841****	-0.39775	0.65066**
	(0.1152)	(0.1910)	(0.3049)	(0.1910)	(0.1166)	(0.2569)	(0.3187)
Fertilizer price	-0.05056	-0.15514**	0.36086*	-0.15514**	0.28715****	-0.91564****	0.11414
	(0.0566)	(0.0751)	(0.1976)	(0.0751)	(0.0864)	(0.2780)	(0.4519)
Pesticide price	-0.00406****	0.00004	-0.00070**	0.00004	-0.00061*	0.00023	-0.00062**
	(0.0009)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0003)	(0.0003)
Used cover crops?	0.35781*		-0.67542		0.35558*		-0.56477
	(0.1977)		(0.4801)		(0.2117)		(0.4686)
Used of mixed species cover crops?	0.02137		1.46276		0.31931		1.36505
	(0.4662)		(1.1845)		(0.4725)		(1.7991)
Used high tunnel?	-0.41531		-1.31789		-1.29895**		-1.30255
	(0.3986)		(0.9873)		(0.5316)		(1.0418)
Used green house?	-0.93567*		-0.89988		-0.74240		-0.71430
	(0.5589)		(0.7547)		(0.5577)		(0.7290)
Age	-0.00532	-0.01316	-0.00181	-0.01316	0.05075	-0.15322*	-0.02907
	(0.0410)	(0.0691)	(0.1199)	(0.0691)	(0.0457)	(0.0813)	(0.1336)
Age squared	-0.00020	-0.00009	-0.00003	-0.00009	-0.00059	0.00102	0.00008
	(0.0004)	(0.0006)	(0.0011)	(0.0006)	(0.0004)	(0.0007)	(0.0011)
Male	0.93342***	1.16002****	-0.11653	1.16002****	0.20747	0.65579*	0.20421
	(0.2947)	(0.3257)	(0.6565)	(0.3257)	(0.2851)	(0.3655)	(0.8035)
Acreage		0.02532		0.02532		0.08435	

		(0.0621)		(0.0621)		(0.0890)	
Constant	0.66283	0.85005	-0.29892	0.85005	-1.38337	6.80878**	0.43831
	(1.1994)	(2.0678)	(3.7522)	(2.0678)	(1.4249)	(2.8859)	(4.3654)
athrho						0.51192	0.51192
						(0.6651)	(0.6651)
lnsigma						0.32426*	0.32426*
						(0.1815)	(0.1815)
N	97	119	49	119	49	91	91
Pseudo/Adjusted R2	0.24	0.16	0.13	0.16			
Log-likelihood	-189.12	-67.38	-80.25	-67.38	-111.59	-119.27	-119.27

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table 2.6 HPC specification test for pesticide demand estimation

Model comparison	H0: The first model is valid	H0: The second model is valid	Decision
	P-value	P-value	
ECE vs. 2PM	0.00	0.36	Reject the first model
ECE vs. M-2PM	0.00	0.36	Reject the first model
ECE vs. Selection	0.00	0.53	Reject the first model
2PM vs. M-2PM	0.65	0.92	Fail to reject either
2PM vs. Selection	0.83	0.88	Fail to reject either
M-2PM vs. Selection	0.72	0.38	Fail to reject either

Table 2.7 Demand for fertilizers

Fertilizer	(1) ECE	(2) 2PM		(3) M-2PM		(4) Selection	
		1st Part	2nd Part	1st Part	2nd Part	1st Part	2nd Part
Output price (farm price)	0.14883****	0.13237	0.15843	0.13237	0.11240****	0.07051	0.22034
	(0.0140)	(0.1985)	(0.1815)	(0.1985)	(0.0136)	(0.2202)	(0.2067)
Fertilizer price	-0.12572****	-0.05383	-0.19058***	-0.05383	-0.09169****	-0.06828	-0.20359***
	(0.0064)	(0.0806)	(0.0584)	(0.0806)	(0.0053)	(0.0827)	(0.0633)
Pesticide price	0.00004**	0.00008	0.00004	0.00008	-0.00000	0.00013	0.00005
	(0.0000)	(0.0003)	(0.0002)	(0.0003)	(0.0000)	(0.0004)	(0.0002)
Used cover crops?	0.28221****		0.30330		0.15639****		0.25633
	(0.0200)		(0.2722)		(0.0201)		(0.2703)
Used of mixed species cover crops?	-0.86018****		-0.92712*		-0.82403****		-0.87751
	(0.0484)		(0.5135)		(0.0487)		(0.5464)
Used high tunnel?	0.69211****		1.02606**		0.64349****		0.85461
	(0.0337)		(0.5139)		(0.0353)		(0.5343)
Used green house?	-0.73677****		-0.31383		-0.57950****		-0.35584
	(0.0407)		(0.4781)		(0.0414)		(0.4664)
Age	-0.04780****	-0.22513**	0.05343	-0.22513**	0.00892*	-0.23833**	0.01823
	(0.0046)	(0.1012)	(0.0584)	(0.1012)	(0.0046)	(0.1107)	(0.0700)
Age squared	0.00051****	0.00206**	-0.00040	0.00206**	-0.00001	0.00217**	-0.00005
	(0.0000)	(0.0009)	(0.0005)	(0.0009)	(0.0000)	(0.0009)	(0.0006)
Male	1.32898****	0.74985**	1.69036****	0.74985**	0.73409****	0.87651**	2.00092****
	(0.0400)	(0.3264)	(0.4385)	(0.3264)	(0.0401)	(0.3565)	(0.4639)
Acreage		0.08238		0.08238		0.14075	
		(0.0766)		(0.0766)		(0.0916)	

Constant	4.37975****	5.63627*	1.36278	5.63627*	3.82138****	5.78892*	1.61272
	(0.1427)	(2.9636)	(1.7104)	(2.9636)	(0.1418)	(3.2978)	(1.9092)
athrho						0.58808	0.58808
						(0.4528)	(0.4528)
lnsigma						0.08944	0.08944
						(0.1293)	(0.1293)
N	108	119	74	119	74	101	101
Pseudo/Adjusted R2	0.18	0.12	0.21	0.12			
Log-likelihood	-6757.55	-62.43	-103.81	-62.43	-3352.17	-151.46	-151.46

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table 2.8 HPC specification test for fertilizer demand estimation

Model comparison	H0: The first model is valid	H0: The second model is valid	Decision
	P-value	P-value	
ECE vs. 2PM	0.56	0.73	Fail to reject either
ECE vs. M-2PM	0.28	0.54	Fail to reject either
ECE vs. Selection	0.37	0.60	Fail to reject either
2PM vs. M-2PM	0.95	0.95	Fail to reject either
2PM vs. Selection	0.71	0.29	Fail to reject either
M-2PM vs. Selection	0.85	0.83	Fail to reject either

Table 2.9 Consumer preference for tomatoes

	(1) CL	(2) MXL-UC	(3) MXL-C
Mean			
Retail price of tomatoes	-0.22413**** (0.0519)	-0.27369**** (0.0589)	-0.54976**** (0.0866)
Application of chemical fertilizers (lb/acre/year)	-0.00587**** (0.0007)	-0.00869**** (0.0010)	-0.01681**** (0.0023)
Application of chemical pesticides (lb/acre/year)	-0.06497**** (0.0054)	-0.08375**** (0.0074)	-0.17295**** (0.0208)
Application of chemical pesticides * application of chemical fertilizers	0.00029**** (0.0001)	0.00043**** (0.0001)	0.00117**** (0.0002)
Standard Deviation			
Application of chemical pesticides (lb/acre/year)		0.04974**** (0.0066)	
Application of chemical fertilizers (lb/acre/year)		0.00889**** (0.0009)	
Application of chemical pesticides * application of chemical fertilizers		-0.00036**** (0.0001)	
The Cholesky Matrix (lower-triangular)			
l11			0.23999**** (0.0227)
l21			0.02981**** (0.0027)
l31			-0.00153**** (0.0002)
l22			-0.00633**** (0.0015)

l32			0.00044**
			(0.0002)
l33			-0.00062****
			(0.0001)
Log-likelihood	-1737.42	-1678.58	-1544.03
AIC	3482.84	3371.16	3108.06
BIC	3509.11	3417.13	3173.73
N	5253	5253	5253

Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table 2.10 Relationship between farm and retail prices of tomatoes

	(1) Fixed farm share	(2) Linear
farm price	3.7037****	2.0532****
	(0.109)	(0.429)
constant		0.6543****
		(0.167)
N	22	22

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table 2.11 Baseline scenario

Variable	Value
Grower Characteristics***	
Age (years)	59.752
Age squared	3726.966
Male (1=yes, 0=no)	0.794
Acreage (acre)	1.342
Production***	
Retail price of tomatoes	1.44
Pesticide price	252.128
Fertilizer price	2.014
Technology Adoption	
Use of organic farming (1=yes, 0=no)	0
Use of cover crop (1=yes, 0=no)	0
Use of mixed-species cover crop (1=yes, 0=no)	0
Use of high tunnel (1=yes, 0=no)	0
Use of greenhouses (1=yes, 0=no)	0

*: Calculated at the conventional grower sample mean except for the retail price. The retail price is set as the national average retail price of field grown fresh tomatoes from 1992 to 2013. The corresponding farm price is calculated from the retail price under different relationship assumptions.

Table 2.12 Consumers' MWTP for farmers' technology adoption

MWTP for	Benchmark: $p_r = p_f$			Fixed farm share: $p_r = \theta p_f$			Linear with constant: $p_r = \alpha + \beta p_f$		
	CL	MXL-UC	MXL-C	CL	MXL-UC	MXL-C	CL	MXL-UC	MXL-C
<u>Organic Farming</u>									
Single-market equilibrium: mean	2.57	3.03	2.86	2.09	2.49	2.38	2.09	2.49	2.38
Multimarket equilibrium: mean	2.57	3.03	2.86	2.09	2.49	2.38	2.09	2.49	2.38
<u>Mixed-Species Cover Crops</u>									
Single-market equilibrium: mean	0.72	0.91	0.84	0.72	0.89	0.84	0.72	0.89	0.84
Multimarket equilibrium: mean	0.44	0.54	0.52	0.65	0.80	0.76	0.61	0.74	0.70
<u>Greenhouses</u>									
Single-market equilibrium: mean	1.29	1.52	1.41	1.07	1.28	1.21	1.07	1.27	1.21
Multimarket equilibrium: mean	0.95	1.08	1.03	1.01	1.20	1.14	0.96	1.13	1.08

Chapter 3 Rainfall Variability, Migration, Off-farm Activities, and Transfers: Evidence from Rural Ethiopia*

3.1 Introduction

In many developing countries, income risks driven by fluctuating weather conditions pose an important threat to rural population who relies heavily on *rainfed agriculture*. Rural households employ a variety of *ex ante* and *ex post* coping and/or adaptation strategies to protect against rainfall fluctuations and associated income risks. First, farmers can switch to more resilient cropping practices by adopting drought-resistant crop varieties, investing in irrigation infrastructure, and changing crop management practices. Second, farmers may diversify their income source by engaging in off-farm activities. Third, family members of the farm households can migrate to urban areas for employment, which frees up resources for the remaining members, and enables remittances from the migrants during hard times at home. Fourth, farmers can participate in transfer programs either by applying for social assistance programs offered by the government, or by participating in informal social safety nets (ISSN) that are often kinship based.

A growing body of literature has examined the relationship between weather shocks and rural households' migration, off-farm labor supply, and transfers. Yet empirical studies generate more disagreement than consensus. For example, while some find strong migration-climate linkages (see Barrios, Bertinelli, and Strobl 2006; Henderson,

* I would like to thank Federica Alfani for sharing with me some programs on cleaning the data for the 2004 and 2009 survey rounds, Xavier Vollenweider for sending me a village-level shapefile for Ethiopia, Carlo Azzarri for help with some data issues, and Genti Kostandini for helpful comments and suggestions on an earlier version of this paper. Financial support from the Global Center for Food Systems Innovation at Michigan State University is also gratefully acknowledged.

Storeygard, and Deichmann 2015; Marchiori, Maystadt, and Schumacher 2012 for macroeconomic evidence, and Dillon, Mueller, and Salau 2011; Mueller, Gray, and Kosec 2014 for microeconomic evidence), others suggest that rural households' migratory responses to climate change are subtle and nuanced, and sometimes even opposite to what is commonly expected (macro-level evidence: Joseph and Wodon 2013; Marchiori, Maystadt, and Schumacher 2015; Ruyssen and Rayp 2014, and micro-level evidence: Bohra-Mishra, Oppenheimer, and Hsiang 2014; Etzold et al. 2014; Gray 2009; Gray and Mueller 2012a; Gray and Mueller 2012b; Henry et al. 2004; Lewin, Fisher, and Weber 2012; Massey, Axinn, and Ghimire 2010).

Similarly, a number of previous studies have reported mixed results regarding the links between climate change and off-farm labor supply, with some supporting a clear-cut association (Bezabih et al. 2010; Ito and Kurosaki 2009; Porter 2012; Rose 2001), and others suggesting an inconclusive relationship (Bandyopadhyay and Skoufias 2013; Demeke and Zeller 2012; Kijima, Matsumoto, and Yamano 2006; Malapit et al. 2008; Rijkers and Söderbom 2013). In addition, the literature gives different accounts of the motives for and response to public and private transfers (Dercon and Krishnan 2003; Bohra-Mishra 2012; Bouoiyour and Miftah 2015; de Brauw, Mueller, and Woldehanna 2013; Lucas and Stark 1985; Yang and Choi 2007; Kazianga 2006).

The present study investigates the impacts of rainfall variability on migration, off-farm activities and transfers in rural Ethiopia, where evidence remains sparse. Only a handful of studies have examined the effects of rainfall on migration and off-farm labor supply, and to the best of my knowledge no one has evaluated the effects on transfers[10]. In

[10] Many studies in the literature have assessed the impact of transfer on rural households' consumption, poverty alleviation, food security, well-being (Dercon and Krishnan 2003; Berhane et al. 2014; Hunnes 2014; Sumarto, Suryahadi,

terms of existing studies in Ethiopia, Gray and Mueller (2012a) show that drought increases men's labor-related migration, but decreases women's marriage-related migration, concluding that "adverse environmental conditions often increase mobility, but not always". Regarding off-farm labor supply, Bezabih et al. (2010) find that off-farm employment increases with rainfall variability, and Porter (2012) reports that bad rainfall reduces crop earned income, and boosts non-crop earned income, implying that rural households in Ethiopia shift labor from farm to off-farm activities in response to adverse shocks. These findings, however, are not completely consistent with Demeke and Zeller's (2012) as well as Rijkers and Söderbom (2013). Demeke and Zeller (2012) claim that the effect of weather risk on participation in off-farm work depends on the type of off-farm activity, with low levels and high variability of rainfall driving households to low-return activities and away from high-return activities. Rijkers and Söderbom (2013) argue that the likelihood of running a non-farm enterprise is not responsive to *ex ante* climatic risk, measured by the standard deviation of water requirement satisfaction index (WRSI); instead it increases with the contemporaneous climatic shocks as measured by WRSI level.

Our study differs from the above studies in several empirical aspects. First, it considers migration, off-farm labor supply, and social safety nets decisions in the same framework, rather than concentrating on only one aspect. Second, compared with Gray and Mueller (2012a) who utilize reported, endogenous drought data, we use observed, exogenous, high-quality historical rainfall data to characterize weather fluctuations. Thus, we are more likely to identify causal effects of weather anomalies on migration and other outcomes. Third, while four out of the five Ethiopian studies focus on dummy dependent

and Widyanti 2005; Gilligan, Hoddinott, and Taffesse 2009; Hoddinott et al. 2012).

variables for household decisions, this study constructs continuous dependent variables and addresses data censoring issues by employing Tobit models. The estimation strategy makes it possible to elicit information on the magnitude of responses to changes in rainfall means and variability.

The paper contributes to the existing literature in a number of ways. First, it develops a theoretical framework in which family labor is allocated among on-farm, off-farm, and urban (after migration) work. At the same time, participation in public transfer programs as well as family and other ISSN transfers is decided by the household. Hypotheses developed from the framework are then empirically tested. In addition, with more precise historical rainfall data, it identifies the short- and medium- term labor and transfer responses to rainfall shocks. Moreover, it fills a literature gap on the impact of climate change on public and private transfers, and explicitly distinguish the effects of rainfall shock on public transfers from effects on family and other ISSN transfers. Finally, the expected effects of not only levels of rainfall, but also variance of rainfall, are derived in our theoretical framework and subsequently estimated.

The hypotheses derived from the theoretical framework are tested using a multi-wave household survey, the Ethiopian Rural Household Survey (ERHS), and measures of village-level rainfall shocks from a high resolution, historical rainfall dataset. Consistent with expectations from the theoretical framework, we find that the share of out-migrated household members and per capita off-farm labor supply decrease with the ratio of rainfall mean in the main (Meher) growing seasons to the 30-year historical rainfall mean, and increase with the standard deviation of rainfall in the main growing seasons. The level and standard deviation of rainfall are shown to have indeterminate effects on the amount of transfers that households receive from extended family and the ISSN. Contrary to our theoretical predictions, we find that the probability of participating in public transfer programs decreases with increases in the standard deviation of rainfall in the main growing seasons of the five years prior to the survey.

Overall, the results provide a comprehensive view of household adaptation strategies beyond agriculture based activities. The information generated from the study suggests that Sub-Saharan Africa will adapt to climatic change through increased off-farm employment and migration. In light of these findings, climate adaption policies should be designed to support rural households' migration and urban employment, as well as off-farm activities. Both public and informal private transfers appear to be less effective mechanisms for ameliorating impacts of adverse climatic shocks. Informal transfers may be ineffective due to the covariate nature of climatic shocks that reduce transfer supplies from similarly impacted households. By contrast, public transfers may be ineffective due to slow program response in times of crises.

The rest of this paper is organized as follows. Section 2 presents the theoretical framework and section 3 explains the data. Sections 4 and 5 discuss the empirical strategies and the main results. Section 6 distills the implications of the results and concludes.

3.2 Theoretical Framework

Following Ito and Kurosaki (2009), Bellemare, Barrett, and Just (2013) and Kleinwechter and Grethe (2015), we propose a unitary agricultural household model[11], in which the

[11] We did not use a collective household model because of the limitations of data. The household survey does not contain information on bargaining powers of individual household members, and the basic demographic information of those left the household or died since last survey rounds is missing and difficult to be traced back.

household's production (labor demand) and consumption (labor supply) decisions are non-separable, and migration, off-farm activities, participation in public assistance program, and the amount of transfers from ISSN are jointly determined. To maximize household expected lifetime utility, a representative, risk-averse household simultaneously makes three decisions: (1) whether to have adult members migrate, and if so what share of adults should migrate; (2) how much remaining family labor to be allocated to on-farm and to off-farm activities; and (3) whether to participate in a public assistance program. Further, the sender of private transfers decides a transfer level to be received by the household. Rainfall shocks enter the model through the agricultural production function, and affect the household's decisions in two ways: (1) an increase in rainfall level increases expected agricultural income, thus making on-farm activities more attractive; and (2) an increase in rainfall variability increases the variance of agricultural income and the level of food insecurity, thus making steady income flows from urban migrants and local off-farm jobs more attractive. Rainfall shocks also affect the decision of the sender (extended family or other ISSN) of private transfers to the household by changing their income level. We discuss the impact of rainfall mean and variance on transfers and, particularly, the potential differentiated effect on public transfers and transfers from extended family and other ISSNs at the end of the section.

3.2.1 Model setup

Consider a world of three agents: a risk averse rural household, a (risk neutral) government (also a sender of public transfers), and a risk averse extended family or ISSN sender of private transfers. The household is the sole potential recipient of the public and private transfers. The rural household has a total time endowment of $\bar{T}$, to be allocated among on-farm work (T_f), local off-farm work (T_o), urban nonagricultural work after migration (T_m), and leisure (X_l). s is the fraction of total time allocated to urban work ($s = T_m / \bar{T}$).

The government provides a social protection program to help the household cope with climatic shocks. The household must apply to get benefits, and the benefit level depends inversely on the household's agricultural income and off-farm income. Following Moffitt (1983), people choose whether to participate in public programs or not, and may not participate in public programs for which they are eligible due to costs of the program participation including disutility associated with welfare stigma. Thus, participation of eligible households in the public safety net program is decided by the household rather than the government, as part of the household's utility maximization problem.

The sender of extended family or other ISSN transfers decides the amount of transfers to maximize total welfare of the sender and the recipient by allocating its total resources available, G, among both parties. [12]

The climatic conditions of the target rural area can be described by a vector of variables $\mathbf{Z}$ during the growing season, notably the temperature T and the rainfall $\tilde{R}$. For simplicity, we focus on rainfall with mean $\bar{R}$ and variance σ_R^2, with different time durations of these measures as appropriate.

[12] See Fafchamp (1992) for a theoretical framework on social safety network in general and Dercon (2002) for an empirical study on social safety network in Ethiopia.

3.2.2 Weather shocks and agricultural productivity

The household farm's production function is continuous, twice differentiable, and exhibit positive and diminishing marginal products of farm labor and land

$$q = \tilde{R}F(T_f, A),$$

where q is the output of a staple good, and A is fixed land endowment. Denoting the price of agricultural output as p which is fixed and exogenous in our model, the household's agricultural income is pq.

3.2.3 The household's problem

The household's Von Neumann–Morgenstern utility function is given by $\varphi(X_F, X_{NF}, X_l) + \phi(T_o, T_f, s, P)$, where X_F is food consumption, X_{NF} is the numeraire composite commodity for non-food, and P is a continuous variable measuring the extent of participation in the public transfer programs.[13] φ is utility derived from consumption, and ϕ reflects the household's preference over different labor activities and participation in a public transfer program.

The household's budget constraint is

$$pX_F + X_{NF} = w_oT_o + pq + \tilde{\pi}_m REM(s\overline{T}, w_m) + (P * TR_g + TR_{issn}) \triangleq y \qquad (3.1)$$

where w_o is the wage rate for off-farm labor; $\tilde{\pi}_m REM(s\overline{T}, w_m)$ is the value of total remittances the household received from its migrants, which depends on the urban wage rate w_m, total time allocated to urban work, and a multiplicative random term $\tilde{\pi}_m$ with mean

[13] Here p is assumed to be a continuous variable for simplicity of deriving our hypotheses. It can be a dichotomous variable regard which similar hypotheses can be derived from the model.

$\bar{\pi}_m$ and variance σ_m^2 indicating the probability of urban employment; TR_g and TR_{issn} are the value of transfer received from the government and from ISSNs (excluding migrants), respectively; and y is total expenditure on consumption. We assume that $Cov(\tilde{R}, \tilde{\pi}_m) = 0$

Consider a two-period model. In period 1, the rainfall shock is unknown. The household decides on labor supply proactively and enjoys leisure accordingly. After period 1, the output is observed with rainfall shock realized, and the income from labor activities and thus consumption expenditure is determined. In period 2, the household allocates the expenditure into food and nonfood. The household maximizes its expected utility at the beginning of period 1:

$$\max_{\{T_o, T_f, s, P, X_l\}} \mathrm{E}\,\{ \max_{\{X_F, X_{NF}\}} \varphi(X_F, X_{NF}, X_l) + \phi(T_o, T_f, s, P) \}$$
$$\text{s.t.} \begin{cases} pX_F + X_{NF} = w_o T_o + pq + \tilde{\pi}_m REM(s\bar{T}, w_m) + (P * TR_g + TR_{issn}) \triangleq y \\ q = \tilde{R}F[T_f, \mathrm{A}] \\ \bar{T} = T_f + T_0 + s\bar{T} + X_l \\ T_o, T_f, s, P, X_F, X_{NF}, X_l \geq 0 \\ 0 \leq s \leq 1 \\ 0 \leq P \leq 1 \end{cases} \tag{3.2}$$

where the constraints are for budget, production, time, nonnegative migration share and program participation level.

Solving the second-period problem, we can obtain the indirect utility function $V(y, p, X_l) \triangleq \max\ \varphi(X_F, X_{NF}, X_l)\ s.t.\ pX_F + X_{NF} = y$. Then the problem can be rewritten as

$$\max_{\{T_o, T_f, s, P, X_l\}} E\ \{V(y, p, \bar{T} - T_f - T_0 - s\bar{T}) + \phi(T_o, T_f, s, P)\}$$

$$\text{s.t. } \begin{cases} w_o T_o + p\tilde{R}F[T_f, \mathrm{A}] + \tilde{\pi}_m REM(s\bar{T}, w_m) + (P * TR_g + TR_{issn}) = y \\ T_o, T_f, s, P \geq 0 \\ 0 \leq s \leq 1 \\ 0 \leq P \leq 1 \end{cases} \tag{3.3}$$

Using a mean-variance framework (Markowitz 1952; Markowitz 2014), the above problem is equivalent to

$$\max_{\{T_o, T_f, s, P, X_l\}} \mathrm{H}{=}E(y) - 0.5aVar(y) + g(p, \bar{T} - T_f - T_0 - s\bar{T}) + \phi(T_o, T_f, s, P)$$

$$\text{s.t. } \begin{cases} w_o T_o + p\tilde{R}F[T_f, \mathrm{A}] + \tilde{\pi}_m REM(s\bar{T}, w_m) + (P * TR_g + TR_{issn}) = y \\ T_o, T_f, s, P \geq 0 \\ 0 \leq s \leq 1 \\ 0 \leq P \leq 1 \end{cases} \tag{3.4}$$

The solution to this problem can be expressed as

$$\begin{cases} s = s(p, w_o, w_m, \bar{R}, \sigma_R^2, \bar{\pi}_m, \sigma_m^2, A, TR_g, TR_{issn}) \\ T_f = T_f(p, w_o, w_m, \bar{R}, \sigma_R^2, \bar{\pi}_m, \sigma_m^2, A, TR_g, TR_{issn}) \\ T_o = T_0(p, w_o, w_m, \bar{R}, \sigma_R^2, \bar{\pi}_m, \sigma_m^2, A, TR_g, TR_{issn}) \\ P = P(p, w_o, w_m, \bar{R}, \sigma_R^2, \bar{\pi}_m, \sigma_m^2, A, TR_g, TR_{issn}) \end{cases} \tag{3.5}$$

Note that

$$\begin{cases} \dfrac{\partial^2 \mathrm{H}}{\partial s \partial T_f} \leq 0, \dfrac{\partial^2 \mathrm{H}}{\partial s \partial T_0} \geq 0, \dfrac{\partial^2 \mathrm{H}}{\partial s \partial P} \geq 0, \dfrac{\partial^2 \mathrm{H}}{\partial T_f \partial T_0} \leq 0, \dfrac{\partial^2 \mathrm{H}}{\partial T_f \partial P} \leq 0, \dfrac{\partial^2 \mathrm{H}}{\partial T_0 \partial P} \geq 0, \\ \dfrac{\partial^2 \mathrm{H}}{\partial s \partial \bar{R}} \leq 0, \dfrac{\partial^2 \mathrm{H}}{\partial T_f \partial \bar{R}} \geq 0, \dfrac{\partial^2 \mathrm{H}}{\partial T_0 \partial \bar{R}} \leq 0, \dfrac{\partial^2 \mathrm{H}}{\partial P \partial \bar{R}} \leq 0, \\ \dfrac{\partial^2 \mathrm{H}}{\partial s \partial \sigma_R} \geq 0, \dfrac{\partial^2 \mathrm{H}}{\partial T_f \partial \sigma_R} \leq 0, \dfrac{\partial^2 \mathrm{H}}{\partial T_0 \partial \sigma_R} \geq 0, \dfrac{\partial^2 \mathrm{H}}{\partial P \partial \sigma_R} \geq 0, \end{cases}$$

it follows from monotone comparative statics (Milgrom and Shannon 1994; Shannon 1995; Ashworth and De Bueno Mesquita 2006) that the share of out-migration, off-farm labor supply, and public safety net participation decrease with mean rainfall and increase with the variance of rainfall:

$$\begin{cases} (1)\ \dfrac{\partial s}{\partial \bar{R}} < 0 \\ (2)\ \dfrac{\partial T_o}{\partial \bar{R}} < 0 \\ (3)\ \dfrac{\partial P}{\partial \bar{R}} < 0 \\ (4)\ \dfrac{\partial s}{\partial \sigma_R^2} > 0 \\ (5)\ \dfrac{\partial T_o}{\partial \sigma_R^2} > 0 \\ (6)\ \dfrac{\partial P}{\partial \sigma_R^2} > 0 \end{cases}, \tag{3.6}$$

and when P is treated as a dichotomous variable, the corresponding hypotheses are

$$\begin{cases} (3)\ \dfrac{\partial \mathrm{Prob}(P=1)}{\partial \bar{R}} < 0 \\ (6)\ \dfrac{\partial \mathrm{Prob}(P=1)}{\partial \sigma_R^2} > 0 \end{cases}.$$

3.2.4 The transfer sender's problem

The objective of the sender is to maximize total weighted welfare of the sender and the recipient by allocating its available resources among both parties. Its objective function is

$$\omega W_h(\bar{Y}_h + (1-s)N * TR_{issn} - L_h) + (1-\omega)W_s(TR_s),$$

where ω is decision weight to the household, W_h is the recipient household's welfare function, $\bar{Y}_h$ is the expected income in case of no negative rainfall shock, TR_{issn} is the transfer to the household, W_s is the sender's welfare function, TR_s is money kept for the sender itself. Both welfare functions are continuously twice differentiable, increasing and quasi-concave. Note that we assume $\bar{\mathrm{Y}}_h$ is exogenous to the sender, implying that the strategic behavior between the sender and the household is ignored.

If rainfall shocks are covariate, the sender may face a correlated risk with the recipient household, which decreases sender ability to supply transfers when recipient household demand increases. In the case of adverse rainfall shocks (below average rainfall levels, or above average rainfall variations), the household suffers from expected loss $L_1(\bar{R},\sigma_R^2)$, with

$$\begin{aligned} &\frac{\partial L_1}{\partial \bar{R}} < 0 \\ &\frac{\partial L_1}{\partial \sigma_R^2} > 0, \end{aligned} \tag{3.7}$$

and total resource of the sender is also random, with

$$\begin{aligned} &\partial G / \bar{R} > 0, \\ &\partial G / \sigma_R^2 < 0. \end{aligned} \tag{3.8}$$

The sender solves the following problem:

$$\begin{aligned} &\max_{G_{issn},G_s} \ \omega W_h(\bar{\mathrm{Y}}_h + \mathrm{N}^* TR_{issn} - L_h) + (1-\omega) W_s(TR_s), \\ &\text{s.t.} \quad TR_{issn} + TR_s = G \end{aligned}$$

Analysis of the first order condition and the implicit function theorem reveal that the signs of the impacts of rainfall mean and variance on ISSN transfers to the recipient household are ambiguous under assumptions (7) and (8):

$$\begin{aligned} &\frac{\partial TR_{issn}}{\partial \bar{R}} = -\frac{\omega W_h''(-\partial L_1/\partial \bar{R}) - (1-\omega) W_s''(\partial G/\bar{R})}{\omega W_h'' + (1-\omega) W_s''} \quad \begin{pmatrix} > \\ = \\ < \end{pmatrix} 0, \\ &\frac{\partial TR_{issn}}{\partial \sigma_R^2} = -\frac{\omega W_h''(-\partial L_1/\partial \sigma_R^2) - (1-\omega) W_s''(\partial G/\sigma_R^2)}{\omega W_h'' + (1-\omega) W_s''} \quad \begin{pmatrix} > \\ = \\ < \end{pmatrix} 0, \end{aligned} \tag{3.9}$$

Note that the analysis here also applies to transfers from the extended family members (also called “remittance”) as well because essentially they are a form of ISSN and are likely to be affected by the covariate weather shocks. As a result, mean rainfall and variance of rainfall have ambiguous signs. Different impacts of rainfall means and variances on family remittances and other transfers will likely stem from differences in the strength of the covariance of shocks between sender and recipient household.

3.2.5 Public transfers versus transfers from ISSN

Equations (3.6) and (3.9) provide the hypotheses to be tested. The differentiated effects of rainfall shocks on public transfer and on transfers from the ISSN stems from two facts: (1) In the case of a rainfall shock, the supply of transfers from the ISSN will be affected due to covariate shocks to transfer sending households, resulting in a shift in the supply curve of private transfers. By contrast, the supply of public transfers will not be affected by shocks. (2) The participation decision of public transfers is made on the household demand side, whereas the amount decision for private transfers is made on the supply side by sending households.

3.3 Data

Household-level data from ERHS[14] are joined with village-level rainfall data to form a unique panel dataset, which are then used to test the hypotheses developed above. The dataset contains detailed information on migration, off-farm activities, and transfers of

[14] These data have been made available by the Economics Department, Addis Ababa University, the Centre for the Study of African Economies, University of Oxford and the International Food Policy Research Institute. https://dataverse.harvard.edu/dataset.xhtml?persistentId=hdl:1902.1/15646.

approximately 1,500 households in 15 rural villages (kebeles, wards, or peasant associations (PAs)) from 1994 to 2009, as well as local historical daily rainfall records from 1979 to 2009.

3.3.1 Household data

The ERHS was conducted initially in 1989 in seven villages located in three regional states in Ethiopia. Six of the seven villages were revisited and joined by nine new villages in 1994 and subsequent six rounds in 1995, 1997, 1999, 2004 and 2009, giving a sample of about 1500 households in 15 villages across the country (see Figure 3.1 for locations). [15] The villages were selected to account for diversity in the farming systems in Ethiopia, and within each village households were sampled through a stratified random sample.

According to Gray and Mueller (2012a), the 15 villages covered in the ERHS are characterized by seasonal and fluctuating rainfall. Rainfall occurs mainly during the Kiremt season in the summer, and in some villages also during the Belg season in the spring. Average annual precipitation in these villages ranges from 470 to 1300 mm (18 to 51 inches). Historically, severe droughts occurred in 1999, 2002–2003, 2005, and 2008, and their adverse effects could not be fully mitigated by the government's social protection programs.

The survey was implemented by interviewers using a structured questionnaire in each sample household. This questionnaire collected information on household demographics, assets, expenditures, agricultural activities, as well as community level data on electricity and water, sewage and toilet facilities, health services, education, NGO activity, migration,

[15] All figures and tables are placed separately at the end of the chapter.

wages, and production and marketing. Many questions remain the same across survey panel rounds. We use household level panel data from the 1999, 2004 and 2009 rounds, with a total sample size of about 4300 household observations.

The survey has two notable features: (1) Attrition at the household level is very low at 1.3% per year and 13.2% in total between 1994 and 2004. (2) Although only 15 of the thousands of villages in rural Ethiopia were sampled, they are broadly representative of households in non-pastoralist farming systems, and many of the average health and nutrition outcome variables in ERHS were very similar to those in the nationally representative Welfare Monitoring System collected by the Central Statistical Office as of 1994 (Dercon and Hoddinott 2011).

3.3.2 Weather data

Climatic data were drawn from the African Flood and Drought Monitor (AFDM)[16], with precipitation (mm), maximum temperature (K), and minimum temperature (K) on a daily basis. The weather data are at the village level because geographic information system (GIS) information on household plots is not available. This scale is consistent with the notion that weather is a covariate household risk/shock rather than an idiosyncratic one. The unobserved weather data for each village are approximated by the inverse distance weighting interpolation method, using weather data from the four nearest grids around the village.

[16] The AFDM, developed by Princeton University, uses available satellite remote sensing and in-situ information, a hydrologic modeling platform and a web-based user interface for operational and research use in Africa. Based on macro-scale hydrologic modeling, the system employs available data to provide real-time assessment of the water cycle and drought conditions, and puts this in the context of the long-term record dating back to 1950. http://hydrology.princeton.edu/monitor.

The four key climatic variables used in this study are: (1) the mean daily rainfall in the main growing season divided by the historical mean daily rainfall in that season in the past 30 years, (2) the standard deviation of daily rainfall in the main growing season in the five years ending in the year before the survey, (3) total growing degree days (GDD) in the main growing season in the year prior to the survey, and (4) total extreme heat degree days (EHDD) in the main growing season in the year prior to the survey. Daily rainfall is first averaged for the main rainy season (June 16th to September 15th) level in each year, and these yearly rainfall data are used to calculate the running "standard deviation" of average daily rainfall in the main rainy season in the past five years.[17] Total GDD and EHDD in the main growing season are derived using daily maximum and minimum temperatures, as described in Appendix A.

Previous studies generally find that the total number of GDD has a positive impact on agricultural production and hence on agricultural income, whereas the total number of EHDD has a negative impact (Schlenker and Roberts 2006; Schlenker and Roberts 2009; Roberts, Schlenker, and Eyer 2013). Therefore, the total number of GDD and the total number of EHDD are expected to have the same signs as mean rainfall and rainfall variation, respectively, when they are included in the estimation.

We focus on weather measures in the main growing season (Meher) for two reasons. First, Meher is the main growing season when most of annual rainfall occurs and most of annual agricultural income is generated, thus the main season has the greater potential to determine annual agricultural income. Second, while almost all households grow crops in

[17] Strictly speaking, these variable are not standard deviations from rainfall distribution since we only have five data points for each of such variable, but they provide some measure of rainfall variability across year. These inter-annual variations can be perceived by the households, and influence their between season labor market related decisions.

the Meher growing season, only 52% of them grow in the minor (Belg) season. Thus the use of rainfall in the Belg season in regression will greatly decrease village-level variation in rainfall.

3.3.3 Variables and summary statistics

The dependent variables are: (1) the shares of migrated-out household members due to labor market reasons (looking for a job, contract ended, etc.) in the past five years prior to survey; (2) the number of days worked off-farm per capita in the past four months, which is the total number of days worked off-farm by the household divided by the household size before migration; (3) a dichotomous variable indicating whether the household received transfers from the governments in the past year prior to survey, which is the total received transfers from the governments divided by the household size before migration; (4) the per capita real monetary value of transfers from former household members in the past year prior to the survey, which again using the household size before migration as the base; and (5) the per capita real monetary value of transfers from other ISSN in the past year prior to survey.

Tables 3.1 and 3.2 list the variables used in the estimation and present the summary statistics, respectively. On average, a household has eight members before migration, and 3% of them have migrated from rural villages to urban areas. Adult members work off-farm for an average of 16 days (or three days per household member) in the past four months. 24% of the households received public transfers in the past year. Households receive on average 2.73 and 6.50 Birrs in per capita transfers from former household members and the ISSN, respectively. For the main growing season, the average ratio of mean rainfall in the past five years to historical mean rainfall is 1.03, indicating rainfall in the period is roughly at the historical mean. The average standard deviation in the past five years in the main growing season is 1.76. The average ratio of rainfall in the past year to the historical mean is 1.24.

3.4 Empirical Strategies

The empirical models employed account for the nature of corner solutions in the dependent variable. For the participation in public transfer, the dependent variable is a discrete indicator. Consider household i in village j at year t, we specify the following conditional (fixed effects) panel logit model:

$$\text{logit}\{\text{Prob}(y_{ijt} = 1)\} = \alpha_0 + \beta_1 \frac{\bar{R}_{jt}}{\bar{R}_j} + \beta_2 \sigma_{jt} + \mu_{ij} + \nu_{ijt},$$
$$i = 1, \ldots N;\ j = 1, \ldots, 15; t = 1, 2, 3$$

where

y_{ijt} = participation decision for public transfers, equal to 1 if the household participates and 0 if not;

$\bar{R}_{jt}$ = mean daily rainfall in the main growing season in the past year in village j at time t;

$\bar{R}_j$ = mean daily rainfall in the main growing season in the past 30 years in village j;

σ_{jt} = observed standard deviation of rainfall in the main growing season in the past five years village j at time t;

μ_{ij} = household level fixed effect;

v_{ijt} = idiosyncratic random term.

An alternative specification is a panel linear probability model (LPM):

$$y_{ijt} = \alpha_0 + \beta_1 \frac{\bar{R}_{jt}}{\bar{R}_j} + \beta_2 \sigma_{jt} + \mu_{ij} + v_{ijt},$$
$$i = 1, \ldots N;\ j = 1, \ldots, 15;\ t = 1, 2, 3.$$

The other four dependent variables all have a high portion of zero responses. For example, 89.67% of the households reported they did not have any household member migrate to urban areas across the 1999, 2004 and 2009 survey panels, indicating that the distribution of the share of migration variable is highly skewed at 0.

To address this corner solution problem, we use a panel data Tobit model. Consider household i in village j at year t, we specify the following model for the dependent variable:

$$y^*_{ijt} = \alpha_0 + \beta_1 \frac{\bar{R}_{jt}}{\bar{R}_j} + \beta_2 \sigma_{jt} + \mu_{ij} + v_{ijt},$$
$$y_{ijt} = \max[0, y^*_{ijt}], i = 1, \ldots N;\ j = 1, \ldots, 15;\ t = 1, 2, 3$$

where

y^*_{ijt} = the latent dependent variable;

y_{ijt} = the observed dependent variable;

$\bar{R}_{jt}$ = mean daily rainfall in the main growing season in the past five years or the past year in village j at time t;

$\bar{R}_j$ = mean daily rainfall in the main growing season in the past 30 years in village j;

σ_{jt} = observed standard deviation of rainfall in the main growing season in the past five years village j at time t;

μ_{ij} = household level fixed effect;

v_{ijt} = idiosyncratic random term.

The time frame for the rainfall variables employed in the regressions differs in the specifications to be consistent with the time frame the household uses in determining the dependent variable. The share of migration is calculated from the roster card that recorded household members who have left the household since the last round of survey (in our panel the gap between survey rounds is five years), thus the previous five years is the time frame used in constructing both the mean and variance of rainfall. For off-farm labor supply, the households were asked "[How many] Days worked IN THE LAST FOUR MONTHS?" Thus, in order to make sure the time frame includes at least one main season, the time frame for constructing the mean of rainfall is one year prior to the survey. However, the standard deviation is still calculated over the past five year, to allow for household adjustments to a more variable rainfall environment.

The public, family and ISSN transfer variables are built from questions like "Has the household RECEIVED any other income (such as remittances from friends/relatives, gifts, food aid/other aid, payment for health or education, [or] any other transfers) IN THE LAST 12 (13 ETHIOPIAN) MONTHS?", thus one year prior to survey is an appropriate time frame for the mean of rainfall.[18] For the standard deviation of rainfall, we use five years prior to survey as its time frame for all dependent variables to allow for household transfer response to observed village rainfall variability for each village.

There is no parametric fixed effects Tobit model for panel data, so we employ a semiparametric fixed effects Tobit model developed by Honore (1992). This fixed effects model, however, does not allow the calculation of marginal effects of rainfall variables on the dependent variables. As a result, we also estimate parametric correlated random effects panel Tobit models which assume that the unobserved heterogeneity is determined by the vector of time-average independent variables (Mundlak 1978; Chamberlain 1980). The model is specified as

$$y_{ijt}^{*} = \alpha_0 + \beta_1 \frac{\bar{R}_{jt}}{\bar{R}_j} + \beta_2 \sigma_{jt} + \lambda_1 \frac{\sum_{t=1}^{3} \bar{R}_{jt} / 3}{\bar{R}_j} + \lambda_2 \frac{\sum_{t=1}^{3} \sigma_{jt}}{3} + + \mu_{ij} + v_{ijt},$$
$$y_{ijt} = \max[0, y_{ijt}^{*}], i = 1, ...N; j = 1, ..., 15; t = 1, 2, 3$$

where

$\sum_{t=1}^{3} \bar{R}_{jt} / 3$ = mean daily rainfall in the main growing season in the past five years or the past year averaged to village j;

$\frac{\sum_{t=1}^{3} \sigma_{jt}}{3}$ = observed standard deviation of rainfall in the main growing season in the past five years averaged to village j.

[18] The questionnaire can be accessed at: https://dataverse.harvard.edu/dataset.xhtml?persistentId=hdl:1902.1/15646.

3.5 Results and Discussion

Below we describe the estimation results from the out-migration, off-farm labor supply, participation in public transfers, and transfers from ISSN models.

3.5.1 Share of out-migration

The point estimates of the Tobit models for the share of out-migration are presented in Table 3.3. The effects of rainfall levels and rainfall variance on the share of out-migration are significant in both fixed effects and correlated random effects models and are consistent with the predications from the theoretical model. The marginal effects weather variables on the five coping strategies are given in Table 3.8 based on results from the correlated random effects Tobit models. Holding everything else constant, a 10 percent increase in the mean rainfall ratio decreases the share of adult household member out-migration by 0.5 percentage points. By contrast, a one millimeter increase in the standard deviation of daily rainfall in the main growing season over the past five years increases the share of out-migration by 1.1 percentage points.

Out-migration is not responsive to temperature shocks. Total number of GDD and EHDD in the main growing seasons in the past five years do not have significant impacts on the share of out-migration.

3.5.2 Off-farm labor supply

The results of Tobit models for the off-farm labor supply are presented in Table 3.4. The effects of rainfall shocks on the per capita working days off the farm are again significant and consistent with our theoretical predication based on the CRE Tobit model. Holding everything else constant, a 10 percent increase in the mean rainfall ratio decreases per capita off-farm labor supply in the past four months by 0.60 days. A one millimeter increase in the standard deviation of rainfall in the main growing season over the past five years increases the per capita off-farm labor supply in the past four months by 1.2 days. Except for the rainfall ratio, results from the fixed effects Tobit model are consistent with those from the CRE Tobit model in terms of significance and signs.

Off-farm labor supply is responsive to temperature shocks. Total number of GDD in the main growing season in the past year has a negative and significant impact on the per capita working days off the farm, and total number of EHDD has a positive and significant impact. An increase in GDD by 10 degree days reduces per capita off-farm labor supply by 0.4 days, and an increase in EHDD by 10 degree days increases per capita off-farm labor supply by 6.2 days.

3.5.3 Transfers

The results of the decision to participate in public transfers are shown in Table 3.5. Year indicators are included in the regressions to take into account the fact that the survey question about transfers differs across survey rounds. Results on rainfall shocks are generally contrary to the hypotheses. The effect of the ratio of mean rainfall is positive and significant in the fixed effects logit model, but insignificant in the LPM model. The standard deviation of rainfall is significant in both models, but the sign for the standard deviation of rainfall is negative, contrary to our theoretical prediction. In the theoretical model, the total resource of the government is assumed to be fixed and exogenous, which may explain why the results do not agree with the hypotheses. Results on temperature shocks are mixed. Total number of GDD has a negative impact in fixed effects logit model, but has a positive impact in LPM model. Total number of EHDD has a positive and significant impact in both models, implying that applying for and receiving public transfers is responsive to extreme heat shocks.

Results for the value of transfers from former household members and from other ISSNs are shown in Tables 3.6 and 3.7. Consistent with our theoretical model, the mean rainfall level and standard deviation of rainfall are found to have no effect on the real value of remittances from former household members (Table 3.6). Fixed effects Tobit model and correlated random effect Tobit model give different accounts of the effect of rainfall shocks on the real value of transfers from ISSN (Table 3.7). No effects of mean rainfall and standard deviation of rainfall are found in the fixed effect Tobit model, whereas in the random effect Tobit model the standard deviation of rainfall is shown to be significant and positively related to the real value of ISSN transfers. According to the correlated random effect model, a one millimeter increase in the standard deviation of rainfall in the main growing season in the past five years increases the value of transfers from ISSN (excluding remittance) by 1.55 Birrs in 1994 prices.

The two models give conflicting results about the impacts of temperature shocks. Total number of GDD and total number of EHDD do not have significant impacts on remittances and ISSN transfers based on the fixed effects Tobit model. In CRE Tobit model, however, the effect of total number of GDD on the real value of remittances is significant and negative, the effect of total number of GDD on the real value of ISSN transfers is significant and positive, and the effect of total number of EHDD on the real value of remittances is significant and positive.

3.6 Concluding Remarks

The present study evaluates the impacts of rainfall level and variability on migration, off-farm activities and public and private transfers in rural Ethiopia. We develop a theoretical framework in which family labor is allocated among on-farm, off-farm, and urban (after migration) work. Migration and off-farm labor supply decisions are modeled as part of a utility maximization process collectively by the household, and several hypotheses are developed on the relationship between rainfall shocks and migration, off-farm labor supply, and assistance transfers.

The theoretical framework is applied to a household panel data set in Ethiopia. We find that the share of out-migrated household members decreases with increases in the ratio of past five-year mean rainfall level to the 30-year historical mean rainfall level. Out-migration share also increases with the past five-year standard deviation of rainfall in the main growing season. Similarly, per capita off-farm labor supply decreases with the ratio of mean rainfall level in the main growing season of the year prior to the survey to 30-year historical mean rainfall level, and increases with the standard deviation of rainfall in the main growing seasons over the five years prior to the survey. Consistent with expectations for a covariate rainfall shock in the theoretical framework, the level and standard deviation of rainfall are shown to have no effect on the amount of transfer that households receive from the former household members, and only the standard deviation of rainfall has effect on the amount of transfers from ISSN, suggesting that households may build stronger social assistance network networks in more variable rainfall environments. Contrary to hypotheses developed from our theoretical model, the households are less likely to participate in public assistance programs if the standard deviation of rainfall in the main growing seasons over the five years prior to the survey increases. Households also show little response in public transfer use to mean rainfall, suggesting that social programs may need to improve their capacity to scale up social protection coverage in response to adverse climatic conditions.

Overall, the paper presents a coherent picture on the responsiveness of different coping strategies to rainfall shocks in rural Ethiopia. We find that migration and off-farm labor supply do respond to rainfall level and variability, whereas transfers from family and other ISSN do not. This information will improve Sub-Saharan Africa countries' abilities to adapt to and cope with climatic change. For example, policy makers are advised to support investments in interventions that facilitate rural households' migration and urban employment, as well as off-farm activities. At the same time, further research is needed to determine if lack of household use of public transfers to buffer adverse climatic shocks is due to a lack of household demand for increased public assistance or to a lack program response, in terms of transfer supply, to household needs.

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Villages in the Ethiopian Rural Household Surveys

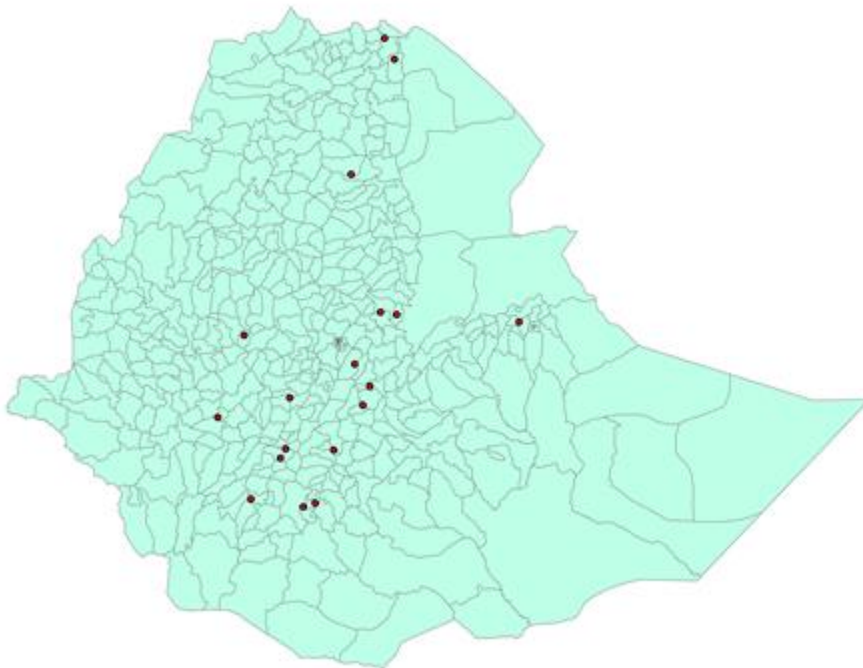


Figure 3.1 Locations of surveys villages

Table 3.1 Variable definition

Variable name	Definition
sharlabmigo	Share of migrated-out household members due to labor market reasons in the past five years
nddwkpc	Number of days worked off-farm per capita in the past four months
dtrsfgov	=1 if the household received transfers from the government in the past year
rvalfhhmempc	Per capita real monetary value of transfers from former HH members in the past year (1994 price)
rvalfissnpc	Per capita real monetary value of transfers from informal social safety nets in the past year (1994 price)
fhhsize	Household size before migration
hhsize	Current household size
ravrainmgp5yL1	Ratio of mean daily rainfall in the main growing season in the past five years of survey to its historical mean, lagged one year
ravainmgyL1	Ratio of mean daily rainfall in the main growing season in the year of survey to its historical mean, lagged one year
sdrainmgp5yL1	Inter-annual standard deviation of mean daily rainfall during the main growing season over past five years of survey, lagged one year
avtgddmgp5yL1	Average total growing degree days in the main growing season in the past five years of survey, lagged one year
avthddmgp5yL1	Average total extreme heat degree days in the main growing season in the past five years of survey, lagged one year
tgddmgyL1	Total growing degree days in the main growing season in the year of survey, lagged one year
thddmgyL1	Total extreme heat degree days in the main growing season in year of survey, lagged one year
ravrainmgp5yL1b	Mean of ravrainmgp5yL1 over survey rounds
ravainmgyL1b	Mean of ravainmgyL1 over survey rounds
sdrainmgp5yL1b	Mean of sdrainmgp5yL1 over survey rounds
avtgddmgp5yL1b	Mean of avtgddmgp5yL1 over survey rounds
avthddmgp5yL1b	Mean of avthddmgp5yL1 over survey rounds
tgddmgyL1b	Mean of tgddmgyL1 over survey rounds
thddmgyL1b	Mean of thddmgyL1 over survey rounds

Table 3.2 Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
sharlabmigo	4631	0.0261	0.0687	0.0000	0.6000
nddwkpc	4631	3.0704	8.2305	0.0000	141.0000
dtrsfgov	4633	0.2359	0.4246	0	1
rvalfhhmempc	4183	2.7282	28.4579	0.0000	1060.3980
rvalfissnpc	4183	6.5028	28.7020	0.0000	577.4697
fhhsize	4631	8.4841	3.6897	1	31
hhsize	4631	5.8013	2.6613	1	18
ravrainmgp5yL1	4633	1.0309	0.1525	0.6876	1.3635
ravrainmgyL1	4633	1.2380	0.4154	0.2646	2.4483
sdrainmgp5yL1	4633	1.7554	0.9519	0.3172	4.9500
avtgddmgp5yL1	4633	213.2354	78.3357	89.6296	363.6250
avthddmgp5yL1	4633	0.9478	2.0046	0.0000	9.1612
tgddmgyL1	4633	215.7937	79.3052	78.7352	372.6747
thddmgyL1	4633	0.7919	2.0186	0.0000	11.0965
ravrainmgp5yL1b	4633	1.0309	0.0945	0.6876	1.3291
ravrainmgyL1b	4633	1.2380	0.1793	0.4899	2.4483
sdrainmgp5yL1b	4633	1.7554	0.6574	0.3172	4.9500
avtgddmgp5yL1b	4633	213.2354	78.1335	92.7292	362.6740
avthddmgp5yL1b	4633	0.9478	1.9815	0.0000	9.0744
tgddmgyL1b	4633	215.7937	78.2436	88.1135	370.6117
thddmgyL1b	4633	0.7919	1.7482	0.0000	9.4142

Table 3.3 Share of out-migration

	(1) FE Tobit	(2) CRE Tobit
fhhsize	0.003	0.017^{****}
	(0.00)	(0.00)
ravrainmgp5yL1	-0.268^{****}	-0.297^{****}
	(0.05)	(0.05)
sdrainmgp5yL1	0.058^{****}	0.065^{****}
	(0.01)	(0.01)
avtgddmgp5yL1	0.000	-0.001
	(0.00)	(0.00)
avthddmgp5yL1	-0.013	-0.023
	(0.01)	(0.02)
ravrainmgp5yL1b		0.317^{****}
		(0.09)
sdrainmgp5yL1b		-0.037^{***}
		(0.01)
avtgddmgp5yL1b		0.000
		(0.00)
avthddmgp5yL1b		0.024
		(0.02)
constant		-0.384^{****}
		(0.08)
sigma_u		0.116^{****}
		(0.01)
sigma_e		0.231^{****}
		(0.01)
Number of observations	4631	4631
Number of left-censored observations		3860
Number of right-censored observations		0
Wald		205.91
p		0.00
BIC	.	2541.09

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table 3.4 Off-farm labor supply

	(1) FE Tobit	(2) CRE Tobit
ravrainmgyL1	0.179	-2.036**
	(0.78)	(0.84)
sdrainmgp5yL1	3.242***	4.061****
	(1.09)	(0.49)
tgddmgyL1	-0.084*	-0.140****
	(0.05)	(0.03)
thddmgyL1	1.404**	2.110****
	(0.55)	(0.39)
ravrainmgyL1b		-3.984
		(3.17)
sdrainmgp5yL1b		-1.106
		(0.91)
tgddmgyL1b		0.181****
		(0.03)
thddmgyL1b		-2.958****
		(0.50)
constant		-16.231****
		(2.61)
sigma_u		7.026****
		(0.63)
sigma_e		16.813****
		(0.41)
Number of observations	4631	4631
Number of left-censored observations		3177
Number of right-censored observations		0
Wald		161.31
p		0.00
BIC	.	15565.10

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table 3.5 Decision for participation in public transfers

	(1) FE Logit	(2) LPM
ravrainmgyL1	0.568****	0.009
	(0.11)	(0.02)
sdrainmgp5yL1	-0.968****	-0.015*
	(0.12)	(0.01)
tgddmgyL1	-0.069****	0.001****
	(0.01)	(0.00)
thddmgyL1	0.354****	0.019****
	(0.06)	(0.00)
year=2004	-0.220	0.015
	(0.15)	(0.02)
year=2009	1.649****	0.026
	(0.18)	(0.02)
constant		0.057**
		(0.03)
Number of observations	2084	4633
Wald	344.83	205.53
BIC	1221.39	.

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table 3.6 Real value of remittances from former household members

	(1) FE Tobit	(2) CRE Tobit
ravrainmgyL1	25.435	41.257
	(56.93)	(26.52)
sdrainmgp5yL1	-5.112	1.574
	(21.30)	(12.00)
tgddmgyL1	-0.933	-2.647***
	(1.20)	(0.94)
thddmgyL1	21.827	22.205*
	(21.96)	(12.39)
ravrainmgyL1b		411.454****
		(85.13)
sdrainmgp5yL1b		-141.044****
		(23.43)
tgddmgyL1b		1.204
		(0.92)
thddmgyL1b		3.175
		(15.09)
constant		-426.149****
		(68.72)
sigma_u		110.254****
		(18.45)
sigma_e		183.336****
		(13.95)
Number of observations	4183	4183
Number of left-censored observations		4018
Number of right-censored observations		0
Wald		56.90
p		0.00
BIC	.	3142.13

Table 3.7 Real value of transfers from informal social safety nets

	(1) FE Tobit	(2) CRE Tobit
ravrainmgyL1	0.942	-1.326
	(9.64)	(5.46)
sdrainmgp5yL1	8.608	9.437***
	(5.92)	(2.98)
tgddmgyL1	0.309	0.493**
	(0.34)	(0.20)
thddmgyL1	-2.765	-1.682
	(5.17)	(2.51)
ravrainmgyL1b		43.395**
		(20.30)
sdrainmgp5yL1b		-24.305****
		(5.41)
tgddmgyL1b		-0.684***
		(0.21)
thddmgyL1b		3.886
		(3.15)
constant		-74.763****
		(15.58)
sigma_u		26.580****
		(5.04)
sigma_e		85.854****
		(2.89)
Number of observations	4183	4183
Number of left-censored observations		3445
Number of right-censored observations		0
Wald		56.90
p		43.42
BIC	.	11013.01

Table 3.8 Responsiveness of coping strategies: marginal effects

	(1) Migration	(2) Off-farm	(3) Public transfers	(4) Remittances	(5) ISSN transfers
fhhsize	0.003****				
	(0.00)				
ravrainmgp5yL1	-0.050****				
	(0.01)				
sdrainmgp5yL1	0.011****	1.187****	-0.015*	0.058	1.546***
	(0.00)	(0.14)	(0.01)	(0.44)	(0.49)
avtgddmgp5yL1	-0.000				
	(0.00)				
avthddmgp5yL1	-0.004				
	(0.00)				
ravrainmgp5yL1b	0.053****				
	(0.02)				
sdrainmgp5yL1b	-0.006***	-0.323		-5.172****	-3.981****
	(0.00)	(0.27)		(0.96)	(0.89)
avtgddmgp5yL1b	0.000				
	(0.00)				
avthddmgp5yL1b	0.004				
	(0.00)				
ravrainmgyL1		-0.595**	0.009	1.513	-0.217
		(0.24)	(0.02)	(0.98)	(0.89)
tgddmgyL1		-0.041****	0.001****	-0.097***	0.081**
		(0.01)	(0.00)	(0.04)	(0.03)
thddmgyL1		0.617****	0.019****	0.814*	-0.275
		(0.12)	(0.00)	(0.46)	(0.41)
ravrainmgyL1b		-1.165		15.089****	7.107**
		(0.93)		(3.37)	(3.33)
tgddmgyL1b		0.053****		0.044	-0.112***
		(0.01)		(0.03)	(0.03)
thddmgyL1b		-0.865****		0.116	0.636
		(0.15)		(0.55)	(0.52)
Number of observations	4631	4631	4633	4183	4183

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

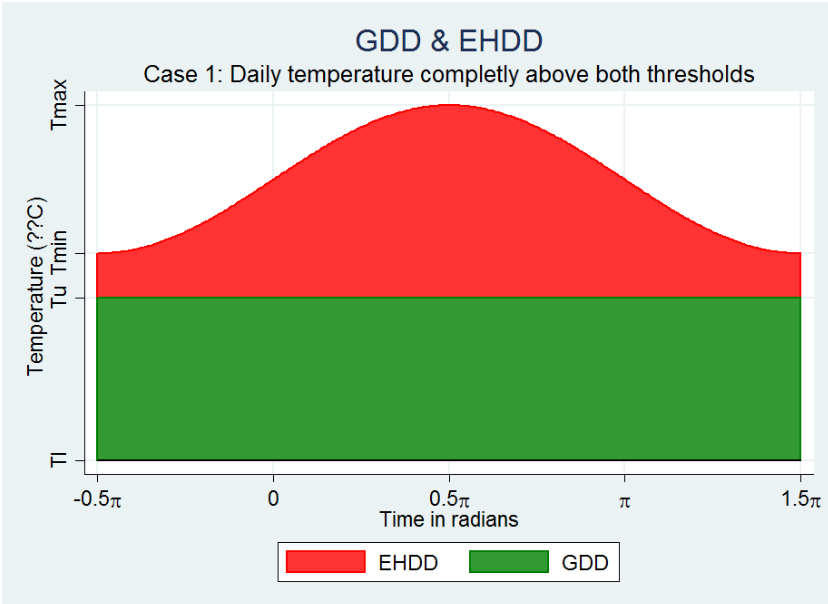
Appendix A Calculation of GDD & EHDD

Diurnal temperature is approximated using a sine curve parameterized with the maximum and minimum daily temperatures:

$$T = \frac{T_{\max} + T_{\min}}{2} + \frac{T_{\max} - T_{\min}}{2} \sin(t),$$

where t is time in radians from $-\pi/2$ to $3\pi/2$, $T_{\max}$ is daily maximum temperature, and $T_{\min}$ is daily minimum temperature (Snyder 1985; Arnold 1960; Baskerville and Emin 1969). Define T_u and T_l as the upper and lower temperature thresholds suitable for crop growth, respectively.[19] Daily growing degree day accumulations can be calculated by integrating the area under the sine curve, under T_u, and above T_l, and daily extreme heat degree day accumulations can be calculated by integrating the area under the sine curve above T_u. Depending on the relationship between daily maximum and minimum temperatures and the upper and lower thresholds, there exist six possible cases for the calculations of GDD and EHDD, as shown below.

[19] The optimal temperature ranges (in degree Celsius) for major staple crops in Ethiopia are: maize (18-33), teff (22-28), wheat (15-23), barley (15-20), and sorghum (27-35) (Source: FAO Ecopcrop database, http://ecocrop.fao.org). Therefore, we set $T_l = 15, T_u = 28$ in our data.

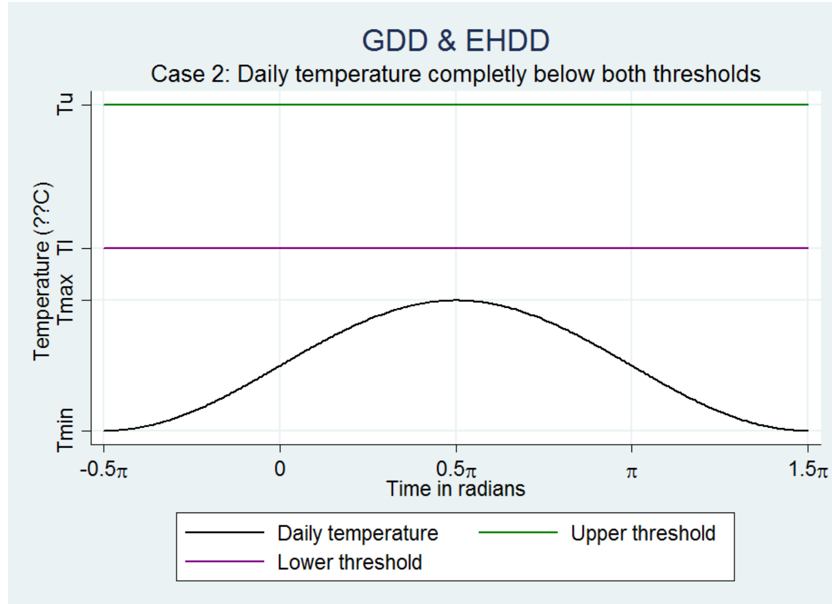


Case 1: $T_l < T_u < T_{\min} < T_{\max}$

$$GDD \ = T_u - T_l$$

$$EHDD = \frac{T_{\max} + T_{\min}}{2} - T_u$$

Figure 3.2 Calculating GDD and EHDD – case 1

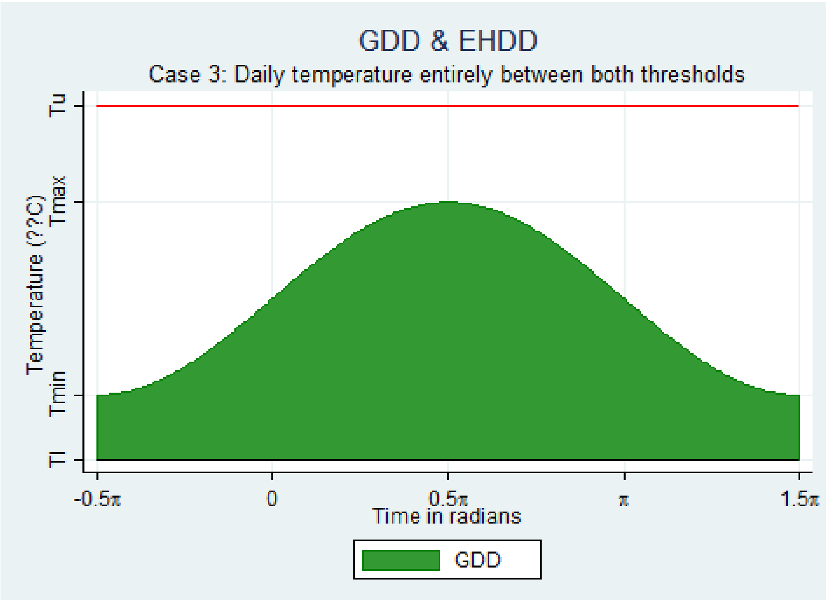


Case 2: $T_{\min} < T_{\max} \leq T_l < T_u$

$$GDD \ = 0$$

$$EHDD = 0$$

Figure 3.3 Calculating GDD and EHDD – case 2

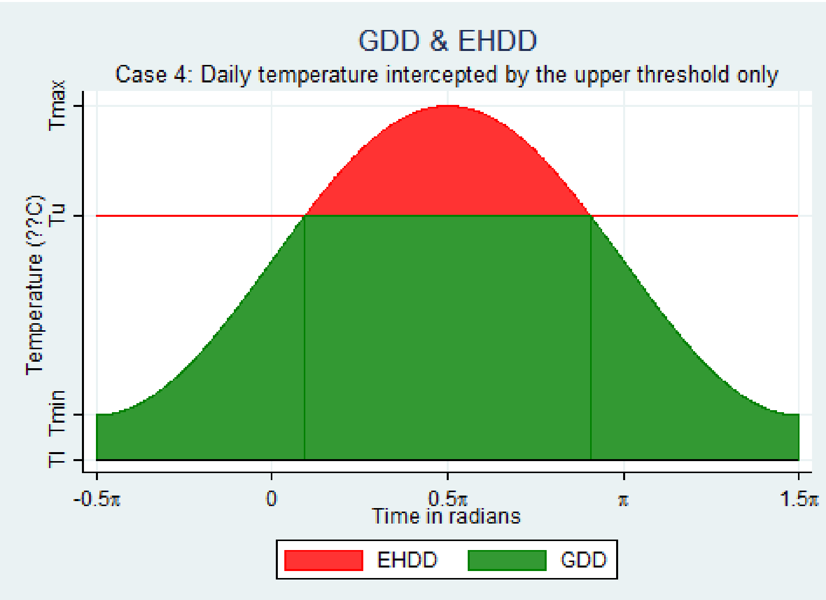


Case 3: $T_l < T_{\min} < T_{\max} \le T_u$

$$GDD = \frac{T_{\max} + T_{\min}}{2} - T_l$$

$$EHDD = 0$$

Figure 3.4 Calculating GDD and EHDD – case 3



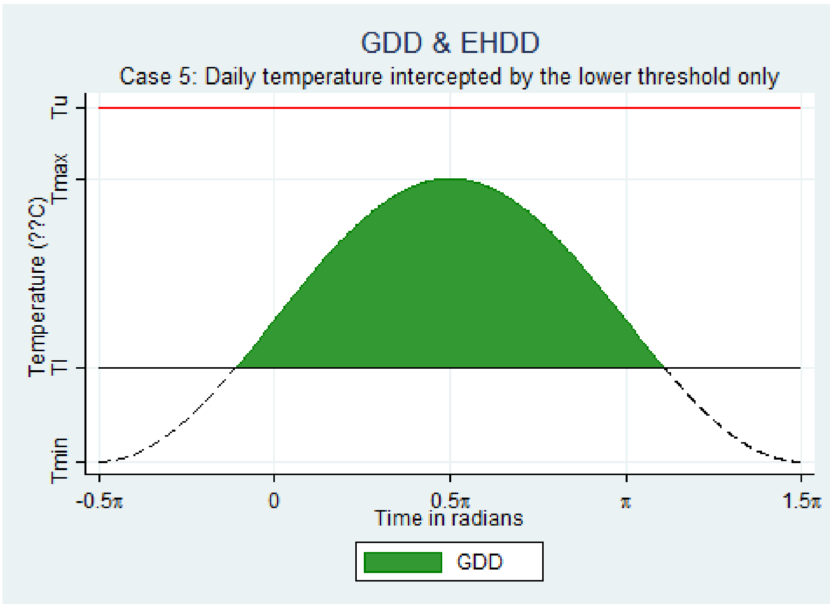
Case 4: $T_l < T_{\min} \le T_u < T_{\max}$

$$GDD = \frac{1}{\pi}\left[\left(\frac{T_{\max} + T_{\min}}{2} - T_l\right)\left(\frac{\pi}{2} + \theta_u\right) + (T_u - T_l)\left(\frac{\pi}{2} - \theta_u\right) - \frac{T_{\max} - T_{\min}}{2}\cos\theta_u \right]$$

$$EHDD = \frac{1}{\pi}\left[\left(\frac{T_{\max} + T_{\min}}{2} - T_u\right)\left(\frac{\pi}{2} - \theta_u\right) + \frac{T_{\max} - T_{\min}}{2}\cos\theta_u \right]$$

$$\theta_u = \arcsin\left[\frac{2T_u - (T_{\max} + T_{\min})}{T_{\max} - T_{\min}} \right]$$

Figure 3.5 Calculating GDD and EHDD – case 4



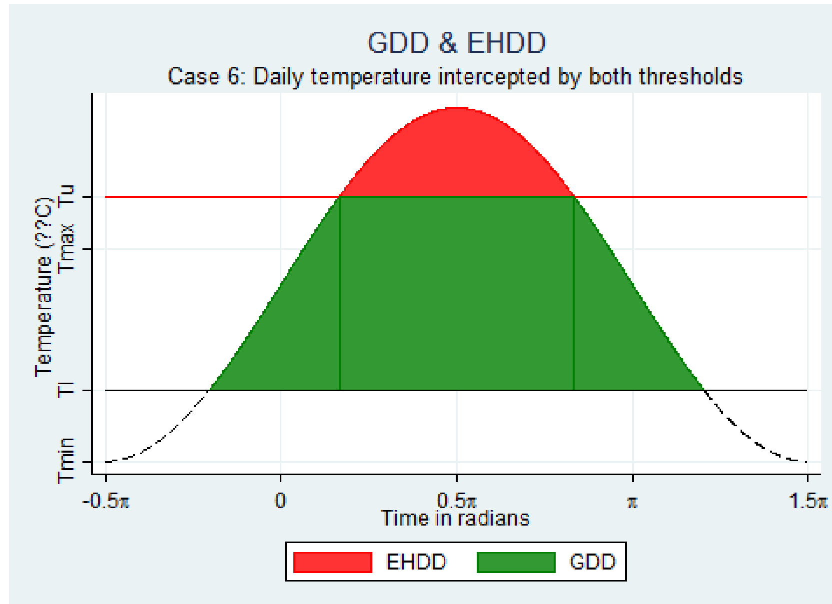
Case 5: $T_{\min} \le T_l < T_{\max} \le T_u$

$$GDD = \frac{1}{\pi}\left[\left(\frac{T_{\max}+T_{\min}}{2} - T_l\right)\left(\frac{\pi}{2} - \theta_l\right) + \frac{T_{\max}-T_{\min}}{2}\cos\theta_l \right]$$

$$EHDD = 0$$

$$\theta_l = \arcsin\left[\frac{2T_l - (T_{\max}+T_{\min})}{T_{\max}-T_{\min}}\right]$$

Figure 3.6 Calculating GDD and EHDD – case 5



Case 6: $T_{\min} \le T_l < T_u < T_{\max}$

$$GDD = \frac{1}{\pi}\left[\left(\frac{T_{\max}+T_{\min}}{2} - T_l\right)(\theta_u - \theta_l) + (T_u - T_l)\left(\frac{\pi}{2} - \theta_u\right) + \frac{T_{\max}-T_{\min}}{2}(\cos\theta_l - \cos\theta_u) \right]$$

$$EHDD = \frac{1}{\pi}\left[\left(\frac{T_{\max}+T_{\min}}{2} - T_u\right)\left(\frac{\pi}{2} - \theta_u\right) + \frac{T_{\max}-T_{\min}}{2}\cos\theta_u \right]$$

$$\theta_u = \arcsin\left[\frac{2T_u - (T_{\max}+T_{\min})}{T_{\max}-T_{\min}}\right]$$

$$\theta_l = \arcsin\left[\frac{2T_l - (T_{\max}+T_{\min})}{T_{\max}-T_{\min}}\right]$$

Figure 3.7 Calculating GDD and EHDD – case 6

Chapter 4 Weather Shocks, Diversification Strategies and Consumption in Rural Ethiopia*

4.1 Introduction

It is well-documented in the literature that adverse (poor or variable) weather conditions tend to reduce the mean yields of agricultural products and increase the output variance in developing countries (Lemi 2005; Cabas, Weersink, and Olale 2010; Felkner, Tazhibayeva, and Townsend 2009; Feng, Krueger, and Oppenheimer 2010; Fisher et al. 2012; Paxson 1992; Schlenker and Lobell 2010; Schlenker and Roberts 2009; Schlenker and Roberts 2006; Thornton et al. 2009; Yang and Choi 2007). When households rely heavily on *rainfed agriculture*, the induced production shock is often transformed into an income shock and, in turn, into a negative consumption shock. To mitigate the adverse impact of these shocks, rural households adopt three major coping strategies, namely farming, diversification, and asset smoothing. Farming strategies are adopted to stabilize or boost agricultural income, including adopting drought resistant varieties, changing planting and harvesting dates, or investing in irrigation infrastructure. Diversification strategies reinvest household resource to increase income flows from nonagricultural activities and transfers by engaging in off-farm activities or non-agricultural small businesses, participating in formal and informal social safety networks (ISSN) to receive various transfers as needed, or sending household members to urban areas to receive

* Part of the data used in this chapter are taken from Porter (2012) and Dercon, Hoddinott, and Woldehanna (2012), for which I am very grateful to Catherine Porter and John Hoddinott for their kindness and willingness to share data and their help with replicating their papers. I would like to thank Yisehac Yohannes for his assistance with the Ethiopian Rural Household Surveys data. Financial support from the Global Center for Food Systems Innovation at Michigan State University is also gratefully acknowledged.

remittances from them. Asset smoothing strategies seek an intertemporal equilibrium by reallocating the stream of assets over time more efficiently. For example, households can accumulate livestock assets during good times and sell livestock during hard times.

The net impacts of weather shocks on consumption are the combined results of the direct effects through production impact channels and of the indirect effects through coping strategies. The consensus in the literature is that combinations of these coping strategies are not able to fully mitigate the adverse impacts of weather shocks. For example, Dercon (2004) finds persistently negative impacts of rainfall shocks on consumption growth in rural Ethiopia.

The objectives of this study are to assess the impact of weather shocks on rural Ethiopian household's real consumption, and to evaluate the effectiveness of different diversification strategies in increasing or smoothing consumption. In a closely related study, Porter (2012) examines the impact of rainfall shocks on household welfare as measured by consumption per adult equivalent and shows that only extremely low rainfall shocks cause a significant reduction in consumption. Idiosyncratic shocks and less extreme rainfall shocks do not negatively impact consumption, implying that they have been smoothed by the households using different coping strategies. Regarding the effectiveness of different coping strategies, Gatiso (2015) finds that farming strategies such as crop diversification, using modern varieties, and soil and water conservation are effective in mitigating climatic risks and ensuring household food security. Fafchamps, Udry, and Czukas (1998) and Kazianga and Udry (2006) show that livestock assets play only a marginal role in consumption smoothing in Burkina Faso. Many studies have examined the effectiveness of individual diversification strategies (Pan 2009; Kochar 1999; Taylor, Rozelle, and de Brauw 2003; de Brauw and Harigaya 2007; Christiaensen, Hoffmann, and Sarris 2007; Quisumbing and McNiven 2010), but to the best of my knowledge none have presented a comprehensive evaluation of different diversification strategies in terms of their effectiveness in smoothing consumption, particularly in response to adverse climatic shocks.

This study differs from previous studies in several important aspects. First, it systematically evaluates the effectiveness of rural household diversification strategies in smoothing consumption against weather shock. Second, it extends Porter's (2012) study by using new empirical methods and additional data from the Ethiopian Rural Household Surveys (ERHS). Porter's (2012) main findings are based on dynamic panel data models with an unequally-spaced panel dataset and thus are subject to estimation bias. We construct an equally spaced panel dataset and generate more reliable estimates of impacts on consumption changes across periods. We confirm Porter's (2012) findings that the rainfall impacts on consumption are asymmetric, but find important differences in the response pattern. Study results also identify effective diversification strategies employed by rural Ethiopian households. Identification of these successful existing strategies can assist policy makers in the design of more effective interventions.

The remainder of this paper is structured as follows: section 2 outlines the conceptual and empirical framework; section 3 describes the data; section 4 presents the main results and associated robustness tests; and section 5 concludes the paper.

4.2 Conceptual and Empirical Framework

The benchmark models of household consumption smoothing are the permanent income model and the full insurance model. Both models imply that income shocks may have only a small correlation with changes in household consumption if the household has access to insurance, credit, or liquid assets and if income shocks are predominantly transitory in nature (Bardhan and Udry 1999). When these conditions are not met, the household will employ the alternative coping strategies discussed above to smooth consumption to the extent possible. In the case of weather shocks, agricultural production is directly affected, causing an income shock. Observing or anticipating this shock, the household adopts coping strategies (including farming, diversification, and asset smoothing strategies) to minimize adverse impacts. If coping strategies are effective, then income will be stabilized and consumption will not be affected. Otherwise, the income shock will be transformed into a household consumption shock.

This study focuses on diversification strategies which have not been systematically examined in the literature. Rural households in Ethiopia adopt five primary diversification strategies: (1) sending migrants to urban areas; (2) applying for and receiving transfers from the government (public transfers); (3) requesting and receiving transfers from ISSN; (4) receiving remittances from former household members; and (5) engaging in off-farm activities.

Empirical Models

Following Porter (2012), we use the following stylized dynamic permanent-income model to assess the impact of weather shocks on consumption:

$$\ln(c_{ivt}) = \alpha + \beta_1 \ln(c_{iv,t-1}) + \beta_2 PI_{ivt} + \boldsymbol{\beta}_3 \mathbf{H}_{ivt} + \boldsymbol{\beta}_4 \mathbf{W}_{vt} + \boldsymbol{\beta}_5 \mathbf{IS}_{ivt} + \mu_i + \varepsilon_{ivt}, \qquad (4.1)$$

where

$c_{ivt} =$ consumption of household i in village v at time t;

$c_{iv,t-1} =$ consumption of household i in village v at time t-1;

$PI_{ivt} =$ permanent income of household i in village v at time t;

$\mathbf{H}_{ivt} =$ a vector of characteristics of household i in village v at time t;

$\mathbf{W}_{vt} =$ a vector of weather conditions in village v at time t;

$\mathbf{IS}_{ivt} =$ a vector of idiosyncratic shocks to household i in village v at time t;

$\mu_i =$ household fixed effects;

$\varepsilon_{ivt} =$ idiosyncratic error term.

The weather variables include average daily rainfall in the main rainy season above and below historical mean rainfall to take into account the asymmetric effects of rainfall on consumption. Livestock one year prior to the survey, $lsuL1_{ivt}$, is used as a proxy for permanent income PI_{ivt} (Porter 2012; Dercon, Hoddinott, and Woldehanna 2012). As an important asset of rural households, livestock not only determine the productive capacity of the households, but also signal the wealth of the households, and thus provides a good indicator of the permanent income potential of the households. Household characteristics include household size and composition, and the demographics of the household head. Idiosyncratic shocks that may affect household income include (1) illness, if any household member fell sick in the past five years; (2) death, if any household member died in the past five years; and (3) input prices, if there was large increase in input prices in the past five years.

In this initial specification, the household's coping strategies are not included in equation (4.1), and the coefficients of interest, $\boldsymbol{\beta}_4$, measure the *net* impact of weather shocks on real consumption of the household, after the household has made decisions on the implementation of coping strategies. Formally, if

$$\ln(c_{ivt}) = \alpha + \beta_1 \ln(c_{iv,t-1}) + f(\mathbf{W}_{vt}) + g(\mathbf{S}(\mathbf{W}_{vt}, \mathbf{W}_{v,t-1}, ..., \mathbf{H}_{ivt})) + \mathrm{h}(\mathbf{H}_{ivt}, \mathbf{IS}_{ivt}),$$

where $\mathbf{S}$ is a set of coping strategies which depend on past realizations of weather shocks, then the following relationship holds:

$$\boldsymbol{\beta}_4 = \frac{\partial \ln(c_{ivt})}{\partial \mathbf{W}_{vt}} = \frac{\partial f}{\partial \mathbf{W}_{vt}} + \frac{\partial g}{\partial \mathbf{S}} \frac{\partial \mathbf{S}}{\partial \mathbf{W}_{vt}}.$$

Following Christiaensen, Hoffmann, and Sarris (2007), the following empirical model is then estimated to evaluate the relative effectiveness of diversification strategies in mitigating the impacts of weather shocks on real consumption per adult equivalent:

$$\begin{aligned} \ln(c_{ivt}) = \alpha + \beta_1 \ln(c_{iv,t-1}) + \beta_2 PI_{ivt} + \boldsymbol{\beta}_3 \mathbf{H}_{ivt} + \boldsymbol{\beta}_4 \mathbf{W}_{vt} + \boldsymbol{\beta}_5 \mathbf{IS}_{ivt} + \boldsymbol{\beta}_6 (\mathbf{W}_{vt} * \mathbf{S}_{ivt}) \\ + \beta_7 D_t + \mu_i + \varepsilon_{ivt}. \end{aligned} \quad (4.2)$$

where D_t is time indicator, and $\mathbf{S}_{ivt}$ is a set of dichotomous variables that indicate whether the household has adopted specific crucial diversification strategies. The variables contained in $\mathbf{S}_{ivt}$ are:

> $dlabmigo_{ivt} =$ a dichotomous variable indicating whether household i in village v has sent migrants for labor market reasons between year t-4 and year t;

$dtrsfgov_{ivt} =$ a dichotomous variable indicating whether household i in village v has received public transfers between year t-1 and year t;

$dtrsfissn_{ivt} =$ a dichotomous variable indicating whether household i in village v has received transfers from the informal social safety nets (excluding former household members) between year t-1 and year t;

$drem_{ivt} =$ a dichotomous variable indicating whether household i in village v has received remittance from former household members between year t-1 and year t;

$doffrm_{ivt} =$ a dichotomous variable indicating whether household i in village v has members working off-farm against cash or in kind between year t-1 and year t.

The vector of coefficients of interest, $\boldsymbol{\beta}_6$, measure the relative effectiveness of each strategy in smoothing consumption in the face of weather shocks after controlling for weather, idiosyncratic shocks, and other factors.

Identification Strategy

In equation (4.1), the lagged logarithm of consumption, $\ln(c_{iv,t-1})$, is likely to be positively correlated with the unobserved heterogeneity (such as fixed effects μ_i), thus the ordinary least squares (OLS) estimator of the lagged dependent variable would be biased upwards, and the fixed effects estimator will be biased downwards (Nickell 1981). In equation (4.2), besides the lagged logarithm of consumption, the interaction terms of coping strategies $(\mathbf{W}_{vt} * \mathbf{S}_{ivt})$ are also correlated with unobserved heterogeneity because unobserved household characteristics are likely to influence whether or not a household adopts a strategy. Moreover, reverse causality may be a concern, in that households adopt a diversification strategy because their consumption levels are low. As a result, potential endogeneity of the lagged dependent variable and the strategy variables needs to be controlled for in the estimation.

Holtz-Eakin, Newey, and Rosen (1988), Arellano and Bond (1991), Arellano and Bover (1995) and Blundell and Bond (1998) develop the difference and system Generalized Methods of Moments (GMM) estimators which utilize lags of dependent and independent variables as instruments to control the endogeneity of the lagged dependent variable. Consider the following dynamic panel data model:

$$
\begin{aligned}
& y_{it} = \alpha y_{i,t-1} + \beta_1 x_{it} + \beta_2 w_{it} + \mu_i + \varepsilon_{it}, \quad i = 1, \ldots, N; t = 1, \ldots, T \\
& E(\varepsilon_{it} \mid x_{it}, w_{it}, \mu_i) = 0, \forall i, t
\end{aligned}
$$

where $y_{i,t-1}$ is predetermined, x_{it} is endogenous, and w_{it} is exogenous. The model is also called levels equation, and it can be transformed as a time-differenced equation:

$$\triangle y_{it} = \alpha \triangle y_{i,t-1} + \beta_1 \triangle x_{it} + \beta_2 \triangle w_{it} + \triangle \varepsilon_{it}.$$

In the difference GMM estimation, $\triangle w_{it}$, lags of 1 and deeper of $y_{i,t-1}$, and lags of 2 and deeper of x_{it} can be used as instruments for estimating the transformed equation. In the system GMM estimation, in addition to estimating the transformed equation using the same internal instruments as in difference GMM estimation, w_{it}, $\triangle y_{i,t-1}$ and $\triangle x_{i,t-1}$ are used as instruments for estimating the levels equation.

The identification strategy for equations (4.1) and (4.2) is as follows. First, difference and system GMM are used to estimate the two equations. Second, if the set of instruments is valid and the lagged dependent variable is significant, then the GMM estimators consistently capture the causal effects of weather shocks and/or diversification strategies.

Since the system GMM estimator requires more assumptions especially with respect to initial conditions, it is less preferable than the difference GMM estimator when the two provide conflicting results. If the set of instruments is valid and the lagged dependent variable is not significant, then it is safe to remove the lagged dependent variable and re-estimate equation (4.1) using fixed effects models. For equation (4.2), reverse causality can be ignored due to the timing of the dependent variable and the strategy variables. The strategy adoption occurred within five years or one year prior to the survey, whereas the consumption occurred within a week or a month before the survey. Therefore, it is reasonable to assume that strategy adoption affect consumption, rather than that consumption drives prior strategy adoption. In this case, fixed effects models can also be used to consistently estimate equation (4.2) after removing the lagged dependent variable.

4.3 Data and Context

Household-level data from ERHS[20] are joined with village-level rainfall data to form a unique panel dataset, which contains detailed information on consumption, income, and idiosyncratic shocks of approximately 1,500 households in 15 rural villages (kebeles, wards, or peasant associations (PAs)) from 1994 to 2009, as well as local historical daily rainfall records from 1980 to 2009.

The households were surveyed twice in 1994, and subsequently in 1995, 1997, 1999, 2004 and 2009, giving a sample of about 1500 households in 15 villages across the country. The villages were selected to account for diversity in the farming systems in Ethiopia, and

[20] These data have been made available by the Economics Department, Addis Ababa University, the Centre for the Study of African Economies, University of Oxford and the International Food Policy Research Institute. https://dataverse.harvard.edu/dataset.xhtml?persistentId=hdl:1902.1/15646.

within each village households were sampled through a stratified random sample. We use household level panel data from the 1994, 1999, 2004 and 2009 rounds to form an equally spaced panel dataset[21], with a total sample size of 5,673 observations.

Climatic data were drawn from the African Flood and Drought Monitor (AFDM)[22], with precipitation (mm), maximum temperature (K), and minimum temperature (K) on a daily basis. The rainfall data are at the village level because geographic information system (GIS) information on household plots is not available. This scale is consistent with the notion that rainfall is a covariate household risk/shock rather than an idiosyncratic one. The unobserved weather data for each village are approximated by the inverse distance weighting interpolation method, using weather data from the four nearest grids around the village.

The main climatic variables used in this study are: (1) the average daily rainfall in the main rainy season in the year prior to the survey, (2) the standard deviation of daily rainfall in the main rainy season in the five years ending in the year before the survey, (3) total growing degree days (GDD) in the whole growing season in the year prior to the survey, and (4) total extreme heat degree days (EHDD) in the whole growing season in the year prior to the survey (Schlenker and Roberts 2006; Schlenker and Roberts 2009; Roberts, Schlenker, and Eyer 2013). Daily rainfall is first averaged for the main rainy season (June 16th to September 15th) level in each year, and these yearly rainfall data are used to calculate the running “standard deviation” of average daily rainfall in the main rainy season

[21] For the estimation of static models, an unequally spaced panel dataset is not a problem if an indicator of survey rounds is included. Thus, the static models include all six survey rounds (1994, 1995, 1997, 1999, 2004, and 2009).

[22] The AFDM, developed by Princeton University, uses available satellite remote sensing and in-situ information, a hydrologic modeling platform and a web-based user interface for operational and research use in Africa. Based on macro-scale hydrologic modeling, the system employs available data to provide real-time assessment of the water cycle and drought conditions, and puts this in the context of the long-term record dating back to 1950. http://hydrology.princeton.edu/monitor.

in the past five years.[23] Total GDD and EHDD in the whole growing season (April 1st to September 30th) are derived using daily maximum and minimum temperatures, as described in Appendix A in Chapter 3.

The dependent variable is the logarithm of real monthly consumption per adult equivalent for each household.[24] Following Porter (2012) and Dercon, Hoddinott, and Woldehanna (2012), the monthly consumption measure consists of food consumption (including food expenditure and value of food received as gifts) and non-investment non-food consumption (excluding investment type consumptions such as durables, health and education expenditure). Some food consumption data are projected from consumption over a one-week recall period to make the aggregate household consumption comparable across survey rounds. The monthly nominal consumption measure is then deflated by a food price index (FPI) constructed from village level data collected at the same time as the household survey, as described in Dercon and Krishnan (1998). The adult equivalence scales are based on nutrition (calorie) needs for different age and gender groups as guided by the World Health Organization (WHO). A detailed scales table can be found also in Dercon and Krishnan (1998).

Table 4.1 presents the summary statistics for real monthly consumption per adult equivalent from 1994 to 2009.[25] Mean real consumption in 1994 is 85.80 birr per adult equivalent per month, and steadily rises to 105.34 birr in 1999 and to 116.00 birr in 2004.

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[23] Strictly speaking, these variable are not standard deviations from rainfall distribution since we only have five data points for each of such variable, but they provide some measure of rainfall variability across year. These inter-annual variations can be perceived by the households, and thus influence their coping strategies.

[24] We focus on consumption rather than income data because the latter is generally underreported in the ERHS. As Bezu, Barrett, and Holden (2012) note, average household consumption expenditure per adult equivalent is $125 while household income per adult equivalent is $68 (both in 2000 constant prices). Moreover, income data was derived from a four-month recalling period which changes over survey rounds, causing possible measure error (Josephson and Michler 2015).

[25] All figures and tables are placed separately at the end of the chapter.

In 2009, mean real consumption sharply drops to 70.52 birr per adult equivalent per month in 1994 prices, probably due to severe droughts that occurred in several villages in Tigray region and Southern Nations, Nationalities, and Peoples' Region, and the effect of rapid world staple food price increases in 2008 (Dercon, Hoddinott, and Woldehanna 2012).

Tables 4.2 reports the summary statistics of the independent variables included in the main analyses. On average, a household has six members, with a real monthly consumption per adult equivalent of 96 Birr and a livestock holding of three livestock units at one year prior to survey. A large share, 71%, of the households have a male head, and 10%, 15%, and 9% of the households experience illness, input price, and death shocks between survey rounds, respectively.

Rainfall in the study villages varies considerably. Daily temperature fluctuates little over time, but shows heterogeneity across space. Total growing degree days and total extreme heat degree days change substantially over time, and show significant spatial heterogeneity.

Data on average adoption rate of each diversification strategy by year from 1994 to 2009 are presented in Table 4.3. Overall, engaging in off-farm activities is the most prevalent (with 33% of the households adopted it), followed by receiving public transfers (21%), receiving transfers from ISSN (17%), and sending migrants for labor market reasons (15%), and receiving remittances has the lowest adoption rate (3%). The use of all these coping strategies has increased between 1994 and 2009, with income from transfers from informal social safety nets, family remittances, and off-farm activities increasing steadily over the years. Households that have sent migrants to urban areas may not receive remittances: only 0.2% of all households sent migrants and received remittances in 1994, and this percentage went up slightly to 2.1% in 2009. Both information of the strategy mix employed and increasing prevalence of strategies over time in our sample make rural Ethiopia a particularly interesting case-study of the effectiveness of alternative coping strategies.

4.4 Results and Discussion

4.4.1 The impact of weather shocks on consumption

To investigate the asymmetric effects of rainfall shocks on consumption, several specifications of equation (4.1) are estimated. Rainfall variables are defined as continuous in columns (1)-(3) of Table 4.4, and dichotomous in columns (4)-(6). In the first specification, average daily rainfall is reconstructed into two variables: average daily rainfall if it is above the historical mean and if it is below the historical mean. Standard deviation of rainfall is also reconstructed into two variables: standard deviation of rainfall if it is above the historical mean and if it is below the historical mean. If asymmetric effects exist, the coefficients for each pair are expected to be significant and different. In the second specification, two dichotomous variables are used to indicate whether average daily rainfall is below the historical mean and whether the standard deviation of rainfall is above the historical mean. If asymmetric effects exist, the coefficients for the two variables are expected to significant.

In both the two specifications, equation (4.1) are first estimated using the Arellano-Bond (difference) and Blundell-Bond (system) GMM estimators (Roodman 2009), and Sargen and Hansen tests show that the set of instruments is valid. However, the lagged dependent variable is not significant in both specifications with difference GMM estimation, thus equation (4.1) are re-estimated using fixed effects models in columns (3) and (6). Results show that absolute rainfall levels have positive and significant impacts on real consumption per adult equivalent and the impacts are a little bit asymmetric: rainfall levels above the historical mean have a larger effect than those below the historical mean. If average daily rainfall is above the historical mean and increases further by 10%, real consumption increases by 3.4%; if average daily rainfall is below the historical mean and decreases further by 10%, real consumption drops by 3.0%. On average below-historical-mean rainfall decreases per capita consumption by 17.3% compared to above-historical-mean rainfall. Extreme temperature also influences per-capita consumption. If total extreme heat degree days in previous year increases by 10%, real consumption drops by 0.2%-0.3%. Total growing degree days and the standard deviation of rainfall in the past five years are not significant. Note that these are net effects of weather shocks after households have adjusted their coping strategies, therefore it is evident that households are unable to fully smooth their consumption against weather shocks.

The illness and death shocks do not significantly affect consumption, suggesting that these idiosyncratic shocks appear to be successfully smoothed by the household. Counter to expectations, the input price shock has a positive and significant impact on consumption. Livestock holdings have a positive impact on consumption as expected.

As a robustness check, additional specifications using a single average rainfall variable, and using quintile variables in average rainfall distributions as in Porter (2012) are estimated, and the results are presented in Tables 4.7 and 4.8 in Appendix B. The single average rainfall variable is still positive and significant (column (3) of Table 4.7), but the quintile variables show a pattern different from Porter's, notably that the bottom rainfall distribution quintile has a positive and significant impact on consumption (column (3) of Table 4.8). It might be the case that rainfall quintiles and consumptions are not a good match, since the former are relative rainfall measures with respective to their historical distribution and the latter are absolute consumption measures. The Porter (2012) specification implies that rainfall in a drought-prone village has the same consumption elasticity as that in a rainfall-abundant village, which may not be realistic. To reconcile with Porter's results, rainfall quintiles are interacted with rainfall levels, and the results show that an increase in rainfall levels in the bottom quintile has the largest impact on consumption than the same increase in any other quintiles (column (6) of Table 4.8). Interestingly, an increase in rainfall levels in the middle quintile has the smallest impact on consumption compared to other quintiles.

4.4.2 The effectiveness of diversification strategies

Estimation results for equations (4.2) are reported in Tables 4.5. Sargen and Hansen tests confirm the validity of instruments for the difference GMM specification (column 1), but not for the system GMM specification (column 2). The lagged dependent variable is not significant in column 1, so a fixed effects model with weather shocks – strategies interaction terms is estimated and presented in column 3. For comparison purpose, a fixed effects model without weather shocks – strategies interaction terms is estimated to gauge the net impact of weather shocks on consumption, and presented in column 4.

When households don't adopt any diversification strategy, the effect of adverse rainfall shock (below average rainfall) on consumption is negative and significant: compared to above-historical-mean rainfall, below-historical-mean rainfall on average decreases per capita consumption by 20.3% (column 3). This reduction is larger in magnitude than the net effect of below-historical-mean rainfall after considering the adoption of diversification strategies (17.4% as implied by column 4). The effect of adverse temperature shock (above average extreme heat degree days) on consumption is negative and significant: an increase in extreme heat degree days by 10% reduce consumption by 2.8%. This reduction is also larger in magnitude than the net effect of increase in extreme heat degree days after considering the adoption of diversification strategies (2.4%). These findings imply that at least some diversification strategies work.

Among the five coping strategies, receiving public transfers is effective in smoothing consumption against adverse rainfall shocks, and participation in off-farm employment is effective in smoothing consumption against adverse temperature shocks. When an adverse rainfall shock occurs, receiving public transfers can boost real consumption per adult equivalent by 12.0% compared with those who do not receive public transfers. When an adverse temperature shocks occurs, participating in off-farm employment can increase consumption by 1.8% compared with those who do not participate.

Sending migrants to urban areas for labor market reasons is not effective in smoothing consumption against adverse rainfall or temperature shocks. The major motive for migration might be to improve the well-being of those that migrated out as shown in de Brauw, Mueller, and Woldehanna (2013), rather than those who stay at home. Receiving transfers from ISSN or former household members has no significant effects on consumption as well. These results are consistent with findings in Chapter 3 that weather shocks have indefinite impacts on transfers from ISSN or former household members.

The marginal effects of weather shocks and diversification strategies are presented in Table 4.6. Only receiving public transfers and participating in off-farm activities have positive and significant impact on consumption: on average the former can increase consumption by 4.72% and the latter by 3.17%. The net impacts of migration and receiving remittances or transfers from ISSN are not significant.

4.5 Concluding Remarks and Policy Implications

In this article, we investigate the impacts of weather shocks on household's real consumption per adult equivalent, and evaluate the effectiveness of different diversification strategies in smoothing consumption. Our results show that decreased rainfall levels and increased extreme high temperatures can reduce real consumption. The results also indicate that while participating in off-farm activities and receiving public transfers can effectively smooth consumption against adverse weather shocks, their use does not completely remove the impacts of adverse weather shocks on household per-capita consumption. Our findings on the impacts of weather shocks and idiosyncratic shocks on consumption are generally consistent with other studies in the literature such as Pan (2009) and Porter (2012), but we also demonstrate a pattern of asymmetric impacts of rainfall shocks on consumption different from what Porter (2012) finds.

Chapter 3 shows that migration and off-farm employment are responsive to rainfall shocks, whereas receiving public transfers, and the amount of remittances and transfers from ISSN are not responsive. In this Chapter, we find that receiving public transfers and participation in off-farm activities are effective in smoothing consumption against adverse weather shocks, but migration and receiving remittances and transfers from ISSN are not effective. To sum up, off-farm employment are both responsive to weather shocks and able to smooth consumption against adverse weather shocks. Applying for public transfers are not responsive to weather shocks, but once households adopted this strategy, it can effectively stabilize consumption against adverse weather shocks.

To better cope with adverse weather shocks, the Ethiopian government should strengthen rural economy and free up rural labor market for local employment since sending rural population to urban areas does not help to smooth consumption at home. Policy makers need to remove barriers to off-farm activities, open off-farm activities for more households, and support more rapid off-farm employment growth. In addition, public social protection programs should be reformed to be more adaptive and more responsive to weather shocks so as to increase their adoption rate when weather shocks hit. Moreover, since these diversification strategies are not able to fully buffer against weather shocks, other coping strategies, especially the farming strategies, should also receive attention. For example, the government can design subsidy programs to encourage rural households to adopt drought tolerant seeds and take out indexed-based rainfall insurance.

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Table 4.1 Real consumption per adult equivalent, 1994-2009

Year	Mean	Std. Dev.	Min	Max
1994	85.80	83.89	1.07	965.12
1999	105.34	90.39	4.81	688.39
2004	116.00	124.24	2.63	2133.45
2009	70.52	50.97	4.06	423.84

Note: Calculated from the ERHS. Consumption per adult equivalent is measured in 1994 price per month. Based on 1234 observations with complete information for all 4 survey rounds.

Table 4.2 Summary statistics

Variable	N	Mean	Std. Dev.	Min	Max
Log of real consumption per adult equivalent	5673	4.2390	0.8066	0.0640	7.6655
Dummy for sending migrants for labor market reasons	5646	0.1399	0.3469	0	1
Dummy for receiving transfer from government	5646	0.2140	0.4101	0	1
Dummy for receiving transfer from ISSN	5646	0.1676	0.3735	0	1
Dummy for receiving remittances from former household members	5646	0.0322	0.1766	0	1
Dummy for participating in off-farm activities	5642	0.3295	0.4701	0	1
Household size	5673	5.7881	2.7365	1	23
No. female adults aged 15-60	5526	1.5288	1.0254	0	10
No. girls aged 5-15	5526	0.8762	0.9919	0	6
No. girls aged <5	5526	0.3485	0.5957	0	5
No. females aged >60	5526	0.1811	0.4172	0	3
No. male adults aged 15-60	5526	1.4171	1.1053	0	9
No. boys aged 5-15	5526	0.8927	1.0009	0	7
No. boys aged <5	5526	0.3569	0.6047	0	4
No. males aged >60	5526	0.1716	0.4026	0	6
Livestock units, lagged one year	5625	2.9618	3.2982	0	62
Sex of household head (mal=1, fem=0)	5525	0.7073	0.4550	0	1
Dummy for illness shock	5292	0.1024	0.3032	0	1
Dummy for input price shock	5292	0.1497	0.3568	0	1
Dummy for death shock	5292	0.0896	0.2856	0	1
Log of average daily rainfall in main rainy season, lagged one year	5673	1.6419	0.4202	0.4960	2.5384
Log of average daily rainfall in main rainy season if above historical average, lagged one year	5673	0.9705	0.9624	0.0000	2.5384
Log of average daily rainfall in main rainy season if below historical average, lagged one year	5673	0.6714	0.7442	0.0000	2.1200
Log of standard deviation of average daily rainfall in main rainy season in past five years, lagged one year	5673	0.1794	0.5517	-1.1904	1.4151
Log of total growing degree days in whole growing season, lagged one year	5673	6.7458	0.3482	5.9376	7.2728
Log of total extreme heat degree days in whole growing season, lagged one year	5489	1.6751	2.2059	-4.3801	4.8263
Dummy for average daily rainfall in main rainy season below historical mean, lagged one year	5673	0.4839	0.4998	0	1
Dummy for standard deviation of average daily rainfall in main rainy season in past five years above historical mean, lagged one year	5673	0.3598	0.4800	0	1

Table 4.3 Average adoption rate of different diversification strategies, 1994-2009

Diversification strategies	1994	1999	2004	2009	All
Sending migrants to urban areas for labor market reasons	4.38%	8.83%	24.47%	20.42%	14.53%
Receiving public transfers	9.32%	24.80%	22.45%	26.74%	20.83%
Receiving transfers from ISSN	7.29%	13.53%	17.83%	29.58%	17.06%
Receiving remittances	1.13%	2.35%	4.54%	5.11%	3.28%
Engaging in off-farm activities	3.59%	19.53%	33.79%	44.57%	33.45%
Sending migrants for labor market reasons AND receiving remittances	0.16%	0.57%	3.08%	2.11%	1.48%
Sending migrants for labor market reasons AND NOT receiving remittances	4.21%	8.27%	21.39%	18.31%	13.05%

Calculated from ERHS. The percentage numbers refer to the shares of household in all villages that have adopted a certain diversification strategy. Based on 1234 observations with complete information for all four survey rounds.

Table 4.4 Weather shocks and consumption

	(1) **Diff1**	(2) **Sys1**	(3) **FE1**	(4) **Diff2**	(5) **Sys2**	(6) **FE2**
Log of real consumption per adult equivalent, lagged one round (five years)	0.0256	-0.0328		0.0132	-0.0453**	
	(0.029)	(0.022)		(0.028)	(0.023)	
Livestock units, lagged one year	0.0282****	0.0494****	0.0348****	0.0299****	0.0625****	0.0352****
	(0.007)	(0.004)	(0.006)	(0.007)	(0.004)	(0.007)
Dummy for illness shock	0.0555	0.0163	0.0455	0.0508	-0.0061	0.0482
	(0.039)	(0.032)	(0.036)	(0.039)	(0.033)	(0.037)
Dummy for input price shock	0.0955***	0.0492	0.0758**	0.1146***	0.0017	0.0868***
	(0.036)	(0.030)	(0.034)	(0.036)	(0.030)	(0.033)
Dummy for death shock	0.0175	0.0456	0.0301	0.0196	0.0533	0.0331
	(0.038)	(0.033)	(0.035)	(0.039)	(0.034)	(0.036)
Log of average daily rainfall in main rainy season if above historical average, lagged one year	0.4367****	0.4875****	0.3412****			
	(0.059)	(0.032)	(0.051)			
Log of average daily rainfall in main rainy season if below historical average, lagged one year	0.4977****	0.5828****	0.3026****			
	(0.080)	(0.046)	(0.066)			
Log of standard deviation of average daily rainfall in main rainy seasons in past five years if above historical mean, lagged one year	-0.1082**	0.0508	-0.0134			
	(0.051)	(0.036)	(0.036)			
Log of standard deviation of average daily rainfall in main rainy seasons in past five years if below historical mean, lagged one year	-0.1280****	0.0299	0.0154			
	(0.039)	(0.031)	(0.033)			
Log of total growing degree days in whole growing season, lagged one year	2.4208****	0.1897**	0.2157	3.8124****	-0.4660****	0.3057
	(0.584)	(0.093)	(0.390)	(0.536)	(0.083)	(0.380)
Log of total extreme heat degree days in whole growing season, lagged one year	-0.0363**	-0.0467****	-0.0344**	-0.0176	0.0393***	-0.0238*
	(0.017)	(0.014)	(0.014)	(0.017)	(0.013)	(0.014)
Dummy for average daily rainfall in main rainy season below historical mean, lagged one year				-0.1209****	-0.1523****	-0.1903****
				(0.029)	(0.027)	(0.026)
Dummy for standard deviation of average daily rainfall in main rainy seasons in past five years above historical mean, lagged one year				-0.1198****	-0.0380	0.0252
				(0.031)	(0.027)	(0.025)
Constant		2.8817****	2.6416		8.1477****	2.6561
		(0.661)	(2.597)		(0.573)	(2.541)
Number of observations	2506	3858	5039	2506	3858	5039
Number of instruments	24	27		22	25	
AR(1)	0.00	0.00		0.00	0.00	

Sargen	0.57	0.17		0.73	0.74	
Hansen	0.54	0.22		0.71	0.77	

Standard errors in parentheses. Household characteristics and composition variables, and survey round indicators are included in the estimation but omitted from the table.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table 4.5 Effectiveness of diversification strategies in mitigating the impact of weather shocks

	(1) Diff	(2) Sys	(3) FE 1	(4) FE 2
Log of real consumption per adult equivalent, lagged one round (five years)	0.0808	0.0202		
	(0.061)	(0.039)		
Livestock units, lagged one year	0.0336***	0.0619****	0.0354****	0.0353****
	(0.012)	(0.008)	(0.007)	(0.007)
Dummy for illness shock	0.0347	0.0054	0.0459	0.0475
	(0.065)	(0.044)	(0.037)	(0.037)
Dummy for input price shock	-0.0108	0.0096	0.0855**	0.0866***
	(0.062)	(0.045)	(0.034)	(0.034)
Dummy for death shock	0.0189	0.0561	0.0379	0.0325
	(0.063)	(0.046)	(0.036)	(0.036)
Dummy for average daily rainfall in main rainy season below historical mean, lagged one year	-0.4309	-0.0400	-0.2267****	-0.1915****
	(0.351)	(0.167)	(0.034)	(0.026)
Log of standard deviation of average daily rainfall in main rainy seasons in past five year, lagged one year	-0.2962***	0.1320***	0.0228	0.0132
	(0.110)	(0.046)	(0.026)	(0.025)
Log of total growing degree days in whole growing season, lagged one year	6.7274**	-0.1480	0.5042	0.2725
	(3.251)	(0.163)	(0.428)	(0.381)
Log of total extreme heat degree days in whole growing season, lagged one year	0.0052	0.0536	-0.0278*	-0.0239*
	(0.056)	(0.043)	(0.015)	(0.014)
Dummy for average daily rainfall in main rainy season below historical mean, lagged one year * Dummy for sending migrants for labor market reasons	0.3407	0.5454	0.0602	
	(0.767)	(0.633)	(0.057)	
Dummy for average daily rainfall in main rainy season below historical mean, lagged one year * Dummy for receiving transfer from government	1.1167*	-0.3943	0.1129**	
	(0.611)	(0.360)	(0.051)	
Dummy for average daily rainfall in main rainy season below historical mean, lagged one year * Dummy for receiving transfer from ISSN	0.7073	1.3317*	0.0464	
	(1.136)	(0.754)	(0.059)	
Dummy for average daily rainfall in main rainy season below historical mean, lagged one year * Dummy for receiving remittances from former household members	0.4818	0.2270	-0.0434	
	(1.979)	(1.142)	(0.105)	
Dummy for average daily rainfall in main rainy season below historical mean, lagged one year * Dummy for participating in off-farm activities	-0.1661	-1.0493***	0.0007	
	(0.571)	(0.404)	(0.040)	
Log of total extreme heat degree days in whole growing season, lagged one year * Dummy for sending migrants for labor market reasons	-0.3134	-0.2663*	-0.0168	
	(0.206)	(0.148)	(0.014)	
Log of total extreme heat degree days in whole growing season, lagged one year * Dummy for receiving transfer from government	0.1460	-0.0445	-0.0032	
	(0.097)	(0.053)	(0.010)	
Log of total extreme heat degree days in whole growing season, lagged one year * Dummy for	-0.3484***	-0.1794*	0.0012	

receiving transfer from ISSN	(0.129)	(0.101)	(0.012)	
Log of total extreme heat degree days in whole growing season, lagged one year * Dummy for receiving remittances from former household members	-0.2970	-0.4616	-0.0249	
	(0.545)	(0.430)	(0.030)	
Log of total extreme heat degree days in whole growing season, lagged one year * Dummy for participating in off-farm activities	0.0897	0.1846****	0.0183**	
	(0.086)	(0.055)	(0.009)	
Constant		5.6497****	1.3514	2.8881
		(1.095)	(2.864)	(2.552)
Number of observations	2506	3858	5036	5039
Number of instruments	41	53		
AR(1)	0.00	0.00		
Sargen	0.24	0.00		
Hansen	0.33	0.00		

Standard errors in parentheses. Household characteristics and composition variables, and survey round indicators are included in the estimation but omitted from the table.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table 4.6 Marginal effects of weather shocks and strategies on consumption

	Marginal effects
Dummy for average daily rainfall in main rainy season below historical mean, lagged one year	-0.1863****
	(0.027)
Log of standard deviation of average daily rainfall in main rainy seasons in past five year, lagged one year	0.0228
	(0.026)
Log of total growing degree days in whole growing season, lagged one year	0.5042
	(0.428)
Log of total extreme heat degree days in whole growing season, lagged one year	-0.0255*
	(0.014)
Dummy for sending migrants for labor market reasons	-0.0008
	(0.026)
Dummy for receiving transfer from government	0.0472*
	(0.026)
Dummy for receiving transfer from ISSN	0.0237
	(0.029)
Dummy for receiving remittances from former household members	-0.0629
	(0.053)
Dummy for participating in off-farm activities	0.0317*
	(0.018)
N	5036

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Appendix B Robustness check

Table 4.7 Weather shocks and consumption: symmetric rainfall effects

	(1) Diff	(2) Sys	(3) FE
Log of real consumption per adult equivalent, lagged one round (five years)	0.0245	-0.0365	
	(0.029)	(0.022)	
Livestock units, lagged one year	0.0287****	0.0509****	0.0346****
	(0.007)	(0.004)	(0.006)
Dummy for illness shock	0.0532	0.0110	0.0457
	(0.039)	(0.032)	(0.036)
Dummy for input price shock	0.0920**	0.0357	0.0805**
	(0.036)	(0.029)	(0.033)
Dummy for death shock	0.0174	0.0484	0.0294
	(0.038)	(0.033)	(0.035)
Log of average daily rainfall in main rainy season, lagged one year	0.3449****	0.4112****	0.3923****
	(0.044)	(0.029)	(0.041)
Log of standard deviation of average daily rainfall in past five year, lagged one year	-0.1249****	0.0421*	0.0084
	(0.036)	(0.025)	(0.025)
Log of total growing degree days in whole growing season, lagged one year	2.8235****	0.0150	0.0798
	(0.548)	(0.088)	(0.372)
Log of total extreme heat degree days in whole growing season, lagged one year	-0.0302*	-0.0240*	-0.0322**
	(0.016)	(0.014)	(0.014)
Constant		4.2343****	3.4296
		(0.632)	(2.492)
Number of observations	2506	3858	5039
Number of instruments	22	25	
AR(1)	0.00	0.00	
Sargen	0.65	0.19	
Hansen	0.62	0.24	

Standard errors in parentheses. Household characteristics and composition variables, and survey round indicators are included in the estimation but omitted from the table.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table 4.8 Weather shocks and consumption: other forms of asymmetric rainfall effects

	(1) Diff1	(2) Sys1	(3) FE1	(4) Diff2	(5) Sys2	(6) FE2
Log of real consumption per adult equivalent, lagged one round (five years)	0.0306	-0.0479**		0.0220	-0.0343	
	(0.029)	(0.023)		(0.028)	(0.023)	
Livestock units, lagged one year	0.0306****	0.0500****	0.0345****	0.0304****	0.0467****	0.0333****
	(0.008)	(0.004)	(0.007)	(0.007)	(0.004)	(0.006)
Dummy for illness shock	0.0452	0.0057	0.0344	0.0520	0.0105	0.0399
	(0.039)	(0.033)	(0.037)	(0.038)	(0.032)	(0.035)
Dummy for input price shock	0.0894**	-0.0029	0.0485	0.0761**	0.0173	0.0433
	(0.036)	(0.030)	(0.033)	(0.036)	(0.030)	(0.032)
Dummy for death shock	0.0314	0.0444	0.0363	0.0422	0.0402	0.0352
	(0.039)	(0.034)	(0.036)	(0.039)	(0.033)	(0.035)
Dummy for average daily rainfall in main rainy season in bottom quintile, lagged one year	0.3521****	0.3208****	0.2484****			
	(0.083)	(0.060)	(0.051)			
Dummy for average daily rainfall in main rainy season in second quintile, lagged one year	0.0109	-0.2673****	-0.0712*			
	(0.052)	(0.047)	(0.037)			
Dummy for average daily rainfall in main rainy season in fourth quintile, lagged one year	0.2701****	0.1885****	0.2669****			
	(0.055)	(0.045)	(0.044)			
Dummy for average daily rainfall in main rainy season in top quintile, lagged one year	0.2676****	0.1178**	0.2351****			
	(0.053)	(0.048)	(0.042)			
Log of standard deviation of average daily rainfall in past five year, lagged one year	0.0687	0.2274****	0.0846***	0.1470***	0.1352****	0.1280****
	(0.051)	(0.028)	(0.028)	(0.051)	(0.028)	(0.027)
Log of total growing degree days in whole growing season, lagged one year	3.1360****	-0.5987****	-0.4805	0.8515	-0.0188	-1.8200****
	(0.578)	(0.109)	(0.398)	(0.656)	(0.113)	(0.417)
Log of total extreme heat degree days in whole growing season, lagged one year	-0.0403*	0.0506***	-0.0381**	-0.0154	-0.0219	-0.0326*
	(0.022)	(0.018)	(0.017)	(0.023)	(0.018)	(0.017)
Dummy for average daily rainfall in main rainy season in bottom quintile, lagged one year * Log of average daily rainfall in main rainy season, lagged one year				1.1044****	0.6551****	1.1975****
				(0.133)	(0.048)	(0.100)
Dummy for average daily rainfall in main rainy season in second quintile, lagged one year * Log of average daily rainfall in main rainy season, lagged one year				0.8087****	0.3646****	0.8933****
				(0.110)	(0.047)	(0.086)
Dummy for average daily rainfall in main rainy season in middle quintile, lagged one year * Log of average daily rainfall in main rainy season, lagged one year				0.6686****	0.3875****	0.7547****
				(0.103)	(0.047)	(0.076)

Dummy for average daily rainfall in main rainy season in fourth quintile, lagged one year * Log of average daily rainfall in main rainy season, lagged one year				0.8162****	0.4557****	0.8941****
				(0.096)	(0.035)	(0.072)
Dummy for average daily rainfall in main rainy season in top quintile, lagged one year * Log of average daily rainfall in main rainy season, lagged one year				0.6715****	0.4124****	0.7581****
				(0.074)	(0.032)	(0.059)
Constant		8.3336****	7.7543***		4.3860****	15.4716****
		(0.802)	(2.662)		(0.788)	(2.762)
Number of observations	2506	3858	5039	2506	3858	5039
Number of instruments	25	28		26	29	
AR(1)	0.00	0.00		0.00	0.00	
Sargen	0.50	0.13		0.11	0.05	
Hansen	0.48	0.20		0.10	0.09	

Standard errors in parentheses. Household characteristics and composition variables, and survey round indicators are included in the estimation but omitted from the table.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$