Three Essays on the Economics of Price Volatility

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Dedication

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Abstract

This dissertation is about how commodity price volatility affects the decision making and welfare of economic agents. The three essays in this dissertation focus on food prices, the volatility of which has been an important topic of policy discussions in the wake of the global food crises of 2008 and 2010-11.

In the first essay, I examine whether food price volatility causes rural-to-urban migration. Using longitudinal household survey data from rural Ethiopia, I find strong and robust evidence that the greater a household's willingness to pay to stabilize food prices, the more likely that household is to see one of its members migrate, a relationship that is more pronounced in villages that lack alternative coping strategies to mitigate the negative welfare effects of price volatility. Thus, my results provide evidence that migration is a strategy that smallholder farmers rely on to cope with food price volatility in the absence of well-functioning credit and insurance markets.

The second and third essays are experimental studies motivated by a need for a clean identification of producer decision making under price volatility. In the second essay, my co-authors and I test Sandmo's (1971) canonical theory of producer behavior under output price uncertainty using a novel experimental protocol. We find that, in stark contradiction with Sandmo's theoretical prediction, which stems from expected utility theory, the presence of price uncertainty causes subjects to produce more than they do under price certainty, but we also find that increases in the degree of price uncertainty cause them to decrease their production. Perhaps more importantly, we also find that subjects exhibit behavior consistent with prospect theory.

In the third essay, we generate unique experimental data to examine how individuals make production decisions under price ambiguity, in which probability distributions of prices are unknown to experimental subjects. We find that, when producers have to make production decisions lacking such information, context matters a great deal, and

individuals rely on past realization of prices as well as heuristics to facilitate decision making.

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Chapter 1

Introduction

During the world food crises of 2008 and 2010-11, the world witnessed sharp increases in food prices as the Food and Agriculture Organization of the United Nations' (FAO) food price index—a summary measure of the international price of food—increased by 38% in 2007-08 and by 27% in 2010-11. Given the historically low food prices of the early 2000s and a substantial reprieve in 2009 in the form of drop in food prices, both crises were largely unexpected.

These extreme movements in world food prices not only raised concerns about high food prices, but they also raised concerns about food price volatility (FAO, 2011). Since 2012, food prices have gradually declined, but unexpected shocks to the supply and demand of food—say, because of extreme weather or oil price shocks—will almost surely lead to increases in food price volatility in the future (FAO, 2011).

Three conflated issues, a sound understanding of which has so far been lacking, matter when studying the welfare effects of food price volatility and in related policy discussions.

First, a distinction must be made between the consequences of high food price *levels* and high food price *volatility* (Bellemare, 2015). Intuitively, it is obvious who wins and who loses when food prices are high: net sellers gain from high prices, and net buyers lose from high prices. The welfare effects of food price volatility, however, are much harder to intuit.

Indeed, theoretical studies have shown that food price volatility can be harmful to both producers and consumers of agricultural commodities in developing countries. Sandmo (1971) has shown that a risk-averse producer—who has to sink resources into producing well before the resolution of output price uncertainty—will underproduce when faced with output price risk.[1] Barrett (1996) has shown that with a high budget share of food and a lack of close substitutes for staples, poor net buyers of staples are likely to experience a welfare loss when facing staple price volatility. Moreover, the fact that a typical rural household in the developing world is both a producer and a consumer of several agricultural commodities further complicates the issue. Bellemare et al. (2013) have shown that the welfare of the average rural households in Ethiopia is adversely affected by price volatility, but Bellemare (2015) has shown that increases in food price volatility do not appear to cause social unrest. There is thus no unambiguous empirical evidence about the welfare impacts of food price volatility.

Second, there is a fundamental difference between income risk and price risk. Indeed, a consumer's indirect utility function $V(p, y)$—the usual measure of welfare in microeconomics—has two arguments: the consumer's income y and the vector of prices p that the consumer faces. Thus, holding income constant, welfare varies in response to price volatility because the terms of the V_{pp} sub-Hessian matrix of $V(p, y)$ are unlikely to be equal to zero. There exists a vast literature on income risk, which involves the curvature of the utility function (and thus of the indirect utility function, given that the latter is simply what we call the former when it is maximized) with respect to income V_{yy}, but we lack a sound understanding of how preferences toward price risk, represented by V_{pp}, affect behavior.

Third, price volatility of a known nature (i.e., price risk) and price volatility of

[1] I use the terms "price volatility," "price fluctuations," and "price risk" interchangeably to refer to the variance of the price distribution when it is known by economic agents. I will use the terms "price ambiguity" or "price uncertainty" to refer to the variance of the price distribution when it is not known by economic agents.

an unknown nature (i.e., price ambiguity, or Knightian uncertainty) are very different phenomena. For instance, changes in prices due to seasonality are usually predictable, whereas the changes in prices due to unexpected weather shocks are equally unexpected (FAO, 2011). Theoretical results on the welfare effects of price volatility for producers (Sandmo, 1971; Batra and Ullah, 1974), consumers (Turnovsky et al., 1980), and agricultural households (Finkelshtain and Chalfant, 1991) are built on the assumption that both the mean and the variance of the price distribution are known to the economic agents under study. That assumption, however, is not likely to hold in developing countries, where market information like expected prices and the variance of price distributions for staples are often simply not available due to the absence of commodity exchanges and of futures and options markets.[2]

This dissertation picks up where recent studies by Bellemare et al. (2013), Mason and Myers (2013), and Bellemare (2015) have left off in order to improve our understanding of the welfare effects of price volatility. Using both observational and experimental methods, the three essays contained therein address topics under the broad theme of decision making in the face of price risk, especially as it pertains to agricultural producers in developing countries.

Chapter 2 examines rural-to-urban migration from a new angle, viz. as a household strategy to mitigate the effect of price risk in the absence of well-functioning credit, labor, and insurance markets. In many developing countries, people often migrate from rural to urban areas even when expected income is relatively lower in urban areas. I model an agricultural household's decision to send members to urban areas in the face of two types of risk: the price risk associated with agricultural production, and the income risk associated with migration. For my empirical analysis, I use longitudinal data on households in rural Ethiopia. As a measure of household price risk preferences, I use household-level willingness to pay (WTP) for price stabilization measure, which was

[2] A notable albeit recent example of a commodity exchange in a developing country is the Ethiopia Commodity Exchange, which was established in 2008, and which has been shown to reduce the average price spread of the commodities for which it allows trading (Andersson et al., 2017).

derived and estimated by Bellemare et al. (2013).

I find strong, robust evidence that a higher WTP for price stabilization is positively associated with rural out-migration, and that this relationship is more pronounced in villages that lack mechanisms to mitigate the negative welfare effects of price volatility, such as food-for-work programs and food aid deliveries. I also find that the high price volatility of coffee and teff—both important cash crops in rural Ethiopia—are significantly related to migration from rural to urban areas.

An important limitation of the extant empirical studies on the welfare effects of price risk (Barrett, 1996; Bellemare et al, 2013; Mason and Myers, 2013), and thus of chapter 2 of this dissertation, is that they rely on observational data, which suffer from measurement error and imprecision, and which prevent one from making causal statements. **Chapter 3** thus uses experimental methods to look at producer behavior in the face of price risk. In that chapter, my coauthors and I test Sandmo's (1971) canonical theoretical model of producer behavior in the face of output price risk. Per Sandmo, output price uncertainty causes producers to underproduce relative to a situation of price certainty. To test this theory, we develop an experimental protocol that closely mimics Sandmo's theoretical model. For identification, we use a two-stage randomization strategy aimed first at studying the effect of price uncertainty relative to price certainty on production, and then the effect of increases in the degree of price uncertainty conditional on there being price uncertainty. To improve on external validity, we conducted lab experiments at Cornell and Minnesota, and we conducted lab-in-the-field experiments with smallholder farmers in Peru's Lima province.

We find that, in stark contrast with Sandmo's core prediction, the presence of price risk causes subjects to produce more than they would in situations of price certainty. Somewhat paradoxically, we also find that subsequent increases in the degree of price risk cause them to decrease their production. Having shown that the behavior of our experimental subjects is inconsistent with expected utility theory, we provide evidence that prospect theory (Kahneman and Tversky, 1979) provides a better description of producer behavior in the face of output price risk. Lastly, we use our data to study the problem structurally, as in Barrett (1996) and Bellemare et al. (2013), and find that our structural results are consistent with our reduced-form results but that there is a great deal of heterogeneity in estimated price risk preferences, which suggests that any policy used to deal with price volatility is likely to create winners and losers.

Chapter 4, in which we experimentally examine how production decisions are made under price ambiguity—a situation wherein the price distribution is unknown—completes our experimental study of producer behavior in the face of price volatility. Here, instead of the two-stage randomized design used in chapter 3, we use a simple, one-step randomization process in which subjects are randomly presented with either a certain price or an ambiguous price, i.e., a price drawn from an unknown distribution, but whose shape gradually reveals itself through observed prices. Again, theses experiments were conducted at Cornell, Minnesota, and in Peru.

We find that price ambiguity causes subjects to raise their output, but that results are sensitive to the prices drawn during earlier rounds as well as to our subjects' risk preferences. We also find patterns of decision making consistent with the gambler's fallacy (Tversky and Kahneman, 1971).[3] All in all, we find that when individuals have to make production decisions without information on the price distribution, the information that is available to them matters a great deal, as they rely on past realizations of price as well as on heuristics to facilitate decision making.

This dissertation contributes to the literature on food price volatility as well as to the broader literature on decision making under risk and uncertainty in three ways.

First, this dissertation moves the frontier of research on risk and uncertainty by addressing new research questions using a mix of observational and experimental methods. Chapter 2 is the first to examine the impact of commodity price volatility on migration, and my finding that both attitudes towards and exposure to price volatility positively

[3]The gambler's fallacy is the mistaken expectation that "any deviation in one direction will soon be canceled by a corresponding deviation in the other," or one's belief that sampling is a "self-correcting process" (Tversky and Kahneman, 1971).

influence rural out-migration can offer a new explanation for rural-to-urban migration decisions, and it complements the evidence on migration as an income risk management strategy (Stark and Levhari, 1982; Rosenzweig and Stark, 1989; Heitmueller, 2005; Jaeger et al., 2010; Bryan et al. 2014). Similarly, chapter 3 is the first paper to test Sandmo's seminal theoretical result on production decisions in the face of price risk based on a novel experimental design, and chapter 4 is the first to examine how production decisions are made under price ambiguity.

Second, the findings in this dissertation can inform agricultural policy in the developing world. Ethiopia is one of the least urbanized countries in the world, and chapter 2 sheds light on the important connection between food insecurity and urbanization. In that chapter, I find that farmers exit agriculture due to high food price volatility, especially in villages lacking local infrastructure and safety nets that offer alternative strategies for price risk management. This suggests that policymakers need to consider price volatility as a factor when making migration and urbanization policies. Chapters 3 and 4 examine production decisions in the face of price risk and uncertainty in situations without insurance and credit markets and without storage technology. This closely resembles the production conditions faced by many smallholder farmers in many developing countries, and so the experimental findings in chapters 3 and 4 can help inform policies aimed at improving the welfare of those smallholder farmers.

Lastly, this dissertation explores alternatives to expected utility theory, the workhorse model of decision making under risk and uncertainty. In chapter 3, we find that subjects exhibit behavior consistent with prospect theory when they know the distribution of prices. In chapter 4, in which subjects do not know the distribution of prices, we find that they exhibit behavior consistent with the gambler's fallacy. This suggests that policy measures to address food price volatility formulated on the basis of expected utility theory might need to be rethought on the basis of those behavioral insights.

Chapter 2

Commodity Price Volatility and Migration: Evidence from Rural Ethiopia[1]

2.1 Introduction

The proportion of urban population over the world has steadily increased over the past half-century. Internal migration from rural to urban areas has been recognized as the main driver for this urbanization process. Reallocation of labor from agriculture to industry due to migration contributes to the structural transformation that is key to economic development. Consequently, motivations for internal migration have been an important area of research. Todaro (1969) and Harris and Todaro (1970) developed

[1]I am grateful to Marc Bellemare, Metin Çakir, Liz Davis, Paul Glewwe, Terry Hurley, Jason Kerwin, Robert King, Linden McBride, seminar participants at Mississippi State University, University of Alberta, University of Connecticut, University of Guelph, University of Minnesota, and Virginia Tech, and participants at 2017 Center for the Study of African Economics (CSAE) Annual Meeting, 2016 AEA/ASSA Annual Meeting, 2016 Midwest International Economic Development Conference (MIEDC), 2016 Population Association of America (PAA) Annual Meeting, 2015 Agricultural & Applied Economics Association (AAEA) Annual Meeting, and 2015 European Association of Agricultural Economics (EAAE) Ph.D. Workshop, for helpful comments.

models in which higher expected income in urban areas explains rural-to-urban migration. Katz and Stark (1986) later offered a theoretical explanation that income risk aversion can motivate rural-to-urban migration, even when the expected income is lower in urban areas. Migration is one strategy that rural households use to manage income risk (Stark and Levhari, 1982; Rosenzweig and Stark, 1989), and a body of recent empirical literature has examined the direct relationship between income risk aversion and migration (Heitmueller, 2005; Jaeger et al., 2010; Bonin et al., 2009; Constant et al. 2011; Hao et al., 2014).

To better understand the mechanism of rural-to-urban migration in developing countries, it is important to understand not only the income risk, but also the price risk[2] of agricultural commodities, for several reasons. First, agriculture constitutes a substantial part of economic activities in developing countries, in terms of both production and consumption. On the production side, shares of agriculture in GDP in developing countries are more than double the shares in developed countries (World Bank, 2014a). Especially in Africa, a higher share of population depends on agriculture for its living than in any other region (Minot, 2011). On the consumption side, the shares of food in households' budgets are much higher in developing countries than in developed countries.[3] Second, food price volatility has been considered harmful for both producers and consumers of agricultural commodities in developing countries. Given that production decisions must be made well before prices are realized, and that such decisions are hard to reverse once prices are realized, an income risk-averse producer is likely produce at a sub-optimal level (Sandmo, 1971). Proper insurance schemes to help producers manage price risks often do not exist in developing countries. High food price volatility can also create food security stress for consumers in developing countries (Barrett, 1996) where the budget shares of food are very high, and close substitutes for

[2]Hereafter I will use the terms "volatility," "fluctuation," "risk," and "uncertainty" interchangeably. I will use "price" to mean either producer, wholesale, or consumer price, and will focus on staple food prices.

[3]In countries such as Egypt, Malawi, Mozambique, Peru, and Nepal, shares of household expenditure on food in urban areas range from 37% to 69%. For all these countries the shares are even higher in rural areas (FAO, 2004). On the contrary, the share is only around 10% in the U.S. (USDA ERS, 2014), and ranges from 13% to 20% in OECD countries (OECD and FAO, 2008) for the same time period.

staples are often unavailable when food prices soar. Moreover, typical rural households in developing countries both produce and consume several agricultural commodities, resulting in exposure to price risks in terms of both production and consumption.

In this paper, I examine the role of agricultural price risk as a push factor on rural-to-urban migration by investigating two potential channels by which commodity price risk can affect rural out-migration. The main research questions are: (i) Do household risk attitudes towards commodity prices affect rural out-migration?, and (ii) Does a high degree of commodity price volatility increase rural out-migration? The former question focuses on the role of preferences, whereas the latter focuses on the direct impact of price volatility at a village level.

I model a household's decision to send one or more of its members to urban areas as a family labor allocation decision, adapting the standard agricultural household model (Singh, Squire, and Strauss, 1986) in which a rural household can produce an agricultural commodity and can consume some of it. Theoretical predictions are derived assuming that uncertainty lies in both the commodity prices in rural areas as well as the future wage that a potential migrant will receive in an urban area. For empirical analysis, I focus on rural households of Ethiopia by using several rounds of data from the Ethiopian Rural Household Survey (ERHS). Regarding the first research question, to measure households' risk attitudes towards prices I use the household-level willingness to pay (WTP) to stabilize the commodity prices in rural Ethiopia estimated by Bellemare, Barrett, and Just (2013, BBJ hereafter). This WTP measure has two advantages. First, it is derived from the agricultural household framework which allows a household to be both a producer and a consumer of the same crop. Second, it allows production and consumption of multiple crops. These features better reflect the situation of typical rural households in developing countries.

I find a significant relationship between higher WTP for price stabilization and higher incidence of migration, in terms of both extensive and intensive margins. In other words, a rural household whose welfare is decreasing in price volatility is more likely to send members to urban areas and have a greater number of household members migrate than a household whose welfare is unaffected by price volatility. Due to the inherent challenges in attaining an exogenous measure of the WTP, this paper may not accomplish perfect identification of the causal impact of price risk attitudes on migration. A linear probability model with district-time fixed effects is used as a main specification, and a battery of careful robustness checks are conducted. The results are remarkably robust to the inclusion of various levels of fixed effects, an alternative definition of the WTP, various definitions of internal migration, linear and non-linear specifications, as well as falsification tests. Further analysis finds that this significant relationship between price risk attitudes and migration is more pronounced in the villages where daily markets, producer co-ops, and food aid, food-for-work, and cash-for-work programs are unavailable. These results suggest that negative welfare impacts of price volatility are a push factor on migration, especially in the villages that are systematically more vulnerable to price risk. I also find evidence that not only attitudes towards, but also exposure to, price volatility matter for migration decisions. Higher village-level price volatility of coffee and teff is each significantly related to out-migration of the households that produce and consume coffee and teff, respectively.

The contribution of this paper is threefold. First, this is the first to examine the relationship between price risk, as distinct from income risk, and migration, both in terms of preference and the volatility of market prices. The indirect utility function $V(p, y)$, which can be used as a measure of welfare, is defined over a vector of prices p and income y. Existing empirical studies on risk and migration have primarily focused on one's attitudes to *income* risk, that is, $-\frac{V_{yy}}{V_y}$,[4] (Heitmueller, 2005; Jaeger et al., 2010; Bonin et al., 2009; Constant et al., 2011, Hao et al., 2016) but we know nothing about how one's attitudes to *price* risk, $-\frac{V_{pp}}{V_y}$, affect migration decisions. A recent study by Bazzi (2016) finds a positive relationship between rainfall and rice price shocks and international migration in

[4] V_x and V_{xx} denote the first-order and the second-order derivatives of V, respectively, with respect to argument x.

Indonesia. His study, however, focuses on the impact of price *levels*, whereas this study focuses on the impact of price volatility. This paper provides evidence that migration is a price risk management strategy of rural households, which could complement the theory of migration as an income risk management strategy. Research on migration is absent in the empirical literature on price risk and welfare (Barrett, 1996; BBJ, 2013; Bellemare, 2015) as well. Finkelshtain and Chalfant (1991) theoretically predicted that peasant households' aversion to price risk can induce an exit from farming. To the best of my knowledge, no study has empirically tested this theory.[5]

This study is important for development policy. Ethiopia is one of the least urbanized countries worldwide, with only about 20% of the population living in urban areas in 2014 (World Bank, 2014b). Yet there has been a consistent increase in the proportion of the population living in urban areas in Ethiopia, and the level of urbanization is expected to increase further in the future. Given the low fertility rate in urban areas, migration has been a major factor in explaining urbanization in Ethiopia. Governments in Ethiopia and in other developing countries, however, have implemented conflicting policies, ranging from encouraging rural-to-urban migration to restricting them (Lall et al., 2006). This study sheds light on the important connection between food insecurity and urbanization. Less competition resulting from farmers exiting agriculture can lead to higher food price levels, which is bad for rural food consumers, and maybe even worse for urban food consumers. Moreover, villages that are systematically more prone to food insecurity will be disproportionately affected, losing more labor force that used to engage in farming. Knowing that price volatility is a source of rural distress, and a driver of migration, policies aimed at promoting market activities and enhancing agricultural value chain

[5] Three features distinguish the Finkelshtain and Chalfant (1991) and the model used this study. First, I assume that there is uncertainty in both the commodity price and the urban wage, whereas the F&C addresses only the uncertainty in the commodity price and assumes away uncertainty in the urban wage. Second, the F&C discusses only the long-term exit from farming, whereas I allow two cases in my model: (i) an entire household quits farming; (ii) Some members migrate to urban areas, while the rest of the household members remain in the rural area. Third, the prediction by the F&C does not take into account the possibility that a peasant household is a net buyer, i.e., a household consumes more than what it produces. I consider the case of a net buyer as well.

may improve the welfare of rural households.

Lastly, this study also informs food policy. Policies designed to decrease food price volatility have been an important policy instrument that have required large amounts of government spending in a number of developing countries, especially after the global food crisis of 2007-08 and the sharp increase in food prices in 2010.[6] These measures, however, are often implemented by governments just to appear to be doing something under political pressure (Poulton et al. 2006) and without careful justification of high implementation costs (Gouel, 2013). If migration is an indication of negative welfare impacts of price volatility, policies designed to decrease food price volatility will reap higher welfare gains if focused on specific commodities that influence migration, such as coffee and teff.

The paper proceeds as follows: Section 2.2 discusses the theoretical framework and the WTP measure. Sections 2.3 and 2.4 describe the data and the empirical strategy, respectively. Empirical results are presented in Section 2.5. Policy implications, limitations, and future directions are discussed in Section 2.6.

2.2 Theoretical Framework

2.2.1 Modeling the Price Risk Attitudes and Migration Decision Making

The Model

In this section, I adapt the standard agricultural household model (Singh, Squire, and Strauss, 1986) and incorporate migration decision making.[7]

[6] In South Asia, Bangladesh, India, Afghanistan, and Sri Lanka used economic measures such as price controls or trade policies to decrease food price volatility (World Bank, 2010). In Africa where food price fluctuations are more severe, Zambia and Malawi have taken the most aggressive measures to stabilize food prices (Chapoto and Jayne, 2009).

[7] The basic setup of the model is heavily influenced by Barrett (1996) who, using a simple two-period agricultural household model, demonstrates the inverse farm size−productivity relationship commonly observed in agriculture.

Suppose that a household maximizes a Von Neumann-Morgenstern utility function defined over leisure (L^L), consumption of a staple good (S) that is produced on the household's own farm, and consumption of a non-staple good (N) that is purchased in the market.[8] The utility function $U(\cdot)$ is twice continuously differentiable, strictly increasing in each argument L^L, N, and S, quasi-concave, concave in each argument, and satisfies the Inada conditions with respect to each argument x, i.e., $lim_{x \to 0} U(x) = +\infty$. This is a two-stage model in which the household makes its production and labor-leisure allocation decisions in stage one under uncertainty with regards to both the price of the staple crop (P^S) that it produces and consumes, and the urban wage (W^U). These prices are realized in stage two, when consumption decisions are made for the staple crop and the non-staple good. The price of the non-staple good (P^N) and the rural wage (W^R) are assumed to be known during the stage one. I assume that there are no labor market for farm labors and no credit market. The household's maximization problem is the following.

$$
\begin{gathered}
\max_{L^L, L^F, L^R, L^U} E \max_{N,S} U(L^L, N, S) \\
s.t. \quad P^S S + P^N N \leq Y \\
Y \equiv P^S F(L^F, T) + W^R L^R + (W^U - C) L^U \\
L^0 \geq L^L + L^F + L^R + L^U
\end{gathered}
\tag{2.1}
$$

where E is an expectation operator, L^0 is the total endowment of the hours of household members, which can be allocated to leisure (L^L), working at the household's farm (L^F), working for rural off-farm employment opportunities (L^R), or working in an urban area (L^U). $F(\cdot)$ is a production function that is strictly increasing in the farm labor hours (L^F) and an endowment of land (T).[9] W^R and W^U are wages earned from working for

[8] This is a unitary household model, in which a household maximizes a single utility function. Labor allocation, consumption, and production decisions are assumed to be made by one person. Thus, I abstract away from the issues of intra-household resource allocation, conflicts, and commitment to remit. The unitary household framework is also consistent with BBJ (2013) in which the WTP measure used in this study was estimated.

[9] In order to make the analysis tractable, I assume that production is riskless, and focus on the risks in P^S and W^U.

rural off-farm labor and from migrant household members (if any) working in an urban area, respectively. $C \cdot L^U$, in which $C > 0$ is a constant parameter, is the cost of sending out migrant household members to an urban area, which includes any upfront costs of migration such as transportation and lodging costs, and costs associated with seeking employment opportunities. Thus, the expression $(W^U - C)L^U$ is a gain from migration, which is strictly increasing in W^U and strictly decreasing in $C > 0$.

Given that the household makes its labor-leisure allocation decision in stage one, subject to the expected maximized utility from the optimal consumption choices in stage two, using the concept of duality (Epstein, 1975), the indirect utility function can be used. The benefit of using the indirect utility function instead of the utility function is that it is homogeneous of degree zero in prices and income, i.e., (P^S, P^N, Y). Using P^N as a numéraire, let $p = P^S/P^N$, $y = Y/P^N$, $w^R = W^R/P^N$, $w^U = W^U/P^N$, and $c = C/P^N$. The household's maximization problem can then be expressed as

$$\begin{gathered} \max_{L^L, L^F, L^R, L^U} EV(L^L, p, y) \\ s.t. \quad y = pF(L^F, T) + w^R(L^0 - L^L - L^F - L^U) + (w^U - c)L^U \\ where \quad V(L^L, p, y) \equiv \max_{N,S} U(L^L, N, S) \\ s.t. \quad p\{S - F(L^F, T)\} + N = y \end{gathered} \tag{2.2}$$

The first-order necessary conditions are[10]

$$\begin{gathered} w.r.t. \;\; L^L : E\left[V_{L^L} - V_y w^R\right] \leq 0 \;\; (= 0 \;\; if \;\; L^L > 0) \\ w.r.t. \;\; L^F : E\left[V_y(pF_{L^F} - w^R)\right] \leq 0 \;\; (= 0 \;\; if \;\; L^F > 0) \\ w.r.t. \;\; L^U : E\left[V_y(w^U - c - w^R)\right] \leq 0 \;\; (= 0 \;\; if \;\; L^U > 0) \end{gathered} \tag{2.3}$$

By the Inada condition, $L^L > 0$ at an optimum. Therefore, $E\left[V_{L^L}\right] = E\left[V_y w^R\right]$. But

[10]The Langrangian for this optimization problem is $\mathscr{L} = EV(L^L, p, y) + \lambda[pF(L^F, T) + w^R(L^0 - L^L - L^F - L^U) + (w^U - c)L^U - pS - N]$ where λ is a the Lagrange multiplier.

interior solutions are not guaranteed for L^F and L^U. From the first-order necessary conditions above and the complementary slackness condition, the following condition which must hold if the household has one or more of its members migrate to urban areas (For derivation, see A.1 in appendix).

$$E[\underbrace{w^U - c}_{\substack{\text{Gains from} \\ \text{Migration}}} - \underbrace{pF_{L^F}}_{\substack{\text{Gains from} \\ \text{Agriculture}}}] \geq \frac{F_{L^F} \cdot \overbrace{Cov[V_y, p]}^{\substack{\text{Price Risk} \\ \text{Attitude}}} - \overbrace{Cov[V_y, w^U - c]}^{\substack{\text{Income Risk} \\ \text{Attitude}}}}{E[V_y]} \tag{2.4}$$

The left-hand-side (LHS) is the expected gap between the gains from migration and the gains from agriculture, the latter of which is the marginal value product of farm labor. The right-hand-side (RHS) is determined by signs and relative magnitudes of two covariances, i.e., $Cov[V_y, p]$ and $Cov[V_y, w^U]$, which in turn depend on the household attitudes towards price risk and income risk, respectively.[11] Thus, a household's migration decision is made by comparing the difference between the expected gains from migration, the expected gains from agriculture, and the relative magnitude of income risk and price risk that the household must take by making the decision.

The Coefficient of Absolute Price Risk Aversion

In the standard theory of income risk and uncertainty, $-\frac{V_{yy}}{V_y}$ is Pratt's (1964) coefficient of absolute income risk aversion. This is widely used as a measure of the welfare impact of income risk, or of risk attitudes with respect to income. Likewise, $-\frac{V_{pp}}{V_y}$ can serve as a measure of the welfare impact of price risk. This is the coefficient of price risk aversion developed by Schmitz et al. (1981) for producers, and Turnovsky et al. (1980) for consumers. The concept was later extended to the case of agricultural households by Barrett (1996), and the estimable coefficient of absolute price risk aversion A is defined

[11] To see why, refer to A.2 in appendix.

as:[12]

$$A \equiv -\frac{V_{pp}}{V_y} = -\frac{M}{p} \cdot \{\beta(\eta - R) + \epsilon\} \tag{2.5}$$

where M is the marketable surplus (production (F) - consumption (S)), β is a budget share of the marketable surplus of the commodity ($\frac{pM}{y}$), η is the income elasticity of the marketable surplus ($\frac{\partial M}{\partial y}\frac{y}{M}$), R is the Arrow-Pratt coefficient of relative risk aversion of households, and ϵ is the own-price elasticity of the marketable surplus ($\frac{\partial M}{\partial p}\frac{p}{M}$). $A > (=, or <)\, 0$ if and only if $V_{pp} < (=, or >)\, 0$, which indicates that a household is price risk averse (neutral, or loving).

An intuition behind $A > 0$ is the following. For both net sellers and net buyers, $A > 0$ if and only if $R > \eta + \frac{\epsilon}{\beta}$.[13] For both net sellers and net buyers, ceteris paribus, each of the following characteristics contributes to the aversion to price risk: (i) higher income risk aversion (R), (ii) lower income elasticity of marketable surplus (η), (iii) lower price elasticity of marketable surplus (ϵ), and (iv) higher budget share of marketable surplus (β). These characteristics indicate that, being averse to price risk is associated with being averse to income risk, lacking flexibility in adjusting one's production and consumption according to fluctuations in income and price, and having a lot to lose from unfavorable price shocks.

Testable Hypotheses

In this subsection, testable hypotheses (Propositions I and II) on price risk attitudes and migration are derived based on the discussions so far. Claims I and II below are some necessary intermediate steps for which proofs are shown in appendices.

Claim I. *If a household is a net seller of a normal good S, aversion to price risk ($A > 0$ $\Leftrightarrow V_{pp} < 0$) is a sufficient condition for $Cov[V_y, p] < 0$.*

For proof, see A.5 in appendix.

[12]For derivation, refer to A.3 in appendix.

[13]For proof, see A.4 in appendix.

Claim II. *If a household is a net buyer of a normal good S, aversion to price risk ($A > 0$ $\Leftrightarrow V_{pp} < 0$) is a sufficient condition for $Cov[V_y, p] > 0$.*
For proof, see A.6 in appendix.

Proposition I. *Suppose that a household is a price risk-averse net seller of a normal good S. If the household's welfare effect of price risk (associated with farming) dominates that of income risk (associated with migration), then, compared to the converse, the household is more likely to send its members to an urban area.*

Proof. Consider two price risk-averse net seller households A and B. The following condition must be satisfied in order for a household to be indifferent between having a member migrate to an urban area or having the member work at a family farm.

$$E[w^U - c - pF_{L^F}] = \frac{\overbrace{F_{L^F}}^{(+)} \cdot \overbrace{Cov[V_y, p]}^{(-)} - \overbrace{Cov[V_y, w^U - c]}^{(-)}}{\underbrace{E[V_y]}_{(+)}} \tag{2.6}$$

For both A and B, due to price risk aversion, $Cov[V_y, p] < 0$ by Claim I. Due to income risk aversion, $Cov[V_y, w^U - c] < 0$. Therefore, the sign of the RHS of expression (6) is ambiguous.

Suppose that, for the household A, the welfare effect of price risk associated with farming dominates that of income risk associated with migrating, i.e., $\left|F_{L^F} \cdot Cov[V_y, p]\right| > \left|Cov[V_y, w^U - c]\right|$. Suppose the opposite for the household B, that is, $\left|F_{L^F} \cdot Cov[V_y, p]\right| < \left|Cov[V_y, w^U - c]\right|$. Thus, at an optimum, the RHS of expression (6) < 0 for the household A, and the $RHS > 0$ for the household B. Therefore, the following condition must hold at the optimum.

$$E[w^U - c - pF_{L^F}]^{A*} < 0 < E[w^U - c - pF_{L^F}]^{B*} \tag{2.7}$$

where $E[w^U - c - pF_{L^F}]^{A*}$ and $E[w^U - c - pF_{L^F}]^{B*}$ are the expected differences in the gains from migration and the gains from agriculture that makes the households A and B, respectively, indifferent from farming in rural area and migrating to urban area. In order for the household B to have its members migrate to urban areas, it must be that $E[w^U - c] > E[pF_{L^F}]$. The household A, however, can have its members migrate to urban areas even though $E[w^U - c] < E[pF_{L^F}]$. If the term $E[pF_{L^F}]$ is identical for the households A and B, the household B will require higher gains from migration in order to have $L^U > 0$, than the household A. Thus, household A is more likely to have migrant members than household B. □

According to Proposition I, a rural household can have its members migrate to urban areas even though the expected gains from migration is lower than the expected gains from agriculture, due to the aversion to price risk. This is consistent with Sandmo (1971), who stated that price uncertainty induces income risk-averse producers to produce at a sub-optimal level. This is also consistent with the result of Barrett (1996), who showed that price risk aversion of net sellers results in an underemployment in farm labor, i.e., employment of farm labor under its shadow value. Lastly, this is consistent with the result of Finkelshtain and Chalfant (1991) who predicted that a peasant household's aversion to price risk can induce a long-run exit from farming.

Intuitively, there is a trade-off between lower price risk and higher income risk when a net seller household sends a member to an urban area. This trade-off can also be seen by rearranging the terms in expression (4) above, which is a condition for having $L^U > 0$.

$$E\underbrace{[w^U - c]}_{\text{Gains from Migration}} + \frac{\overbrace{Cov[V_y, w^U - c]}^{\text{Income Risk Attitude (-)}}}{E[V_y]} \geq E\underbrace{[pF_{L^F}]}_{\text{Gains from Agriculture}} + \frac{F_{L^F} \cdot \overbrace{Cov[V_y, p]}^{\text{Price Risk Attitude (-)}}}{E[V_y]} \tag{2.8}$$

On the LHS, the expected gains from migration are weighed against the income risk associated with migration, and on the RHS, the expected gains from agriculture are weighed against the price risk associated with farming. Only if LHS ≥ RHS, a household will have members migrate to the urban area. This suggests that, ceteris paribus, a net seller household that is more price risk-averse is more likely have migrant members.

Proposition II. *If a household is a price risk-averse net buyer of a normal good, it will have a member migrate to an urban area only if the expected gains from migration are strictly greater than those from farming.*

Proof. The following condition must be satisfied in order for a household to have $L^U > 0$.

$$E[w^U - c - pF_{L^F}] \geq \frac{\overbrace{F_{L^F}}^{(+)} \cdot \overbrace{Cov[V_y, p]}^{(+)} - \overbrace{Cov[V_y, w^U - c]}^{(-)}}{\underbrace{E[V_y]}_{(+)}} \tag{2.9}$$

For a price risk averse net buyer household, $Cov[V_y, p] > 0$ by Claim II. $Cov[V_y, w^U - c] < 0$ due to income risk-aversion. Therefore, $RHS > 0$, and accordingly, $LHS > 0$ in order for the household to allocate nonzero L^U. □

Proposition II is consistent with the result of Barrett (1996), who showed that price risk aversion induces overemployment of farm labor by net buyer households. Comparing the migration decision making of price risk-averse net sellers and net buyers predicted in Propositions I and II, we can expect that the positive impact of price risk aversion on migration to be more pronounced for net sellers than for net buyers. This is because net sellers can send out migrants even when the expected gains from migration are lower than the expected gains from agriculture, if the effect of price risk aversion dominates the effect of income risk aversion. For net buyers to have members migrate to urban areas, however, the expected gains from migration must be strictly greater than the expected gains from agriculture.[14]

[14] Considering migration as a coping strategy for negative welfare impacts of food price volatility, this is consistent with Bellemare (2015): "Indeed, as Sandmo (1971) has demonstrated, the negative effects of food price volatility are largely felt by food producers who, by virtue of having to dedicate resources to food production long before the resolution of price uncertainty, cannot make profit-maximizing production decisions in the presence of food price volatility. Food consumers, however, can always adjust their food consumption bundle after the resolution of price uncertainty, and so for them, greater food price volatility means an increased likelihood of enjoying price discounts on food."

2.2.2 Willingness to Pay Measure of Price Risk Preferences

This section connects the theory discussed so far and the measure of household-level price risk attitudes. The coefficient of absolute price risk aversion for a single commodity is given in expression (5) above. Note that $M, p, \beta, \eta, \epsilon$ and R on the RHS are all measurable or estimable using observational data. BBJ (2013) extended this into multiple commodities by considering the covariances between prices. Instead of facing an uncertain price for a single commodity, an agricultural household now faces a vector of k uncertain prices with respect to k agricultural commodities. Extending this concept of the coefficient of absolute price risk aversion into k commodities yields a matrix A of price risk aversion coefficients, defined as the following.

$$A \equiv -\frac{V_{pp}}{V_y} = -\frac{1}{V_y} \cdot \begin{bmatrix} V_{p_1 p_1} & \dots & V_{p_1 p_k} \\ \cdot & & \cdot \\ \cdot & & \cdot \\ V_{p_k p_1} & \dots & V_{p_k p_k} \end{bmatrix} \equiv \begin{bmatrix} A_{11} & \dots & A_{1k} \\ \cdot & & \cdot \\ \cdot & & \cdot \\ A_{k1} & \dots & A_{kk} \end{bmatrix} \tag{2.10}$$

And, each $ij-$element of this matrix can be estimated based on the following form.

$$A_{ij} = -\frac{M_i}{p_j} \cdot \{\beta_j(\eta_j - R) + \epsilon_{ij}\} \tag{2.11}$$

M_i is the marketable surplus of commodity i, which is equal to the difference in the amounts of commodity i sold and i consumed. p_j is the price of commodity j. β_j is the budget share of the marketable surplus of commodity j, which is equal to $\frac{p_j M_j}{y}$. η_j is the income elasticity of marketable surplus of commodity j, and R is the Arrow-Pratt coefficient of relative risk aversion of households. ϵ_{ij} is the cross-price elasticity of the marketable surplus of commodity i with respect to the price of commodity j. The diagonal elements $A_{ii} > (=, or <) \, 0$ means that the household's welfare is decreasing (unaffected by, or increasing) in the volatility of the price of i. BBJ (2013) estimated this matrix A for the seven major commodities in rural Ethiopia—coffee, maize, beans, barley, wheat, teff, and sorghum. In order to make the estimation feasible in an absence of an experimental measure of R, it is assumed that R is equal to one for all households.[15]

In order to conveniently measure the welfare impacts of stabilizing the prices of several commodities, BBJ (2013) estimated the willingness-to-pay (WTP) for price stabilization. Conceptually, WTP can be expressed in the following way.

$$E\{V(E(p), y - WTP)\} = E\{V(p, y)\} \tag{2.12}$$

Thus, WTP is defined as the amount that a household is willing to pay in order to eliminate all price risks such that the prices of the seven major commodities are set to be equal to the expected values.[16] Using a second-order Taylor series expansions, they then show that the WTP can be estimated by summing up the coefficients of price stabilization across the commodities.[17]

$$WTP = \frac{1}{2} \cdot \{ \sum_{j=1}^{k} \sum_{i=1}^{k} \sigma_{ij} A_{ij} \} \tag{2.13}$$

where σ_{ij} denotes the covariance of the prices of commodities i and j. This measure was then divided by income in order to make it comparable across households. I call it as the willingness-to-pay (WTP) from now on. Thus, WTP is the amount of household income that the households are willing to sacrifice in order to eliminate all price risks, expressed in terms of the proportion of income. A positive (negative) value of WTP of a household indicates that the household is price risk-averse (risk-loving). A higher (lower) value of WTP means that the household is relatively more (less) price risk-averse.

[15]Thus, there is no variation of R across households, or within households, which is a shortcoming of the WTP currently being used.

[16]When $WTP > 0$, household welfare is decreasing in price volatility. Therefore, they are willing to pay a positive amount of money in exchange for price stabilization. When $WTP < 0$, household welfare is increasing in price volatility. Therefore, they would like to be compensated for price stabilization.

[17]For the details on the mathematical derivation, refer to BBJ (2013) and its online appendix.

2.3 Data

2.3.1 The Ethiopian Rural Household Survey

The Ethiopian Rural Household Survey (ERHS) is a unique household panel data set that covers villages in rural Ethiopia. The survey started from 1989 collecting data from six villages (or peasant associations, called *kebele* in Ethiopia). In 1994, the project was extended to cover 18 villages in 15 districts (called *woreda*) in 5 regions.[18] Additional rounds of surveys were then collected in late 1994, 1995, 1997, 1999, 2004, and 2009.

This study uses the 1994a, 1994b, 1995, and 1997 rounds of the ERHS based on the following reasons: First, the data set contains information on household consumption and production of agricultural commodities, prices of agricultural commodities, and household migration behavior that are essential for investigating the two research questions of this paper. These rounds of the surveys also contain other household and individual-level variables related to education, health, credit, asset, etc. Also, the WTP measure estimated by BBJ (2013) are available for these rounds of the survey. Second, during the period, the questionnaires were not changed much, which makes the surveys highly comparable across time. Lastly, household-level attrition is particularly low during this period, and is just under 2 percent across the four rounds of the surveys (Dercon and Krishnan 1998). According to the tracing rule used in this survey, "a household was kept in the sample even if the head of the household had left or died. [...] Also, the fact that households cannot obtain land when moving to other areas is clearly a part of the explanation of the low attrition rate" (Dercon and Hoddinott, 2011). Moreover, it is difficult to distinguish attrition from the migration of the whole households in the data. Given these circumstances, this paper focuses on migration in the form of sending household members to urban areas while other members remain in rural areas, rather than entire

[18]Districts, the third-level administrative unit in Ethiopia, form distinct socio-cultural regions with different local history and rural economy (Rahmato, 1984). A peasant association (village) is the smallest administrative unit and is part of a district. It is a network of local organizations, and very few peasants remain outside the village network (Rahmato, 1984).

households exiting rural areas. This is consistent with the form of migration considered in the theoretical framework as well.

2.3.2 Migration Statistics

The sample contains 1,425 households in 18 villages in 15 districts within 6 regions observed over the four rounds, with an attrition rate of about 2 percent. Table 2.1 summarizes the variables used in this study.[19] Table 2.1a summarizes the variables related to migration. The main dependent variable of interest is *Migrate*, which is 1 when there is a household member who left the household since the previous round of the survey, and 0 otherwise.[20] About 18 percent of the households in the sample have members migrated since the previous round of the survey. Marriage migration (10.6 percent) is much more common than migration for work purposes (6.6 percent), which includes leaving households to look for work, to take up jobs, to be near to the place of work, and to run own farm or enterprise. 4.5 percent and 14 percent of the sample have migrants to urban and rural areas, respectively, which indicates that rural-to-rural migration is more commonly observed than rural-to-urban migration. Low migration rates to urban areas and low rates of labor migration both seem to suggest some liquidity or credit constraints that hinder migration, given the high gains from migration observed from the ERHS households in terms of consumption (de Brauw, 2015). See tables A.2 and A.3 in Appendix for more information on the reasons and destinations of migration, respectively.

[19]For the full definitions of the variables, see Table A.1 in appendix.

[20]The lengths of time considered to count the events of leaving households are not identical for different rounds because time periods between consecutive rounds of the surveys are not identical from a round to the next. In the survey, there is also a question about household members who are currently absent, but "absence" includes temporary absence due to seasonal migration, short-term visits, and many other reasons besides long-term migration. Therefore, I opt for using the variable on household members who "left" their households instead of those who are "absent." The cases of leaving households due to deaths are excluded.

2.3.3 Key Explanatory Variables

Table 2.1b presents summary statistics for three sets of selected explanatory variables: price risk attitudes, time-varying household characteristics, and access to credit. The table also displays results from the t-tests for differences in mean values for two sub-samples: households without and with migrant members.

The mean value of the WTP indicates that, on average, a household is willing to give up about 9 percent of its income in exchange for stabilizing the prices of the seven major crops at their mean values. This positive number indicates that households are, on average, averse to price risk. Comparing the households with and without migrants, the households with migrants tend to be more averse to price risk than the households without migrants, and this difference is highly significant.

Households with migrants tend to have significantly greater income, greater income from farming, and larger plot area than households without migrants. Also, households with migrants have significantly greater incidences of taking loans (from both formal and informal sources, for any purpose, either cash or in-kind), taking loans for food purchases and travels than households with no migrants. These results are indicative of liquidity, credit, and resource constraints that hinder migration.

Table 2.1c summarizes the prices of the seven major crops that vary according to each village and each round. Mean, standard deviation, and coefficient of variation are the highest for coffee prices. Given that coffee is the most important cash crop for Ethiopian farmers, high volatility of coffee prices may pose a threat to the welfare of coffee producing farmers.

2.3.4 Household Production and Consumption of Staple Crops

Table 2.2 displays household marketable surpluses (production minus consumption) of the seven major crops. A household is a net seller (net buyer) of commodity k if the marketable surplus is positive (negative). Table 2.2a shows marketable surpluses of all households. On average, households are net buyers of all seven commodities. Table 2.2b shows the marketable surpluses of net sellers and net buyers of each commodity. For all commodities, there are more net buyers than net sellers. For each commodity, there are a number of households that do not produce or consume the commodity (households in autarky). However, there are only 138 in the total of 5,621 households in the sample (about 2.4 percent) that do not produce or consume any of these seven commodities. The average amount of net sales is largest for wheat, teff, and sorghum. The average amount of net purchase is largest for barley, teff, and maize.

2.4 Empirical Framework

2.4.1 Price Risk Attitude and Migration: Extensive Margin

The first research question concerns the impact of household-level price risk attitudes on migration. The main equation to be estimated is the following linear probability model (LPM) with fixed effects.

$$Migrate_{ijt} = \beta_0 + \beta_1 WTP_{ijt} + \beta_2 X_{ijt} + \nu_{jt} + \epsilon_{ijt} \tag{2.14}$$

$Migrate_{ijt}$ is equal to 1 if household i in district j in round t reported that there was a member who left the household since the previous round of the survey and 0 otherwise, and WTP_{ijt} is the household i's WTP to stabilize the prices of the seven major commodities (coffee, maize, barley, beans, wheat, teff, and sorghum) expressed as a fraction of income in round t.[21] X_{ijt} is a vector of time-varying household-level control variables including access to credit according to different sources and uses, income measured by sources, plot area, and household size. ν_{jt} is a district-round fixed effect for a district-round pair jt. Districts in Ethiopia form distinct socio-cultural regions with separate local history and rural economy (Rahmato, 1984). These two-way fixed effects

[21] Due to a possible lag in migration decision, lagged WTP will also be considered in robustness checks.

are included to account for unobserved heterogeneity embedded in each district in each round such as weather events, socio-cultural events, and political conditions. Accordingly, error terms (ϵ_{ijt}) are clustered at the district level given that they might be correlated in the district level. Given that the WTP measure is a structurally estimated measure, the error terms are bootstrapped as well. This equation will be estimated for all households and separately for households that are net sellers and net buyers.

The coefficient estimate β_1 is the parameter of interest that is expected to be positive and significant for the households that are net sellers according to the Proposition I. According to the Propositions I and II, we expect to see a stronger impact of β_1 for net sellers than for net buyers.

For a clean identification of β_1, an ideal data set would contain a direct measure of the WTP for price stabilization that is measured for each household in each round using an experimental method. Such data is not currently available. Alternatively, one would construct the WTP measure by exogenously varying the components such as budget share, marketable surplus, price, and elasticities. Ideally, one could randomly assign the prices of the crops that households produce and consume. It would be nearly impossible, however, to randomly assign other components of the WTP. For example, marketable surpluses are determined by production and consumption of crops which cannot be easily manipulated by researchers. Similar issues persist in manipulating the budget share that depends on income and marketable surplus. Moreover, there are multiple commodities that households produce and consume. Given these inherent difficulties in pursuing a truly exogenous measure of the WTP, we rely on the WTP measure structurally estimated by BBJ (2013) using observational data. The following paragraphs address potential issues that can lead to a biased estimate of β_1 and what identification strategies are used in order to alleviate these concerns.

Reverse Causality If migration of a household member causes any component of the WTP−such as price, marketable surplus, income, and attitudes to income risk−to be affected, there might be a concern of reverse causality. First, price is less of a concern, because households are price takers. In the data, prices vary by communities and not by individual households. Because each community consists of at least 500 households, it is unlikely that a migration decision of a single household affects prices. Second, attitudes to income risk is associated with household preferences, which is unlikely to change over the short period of time (1994-97) that the data set covers. Lastly, migration can affect the marketable surplus and income of a household, and accordingly the WTP. To address this issue, a test for Granger causality (Angrist and Pischke, 2009) is conducted. For there to be no Granger causation, WTP in round $t+1$ should not be significantly related to migration in round t. I find no evidence of such a relationship.

Unobserved Heterogeneity Failing to control for unobserved heterogeneity that might affect migration and is correlated with the WTP can result in a biased parameter estimate. Because commodity prices, production, consumption, and income of a household all comprise the WTP measure, unobserved factors that may affect any of these components and migration can cause an omitted variable bias. Districts, called "woreda" in Ethiopia, form distinct socio-cultural units with separate local history and rural economy (Rahmato, 1984). Thus, district-round fixed effects used in the baseline model are expected to capture time-varying, unobserved economic conditions, political events, and weather conditions common across households in a district that can affect the WTP measure and migration. In addition to the baseline model, specifications with various fixed effects pertaining to different geographic units are considered. District fixed effects are expected to capture time-invariant factors common to households in each district such as socio-cultural, historical, and political backgrounds, distance to the nearest town, and soil quality. Village-round fixed effects are expected to capture shocks in commodity prices because commodity prices vary across villages and over time. Village-round fixed effects and village fixed effects are expected to capture time-varying and time-invariant village-specific characteristics such as local off-farm labor opportunities, access to markets, access to electricity, road conditions, availability of food aid and related programs. Moreover, time-varying household-level controls include factors that can facilitate households' risk management, i.e., plot area, income from businesses, income from non-farm activities, access to credit, loans from various sources, and loans for various purposes including farming and travel.

Measurement Error Commodity prices are reported in a community level. As was documented in BBJ (2013), it is unlikely that there are any systematic errors in the measurement of the commodity prices. Also, it is hard to think of motivations to misreport the commodity prices in a systematic manner. If there was any systematic under- or over-reporting of the commodity prices in a specific community, such tendency must be captured by village fixed effects. Given that household income is zero in 1,082 out of the 5,621 total observations, there is a possibility that there was a systematic under-reporting of income. Regarding the issue of treating the zero-income households, an alternative measure of WTP was estimated following the suggestion of McBride (2016) on the treatment of zero-valued household incomes. To take into account any possibility that migration statuses of household members may be misreported, several alternative definitions of migration in terms of purposes and destinations are considered as the dependent variables. One possible form of misreporting is the following—when asked to recall the events of migration, respondents may be confused and misreport migration in the previous round as migration in the current round of the survey. For this possibility, I report results with lagged values of migration as regressors as well. Lastly, there is a possibility of random measurement error that may induce an attenuation bias and can bias the coefficient estimate towards zero. If this is the case, a positive and significant coefficient on the WTP would be a lower bound of the true coefficient estimate.

The LPM with fixed effects is the main specification, but given the binary dependent variable, results from the logit model with and without fixed effects are also presented.

2.4.2 Price Risk Attitude and Migration: Intensive Margin

The following linear regression with district-round fixed effects is estimated to figure out the relationship between the price risk attitudes and the number of migrants within households with migrants.

$$NumberMigrants_{ijt} = \gamma_0 + \gamma_1 WTP_{ijt} + \gamma_2 X_{ijt} + \nu_{jt} + \theta_{ijt} \tag{2.15}$$

$NumberMigrants_{ijt}$ is the number of household members who had left household i in district j since the previous round of survey. WTP_{ijt}, X_{ijt}, and ν_{jt} are already defined. θ_{ijt} is an error term with mean zero that are clustered at the district level and bootstrapped. Given that the dependent variable is a count data, Poisson and negative binomial regressions with district-round fixed effects will be estimated as well using these variables.

2.4.3 Volatility of Prices and Migration

The second research question concerns the relationship between the community-level commodity price volatility and migration. The purpose is to examine the direct relationship between the price volatility and migration without having to make assumptions regarding utility function and preferences. The following equation will be estimated separately for net sellers and net buyers of each of the seven major crops:

$$Migrate_{ijt} = \delta_0 + \sum_{k=1}^{7} \delta_1 CV_{kj} + \delta_2 X_{ijt} + \psi_{ijt} \tag{2.16}$$

$Migrate_{ijt}$ and X_{ijt} are already defined, and CV_{kj} is the coefficient of variation, which is a standard measure of volatility (calculated as the standard deviation divided by the mean), of the price of crop k for each village j.[22] Lastly, ψ_{ijt} is an error term

[22]Prices vary over crops, survey rounds, and villages. Therefore, the coefficients of variation are calculated over time for each village and each crop. In the empirical framework for the first research question, the effect of time-varying price level is captured by village-round fixed effects, and the effect of

with mean zero clustered at the village level.

The coefficient of interest, δ_1, is expected to be positive and significant.

2.5 Results

2.5.1 Price Risk Attitudes and Migration

This subsection provides evidence that risk attitudes towards commodity prices matter for migration. Both nonparametric and parametric results suggest that there is a positive and significant relationship between the WTP to stabilize the prices of the seven commodities in Ethiopia and migration.

Nonparametric Results

Figure 2.1 shows the kernel density plots of the WTPs for the households with and without migrants. Several aspects of these plots are noteworthy. First, the high density around zero WTP is mainly due to the large proportion of households doing subsistence farming. The two distributions look almost identical in the region of negative WTPs, or the households that are price risk-loving. However, households with migrants seem to have a lower density around zero, and a slightly fatter right-tail. Figure 2.2 shows the kernel density plots of the WTP for the households with and without migrants to cities. The distribution of the WTPs for households with migrants to urban areas seems to have a lower density around zero and also seems to show a larger variance.

Figures 2.3 and 2.4 show the cumulative distribution functions (CDFs) of the WTP for households with and without migrants, for all destinations and urban destinations, respectively. Looking at both figures, it is more evident that the WTPs tend to be higher, especially in the cases of positive WTPs, for households with migrants.

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price volatility measured by coefficient of variation is captured by village fixed effects.

Main Results (1): Extensive Margin

Table 2.3 presents the main results. Columns (1) through (4) show the results for all households. The coefficient estimates on the WTP are positive and significant at 1 percent level of significance in all four specifications. Columns (1) presents the results from a simple linear regression without fixed effects and control variables. Columns (2) through (4) show the results including district-round fixed effects, with different numbers of control variables included. Highlighted results in columns (1)-(4) indicate that households that prefer more stable prices of the seven major crops tend to have higher likelihoods of sending family members out of the households. Specifically, a 10% point increase in the WTP[23] is associated with about 1.1-1.2% point increase in the probability of having at least one household member who migrated.[24] This looks like a modest impact, but recalling that an average household has only about 18% likelihood of having members who migrated, a 1.1-1.2% point increase corresponds to about 6-7% increase in the likelihood of migration.

Column (5) of Table 2.3 provides the results on the sub-sample of households that are net sellers of at least one of the seven commodities.[25] The WTP has a positive coefficient estimate, and it is significant at 10% level. Proposition I states that, in the case of price risk-averse net sellers, having the effect of price risk aversion dominate the effect of income risk aversion increases the probability of migration. Thus, the proposition predicts that, ceteris paribus, a more price risk-averse net seller household is more likely have migrant members. The result in column (5) supports Proposition I.

Column (6) of Table 2.3 displays the results on the sub-sample of households that are net buyers of all the seven commodities. The WTP has a positive coefficient estimate

[23] In the data, an average household is averse to price risk, having a willingness to give up about 9% of its income for price stabilization.

[24] In LPM, the magnitude of the marginal effect is assumed to be constant across the level of WTP (Wooldridge, 2002).

[25] Because households produce and consume multiple commodities, and accordingly, assume different market positions for different commodities, it is tricky to define net sellers and net buyers. There is no observation in the sample that produces all seven commodities.

that is significant at 5% level.

Main Results (2): Intensive Margin

Table 2.4 shows the results on the number of migrants as a dependent variable. Columns (1) and (2) present results from simple OLS regressions without fixed effects, and columns (3) and (4) show the results from district-round fixed effects regressions. Having a higher WTP for price stabilization of the seven commodities is significantly related to having a greater number of migrants in all four specifications.[26] Interestingly, WTP is significant only for the cases of the households that are net sellers of at least one of the seven commodities (column (5)), and is not significant for the cases of net buyers of all the seven commodities (column (6)). Given that the dependent variable (number of migrants) is count data, columns (5) and (6) present the results from Poisson and negative binomial regressions with district-round fixed effects, respectively. The key finding is robust to these alternative specifications.

Proposition II predicts that a price risk-averse net buyer household will have a member migrate to an urban area only if the expected gains from migration are strictly greater than the expected gains from agriculture. This is unlike the case of a price risk-averse net seller household that can send out a migrant even when the expected gains from migration are lower than the expected gains from agriculture (shown in Proposition I). Thus, the positive impact of WTP on migration is expected to be more pronounced for net sellers than for net buyers. Comparing the results in the columns (5) and (6) of Table 2.3, we can see that a greater WTP increases the likelihood of having migrant members in the cases of both net sellers and net buyers, and such effect is slightly more pronounced for the net buyers than the net sellers. Comparing the columns (5) and (6) of Table 2.4, however, we can see that a greater WTP increases the *number* of migrant

[26]Due to the concern on the selection issue, the sample is not restricted to the households with migrant members. When the sample is restricted to only the households with migrants, the WTP still has a positive and significant coefficient.

household members only in the case of net sellers. Thus, empirical results suggest mixed evidence in regards to Proposition II.

Falsification Tests

Table 2.5 displays the results from some falsification tests. Column (1) shows the main results (identical to column (4) in 2.3) with district-round fixed effects. To take into account the possibility that there may be lags in the WTP in affecting migration decisions, lagged WTPs are considered. Specifications in columns (2) and (3) include one-period and two-period lags of the WTP, respectively. One-period lag is positive and significant suggesting that there may be some lag in migration decision making, but the significance of the WTP does not disappear by including the lagged values.

One concern on identification is the possibility of reverse causality, i.e., the possibility that migration in a given round affects the WTP in the next round (Granger causality). Columns (4) and (5) display the results from testing whether migration Granger-causes WTP by including one-period WTP lead, following the suggestion of Angrist and Pischke (2009). Column (4) shows that WTP in round $t+1$ is not significantly related to migration in round t. Column (5) indicates that WTP is still significant when one-period lead WTP is included. These results imply that there is not enough evidence to reject the null hypothesis of no Granger causation.

It is possible that migration in one period is significantly related to migration in the next period, i.e., autocorrelation may be present in the dependent variable. Columns (6) and (7) present the results from including the lagged dependent variables as regressors. Lagged values of migration are indeed a strong predictor of migration, but including lagged values of migration does not wash out the significance of the WTP, the main treatment variable of interest. This result partially alleviates the concern of measurement errors in migration—especially in the form of misreporting past migration as current migration—as well.

Community Characteristics

The community module of the ERHS provides some interesting information on the characteristics of the sample communities. Tables 2.6 and 2.7 exhibit the results from the the analysis of some community characteristics, all of which indicate that migration is a strategy to cope with unfavorable welfare impacts of price volatility especially in the communities with insufficient alternatives to mitigate the negative welfare impacts of price volatility.

Access to Daily Markets When there are shocks in the commodity prices that are unfavorable to consumers, daily markets can facilitate purchases of cheaper substitutes. Having an access to daily markets in the community can help producers mitigate the impact of unfavorable price shocks as well, by making marketing activities more flexible. Columns (1) and (2) of Table 2.6 display the results from the sub-samples of communities where daily markets are unavailable and available, respectively. In both cases, the coefficient estimates on the WTP are positive and significant, but the magnitude of the coefficient is about fourfold for the communities without daily markets (column (1)).

Availability of Producer Cooperatives Producer cooperatives (co-ops) are organizations owned and controlled by producers. Members in producer co-ops pool resources for marketing and production. Producer co-ops, therefore, facilitate access to capital and new technology, and help lower costs associated with production and marketing (Zheng et al. 2011). In Ethiopia where farming is dominated by smallholders, producer co-ops represent "modernization and commercialization of smallholder agriculture" (Bernard and Spielman, 2009). The results in the columns (3) and (4) of Table 2.6 indicate that the coefficient on the WTP is only significant in the communities where producer co-ops are unavailable.

Seasonal Migration Seasonal migration is short-term, mostly rural-to-rural migration seeking off-farm employment opportunities during agricultural slack seasons at home.[27] Seasonal migrants in Ethiopia are predominantly young, single, landless, male farmers from the poorest households, motivated by the shortage of farmland and insufficient local non-farm activities during off-seasons (Asfaw et al., 2010). Columns (5) and (6) of Table 2.6 show the results from the sub-samples of communities without and with seasonal out-migration, respectively. WTP is significantly related to migration only in the communities where there is seasonal out-migration (Column (6)). This indicates that longer-term migration is a coping strategy for unfavorable welfare impacts of price risk, especially in the communities with insufficient viable off-farm employment opportunities during off-seasons.

Food Aid, Cash-for-Work, Food-for-Work Ethiopia has been suffering from droughts and famines for over a century, and food aid has been an important mechanism that poor and food-insecure households in Ethiopia have depended on for many decades. Cash-for-work and food-for-work programs operated by humanitarian organizations offer short-term off-farm employment opportunities that pay wage in cash and in-kind, respectively. Table 2.7 presents the results from the sub-samples of communities without and with food-aid (columns (1) and (2)), cash-for-work (columns (3) and (4)), and food-for-work (columns (5) and (6)). The WTP has positive and significant coefficient only in the sub-samples of communities where food aid and cash-for-work programs are unavailable (shown in columns (1), and (3). Also, the coefficient estimate on the WTP is greater in its magnitude and is more significant in the communities where food-for-work is unavailable. These results suggest that migration is a coping strategy for negative welfare impacts of food price volatility in the communities lacking mechanisms that help alleviate food insecurity.

[27]The main dependent variable of this study is long-term migration, not short-term seasonal migration.

Robustness Checks

The following set of results show that the positive and significant relationship between the WTP and migration is robust to alternative definitions of the dependent and the independent variables, inclusion of the fixed effects pertaining to different levels of geographic units, and non-linear specifications.

Alternative Definitions of Migration Table A.4 in appendix shows the results from using alternative dependent variables in terms destinations and purposes. Columns (1), (2), and (3) show that the key result is robust for migration to urban areas (both within and outside of districts), migration outside of districts, and migration within districts, respectively. Column (4) shows that the WTP is not significant for migration for work purposes such as leaving in order to look for work, to take up jobs, to be near the place of work, and to run own farm or enterprise. There are two possible explanations for this: fear of losing land and liquidity and credit constraints. In Ethiopia, the land use law indicates that the land of the farmers who stay outside of the village for a long period of time or the land of those who have not cultivated their land for two consecutive years will be redistributed (Bezu and Holden, 2014). This policy may create disincentives for labor movement. Secondly, for young landless farmers, start-up costs of migration can be too high even if the potential gains from migration are substantial.

Column (5) shows that the WTP is significant for migration for marriage. According to the paper on assets at marriage in rural Ethiopia, Fafchamps and Quisumbing (2005) noted that, "[I]n agrarian societies,[...] [marriage] typically marks the onset not only of a new household but also of a new production unit, e.g., a family farm. Assets brought to marriage determine the start-up capital of this new enterprise.[...] Farm formation cannot be dissociated from marriage market considerations." For poor households lacking cash and in-kind assets, sending members to cities to look for work may involve high start-up costs and risk of failing to find work opportunities. Instead, poor households can manage price risk by sending daughters to other villages for marriages, given the following: First, marriage migration in Ethiopia typically occur in the form of the wife moving to live in the husband's community (Fransen and Kuschminder, 2009). Second, land rights have been bestowed on men in Ethiopia (Norton et al., 2014). Third, grooms bring much more assets than brides to the new household unit (Fafchamps and Quisumbing, 2005),[28] Indeed, marriage has been an adaptation strategy of poor agricultural households in Ethiopia (Fransen and Kuschminder, 2009). This is also consistent with the finding of Rosenzweig and Stark (1989)—marriage migration significantly decreases the volatility of household food consumption in India.

Alternative Definition of the WTP Figure 2.5 is a reproduction of the fractional polynomial regression of the WTP measure estimated by BBJ (2013). This shows that the WTP for commodity price stabilization increases with income, suggesting that "welfare gains from eliminating price volatility are increasing in household income" (BBJ, 2013). McBride (2016), in her comment, challenged the method used by BBJ (2013). In order to deal with the issue of zero-valued income households, BBJ (2013) used the mean income of all households when calculating the budget share of each household's marketable surplus. Alternatively, McBride (2016) used observed, as opposed to mean, income when available and assigned the minimum income to the households with zero-valued income. Figure 2.6 is a replication of the fractional polynomial regression of this alternative WTP measure that suggests a distributionally progressive benefit of food price stabilization. Table A.5 shows that the WTP still has positive and significant coefficient estimates when this alternative procedure was used in its calculation, in most of the specifications.

[28]Fafchamps and Quisumbing (2005) uses the ERHS data set in their study as well and find that "[G]rooms bring nearly 10 times more assets than brides to the newly formed family unit, an average of 4270 birr (in 1997 prices), compared to 430 birr for brides. For grooms, land is the asset with the highest average value. The next most valuable asset is livestock, followed by grain stocks and other minor assets. In contrast, brides bring very little land to the marriage. They bring some livestock but less than grooms. Two-thirds of the brides report bringing no asset to marriage. [...] The survey area can thus be described as a system where grooms bring most of the start-up capital of the newly formed household."

Heterogeneity Among Geographic Units The results from including the fixed effects associated with different levels of geographic units are presented in Table A.6 The WTP is positive and significant for a variety of specifications: the main specification with district-round fixed effects (column (1)), district fixed effects with a time trend (column (2)), village-round fixed effects (column (3)), village fixed effects with a time trend (column (4)), region-round fixed effects (column (5)), and region fixed effects with a time trend (column (6)).

Non-linear Specification Considering that the dependent variable of interest ($Migrate$) is a binary variable, logistic regression with fixed effects is used for a robustness check, and the results are shown in Table A.7 Various levels of fixed effects are considered in columns (1) through (6). In all specifications, the WTP is positive and significant. When logistic regression without fixed effects is used (Table A.8), the WTP is still positive and significant at 1% level of significance in all specifications.

2.5.2 Volatility of Prices and Migration

This section provides evidence that the volatility of commodity prices matters for migration.

Net Sellers

Table 2.8 shows the results for the net sellers of each of the seven commodities (coffee, maize, beans, barley, wheat, teff, and sorghum) separately in each column. For example, column (1) shows the result from the sub-sample of the households that produce more coffee than what they consume. Top panel contains the OLS regression results from including the coefficient of variation (that vary by each community) of all the seven commodities as well as household-level controls as regressors. Only the coefficient estimate on the own coefficient of variation of each commodity is reported for the sake of brevity. Higher volatility of coffee, beans, and teff prices are each significantly related to higher incidences of out-migration of the net sellers of the respective crops.

Severe volatility in coffee prices can significantly impact the farm economy, because coffee is Ethiopia's major cash crop that accounts for 3.8% of Ethiopia's GDP (Taffessse et al., 2011) and the largest portion in Ethiopia's export. Approximately 15 million people, or 15% of the total population of Ethiopia depend on coffee for their livelihoods (USDA, 2015). Beans are important sources of non-meat protein and income for smallholder producers in Ethiopia. Beans are the third-largest export crop in Ethiopia after coffee and sesame, and a higher-value crop that account for about 13% of cultivated land and about 10% of the agricultural value addition (Yirga et al., 2010). Teff accounts for the largest share of farmland among cereals and is often grown as a cash crop. According to FAO (2015), "Teff is second (to maize) in terms of quantity of production. However, because its market price is often two or three times higher than maize, teff accounts for the largest share of the total value of cereal production."

Losing the farmers producing these crops due to high price volatility may pose a threat to food security and livelihoods of smallholder agricultural households.

Net Buyers

The results for the net buyers of each of the seven crops are presented in Table 2.9. Results indicate that high price volatility of coffee and teff are significantly related to the out-migration of the net buyers of coffee and teff, respectively. This is not surprising given that coffee and teff accounts for the two largest budget shares among the seven crops. According to BBJ (2013) using the same data set, "Purchases of teff and coffee represent the largest household expenditures, with 21% and 15% of the average budget being devoted to them, respectively."

Coffee plays an important part in both social life and culture in Ethiopia. "Ethiopians love to drink coffee at mealtimes, special occasions, and during social gatherings. In terms of per capita consumption, Ethiopia is the largest coffee drinking country in Africa and one of the biggest in the world." (USDA, 2015) Teff is one of the five major cereal crops in Ethiopia (along with wheat, maize, sorghum, and barley) and is high in protein and mineral. Teff is an ingredient for *injera*, an important staple food item in Ethiopia.

Higher volatility of coffee and teff prices is significantly related to the out-migration of both the net sellers and the net buyers of coffee and teff, respectively. This is also consistent with the observation in BBJ (2013): "stabilizing coffee prices is more likely generate welfare gains than stabilizing other commodity prices," if migration implies the negative welfare effects of high price volatility.

2.6 Concluding Remarks

This paper is the first to investigate the role of commodity price volatility in determining migration, a topic with important policy implications for urbanization and food security. Two potential channels by which price volatility can impact migration are examined: (i) individual household's attitudes towards price volatility, and (ii) village-level volatility in the prices of agricultural commodities. Based on the agricultural household model in which a rural household both produces and consumes a commodity, I incorporate migration decisions into family labor allocation decisions that are made under uncertainty in commodity price and urban wage.

Empirical results from the ERHS data for the period 1994-97 indicate that greater aversion to price volatility−represented by higher WTP for price stabilization of the seven most important crops in Ethiopia−is positively and significantly related to migration, both in terms of extensive and intensive margins. These results are remarkably robust to falsification tests, alternative definitions of both independent and dependent variables, the inclusion of various fixed effects pertaining to different levels of geographic units, and linear and non-linear specifications. A high level of WTP is an indication of a lack of flexibility in production, a lack of viable substitutes in consumption, as well as high budget share of food items. Further investigations into the community module indicate that migration is a coping strategy for negative welfare impacts of price volatility, markedly in the communities where daily markets, producer co-ops, food aid, food-for-work, and cash-for-work programs are unavailable. Therefore, price volatility matters when it comes to migration not only for individual households, but also for greater communities that are vulnerable to price volatility. The direct relationship between village-level price volatility and migration is examined as well. I find that high volatility of coffee prices is significantly related to the migrations of both the net sellers and the net buyers of coffee, and I find similar results for teff prices as well. These findings can inform migration policy, local development policy, and price stabilization policy in identifying the losers and winners of price stabilization schemes and determining the type of households, communities, and commodities to be targeted for effective policy implementation.

Coming up with an exogenous measure of price volatility or attitudes towards price volatility is an intrinsically difficult task. Having to depend on secondary longitudinal data for empirical analysis, this study is not without the limitations that are inherent to the use of any observational data. Facing similar challenges, a number of assumptions had to be made by BBJ (2013) in estimating the WTP measure. These issues motivate using an experimental method that can facilitate a cleaner, causal identification.

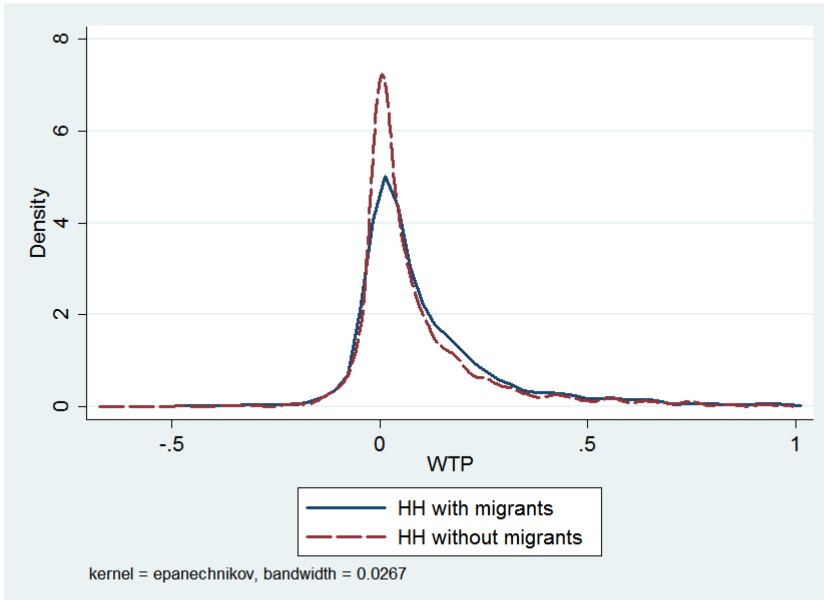

Figure 2.1: Kernel Density Estimation of Household WTP (1)

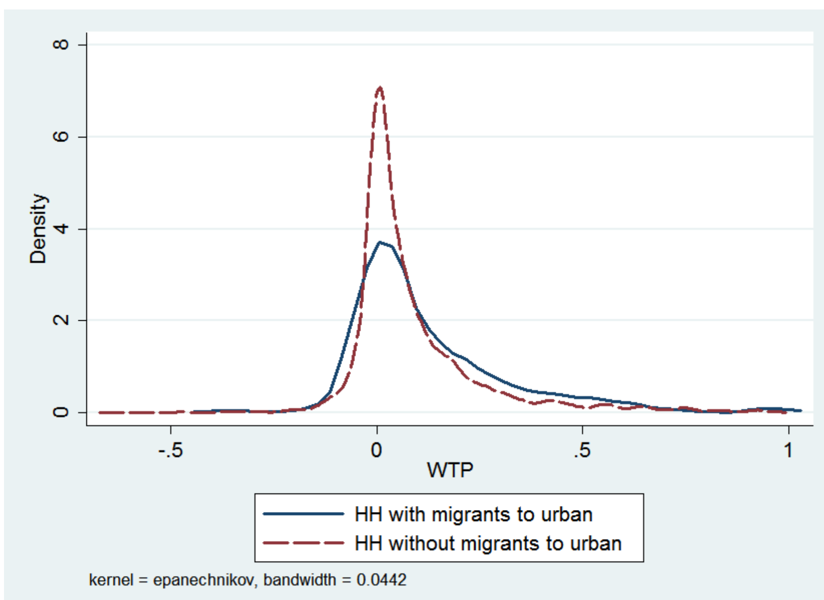

Figure 2.2: Kernel Density Estimation of Household WTP (2)

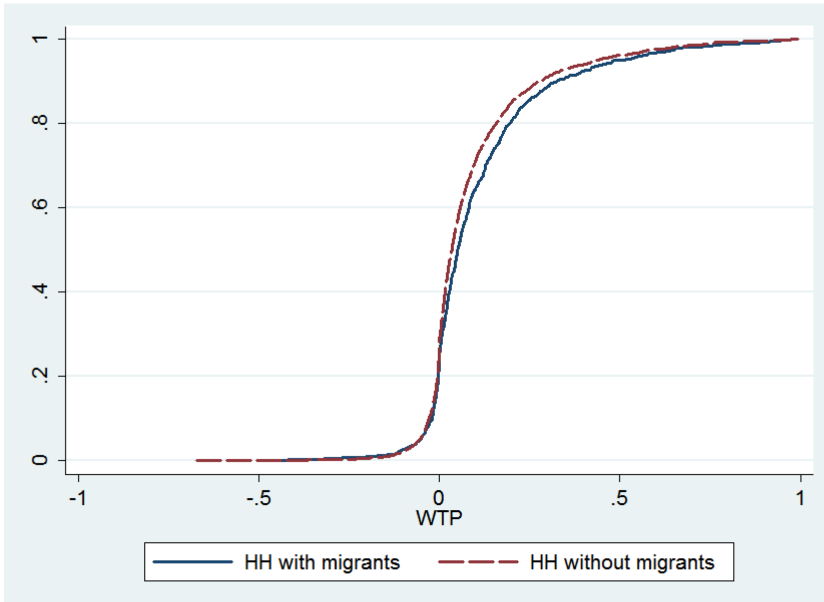

Figure 2.3: Cumulative Distribution Function of Household WTP (1)

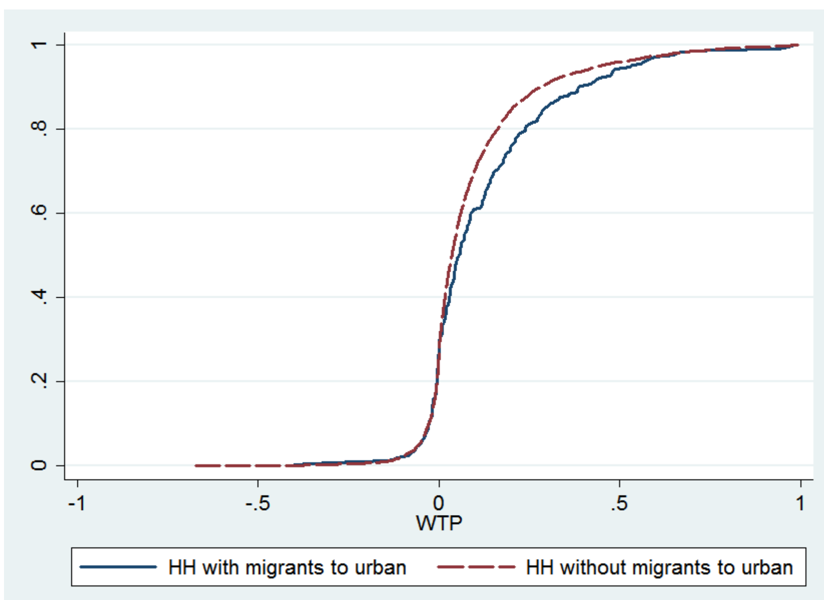

Figure 2.4: Cumulative Distribution Function of Household WTP (2)

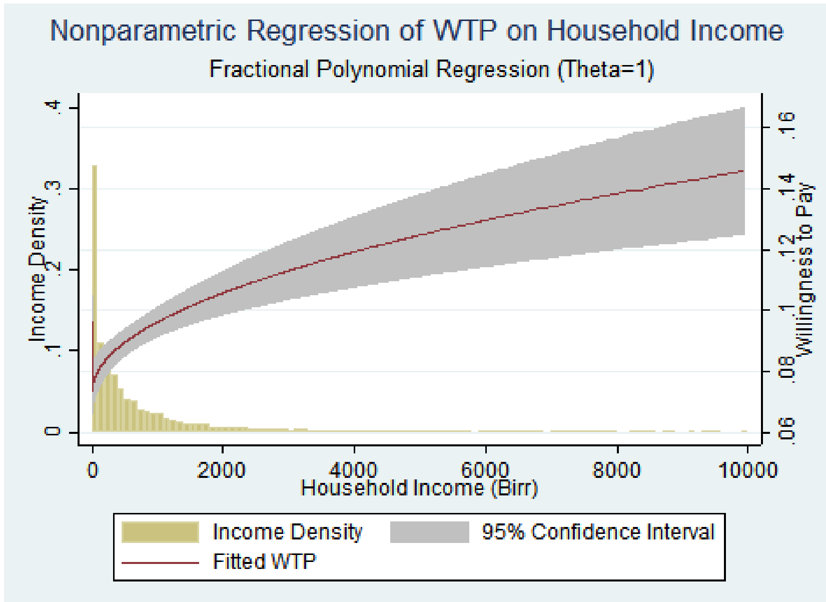

Figure 2.5: Fractional Polynomial Regression of the Original WTP

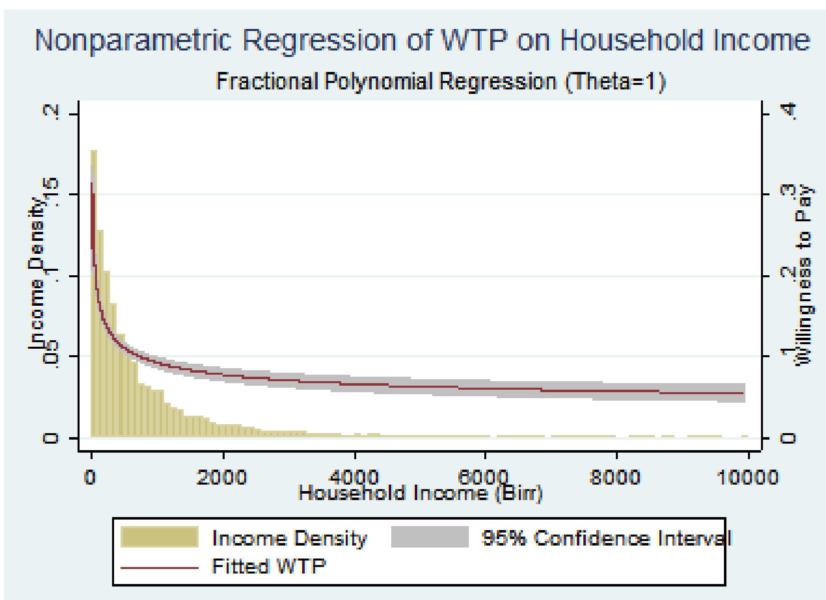

Figure 2.6: Fractional Polynomial Regression of the Alternative WTP

Table 2.1: Summary Statistics

(a) Migration Variables

Variables	**Unit**	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
Migrate	0 or 1	0.181	0.385	0	1	5,613
Migrate for work	0 or 1	0.066	0.249	0	1	5,613
Migrate to urban areas	0 or 1	0.045	0.207	0	1	5,613
Migrate to rural areas	0 or 1	0.140	0.347	0	1	5,613
Migrate to urban areas for work	0 or 1	0.034	0.183	0	1	5,613
Migrate for marriage	0 or 1	0.106	0.307	0	1	5,613
Number of migrants within HHs with migrants	Persons	1.363	0.890	1	10	1,017

Summary Statistics (continued)

(b) Key Explanatory Variables

Variables	Unit	Full Sample (N = 5,613)		Migrate=0 (N = 4,596)		Migrate=1 (N = 1,017)	
		Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Price Risk Attitudes							
WTP***	From -1 to 1	0.09	0.168	0.086	0.164	0.108	0.183
HH Characteristics							
Income***	Birr	816.54	6,268.46	807.47	6,884.70	859.72	1,725.53
Farm income***	Birr	442.80	6,120.09	456.76	6,745.75	380.19	1,171.97
Plot area***	ha	1.402	1.418	1.352	1.392	1.617	1.507
Autarky	0 or 1	0.025	0.155	0.026	0.159	0.015	0.124
Household size	Persons	5.576	3.151	5.578	3.129	5.598	3.227
Access to Credit							
Taken loan**	0 or 1	0.482	0.5	0.475	0.499	0.509	0.500
Loan from friends, rel.	0 or 1	0.314	0.464	0.310	0.462	0.330	0.470
Loan from bank	0 or 1	0.006	0.075	0.005	0.076	0.004	0.070
Loan for food**	0 or 1	0.192	0.394	0.187	0.390	0.212	0.409
Loan for travel***	0 or 1	0.01	0.099	0.008	0.090	0.016	0.128

***: Means for two sub-samples (migrate=0 and migrate=1) are statistically different with p-value<0.01.
**: Means for two sub-samples (migrate=0 and migrate=1) are statistically different with p-value<0.05.
*: Means for two sub-samples (migrate=0 and migrate=1) are statistically different with p-value<0.1.

Summary Statistics (continued)

(c) Commodity Prices (Unit: Birr/kg, N = 5,621)

Variables	**Mean**	**Std. Dev.**	**Coeff. of Var.**	**Min.**	**Max.**
Coffee	14.695	5.607	0.382	3.584	26.685
Maize	1.296	0.392	0.302	0.658	2.859
Beans	1.889	0.414	0.219	1.035	3.153
Barley	1.511	0.434	0.287	0.658	2.532
Wheat	1.756	0.347	0.197	0.921	2.481
Teff	2.274	0.394	0.173	1.035	3.261
Sorghum	1.522	0.421	0.277	0.72	2.609

Table 2.2: Marketable Surpluses of Households (kg)

(a) All Households (N = 5,621)

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Coffee	-7.324	24.565	-290.81	240
Maize	-105.746	298.76	-2610	3,000
Beans	-40.014	93.45	-704.700	310.95
Barley	-93.852	336.199	-3765	1,169.5
Wheat	-61.571	235.956	-3132	2,500
Teff	-96.961	292.471	-2609.5	3,225.6
Sorghum	-36.69	187.805	-1,688	1,600

(b) Net Sellers and Net Buyers of Staple Crops

	Net Sellers			Net Buyers		
	Mean	Std. Dev.	N	Mean	Std. Dev.	N
Coffee	37.81	43.13	458	-14.50	18.22	4,031
Maize	157.23	279.32	702	-349.76	349.44	2,015
Beans	50.06	51.17	155	-124.76	123.12	1,865
Barley	167.69	176.88	577	-435.05	514.02	1,435
Wheat	265.10	388.60	343	-277.29	295.21	1,576
Teff	171.71	327.59	468	-432.78	371.23	1,445
Sorghum	206.90	212.79	354	-344.18	311.03	812

Table 2.3: Main Results (1): Extensive Margin

Dependent Variable: Migrate (0 or 1)						
	(1)	(2)	(3)	(4)	(5)	(6)
	All	All	All	All	Net Sellers	Net Buyers
WTP	0.116***	0.118***	0.117***	0.114***	0.114*	0.123**
	(0.0443)	(0.0411)	(0.0414)	(0.0388)	(0.0613)	(0.0553)
Taken Loan			0.0162	0.0146	-0.0103	0.0293
			(0.0206)	(0.0212)	(0.0309)	(0.0307)
Loan from Friends and Rel.			-0.0291	-0.0329*	-0.00736	-0.0495
			(0.0185)	(0.0176)	(0.0364)	(0.0305)
Loan from Bank			-0.0884	-0.0904	-0.107	-0.0854
			(0.0547)	(0.0680)	(0.0897)	(0.0690)
Loan from NGO			-0.0427**	-0.0485**	-0.0428	-0.0582*
			(0.0205)	(0.0226)	(0.0423)	(0.0300)
Loan for Farming			0.0152	0.0135	0.00530	0.0323
			(0.0271)	(0.0239)	(0.0448)	(0.0374)
Loan for Business			0.0105	0.00827	-0.0522	0.0394
			(0.0463)	(0.0377)	(0.0645)	(0.0539)
Loan for Food			0.0302***	0.0364***	0.0504**	0.0317
			(0.0102)	(0.0112)	(0.0252)	(0.0214)
Loan for Travel			0.122*	0.117*	0.137	0.114*
			(0.0717)	(0.0683)	(0.104)	(0.0625)

Continued on next page

Table 2.3 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)
	All	All	All	All	Net Sellers	Net Buyers
Logged Income				0.0121***	0.0125**	0.0135***
				(0.00203)	(0.00638)	(0.00288)
Logged Nonfarm Income				-0.00575**	-0.00756*	-0.00495
				(0.00260)	(0.00400)	(0.00458)
Logged Business Income				0.0000974	-0.00102	-0.000264
				(0.00235)	(0.00420)	(0.00343)
Plot Area Per Person				0.0527**	0.0576*	0.0473
				(0.0262)	(0.0321)	(0.0346)
Household Size				0.000225	0.00116	-0.000841
				(0.00140)	(0.00235)	(0.00267)
Constant	0.168***	0.171***	0.169***	0.0957***	0.102**	0.0875***
	(0.0118)	(0.0107)	(0.0121)	(0.0154)	(0.0431)	(0.0222)
District-Round F.E.	No	Yes	Yes	Yes	Yes	Yes
N	5,613	5,613	5,604	5,604	2,300	3,304
R^2	0.002	0.002	0.005	0.013	0.012	0.016

Notes: Bootstrapped and clustered (at the district level) standard errors are in parentheses.

*: $p < 0.1$, **: $p < 0.0.05$, ***: $p < 0.0.01$.

Table 2.4: Main Results (2): Intensive Margin

Dependent Variable: Number of Migrants

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	LPM	LPM	FE LPM	FE LPM	Net Sellers	Net Buyers	Poisson	Nega. Bi.
WTP	0.418***	0.376***	0.238***	0.237***	0.358***	0.179	0.484***	0.326***
	(0.104)	(0.106)	(0.0922)	(0.0755)	(0.120)	(0.111)	(0.176)	(0.113)
Taken Loan		0.0910**		0.0847*	0.0698	0.0897	0.207**	0.164*
		(0.0397)		(0.0437)	(0.0646)	(0.0582)	(0.100)	(0.0893)
Loan from Friends and Rel.		-0.00489		-0.0424	-0.00527	-0.0632	-0.102	-0.0895
		(0.0361)		(0.0351)	(0.0550)	(0.0522)	(0.0783)	(0.0877)
Loan from Bank		-0.161		-0.218**	-0.431***	-0.0291	-0.517	-0.635
		(0.140)		(0.0883)	(0.0786)	(0.198)	(1.457)	(1.464)
Loan from NGO		0.0458		-0.0913	-0.0503	-0.139**	-0.206*	-0.256*
		(0.0626)		(0.0558)	(0.0722)	(0.0644)	(0.121)	(0.131)
Loan for Farming		-0.0397		-0.00711	0.0460	-0.0395	-0.0258	-0.0242
		(0.0633)		(0.0795)	(0.133)	(0.0664)	(0.158)	(0.153)
Loan for Business		-0.158***		-0.163*	-0.286***	-0.128	-0.414*	-0.371
		(0.0558)		(0.0865)	(0.111)	(0.104)	(0.229)	(0.248)
Loan for Food		-0.0605*		-0.0305	-0.0735	0.000226	-0.0752	-0.0232
		(0.0327)		(0.0346)	(0.0567)	(0.0469)	(0.0664)	(0.0736)
Loan for Travel		0.0658		0.00848	0.0975	-0.105	-0.00654	0.145
		(0.0946)		(0.124)	(0.218)	(0.150)	(0.254)	(0.237)

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Table 2.4 (continued)

	(1) LPM	(2) LPM	(3) FE LPM	(4) FE LPM	(5) Net Sellers	(6) Net Buyers	(7) Poisson	(8) Nega. Bi.
Logged Income		0.0356***		0.0341***	0.0639***	0.0319***	0.100***	0.0943***
		(0.00901)		(0.00693)	(0.0247)	(0.00709)	(0.0183)	(0.0156)
Logged Nonfarm Income		-0.0102		-0.0112**	-0.0261***	-0.00144	-0.0273*	-0.0272**
		(0.00952)		(0.00568)	(0.00855)	(0.00759)	(0.0145)	(0.0136)
Logged Business Income		-0.0152		-0.00671	-0.00859	-0.00935	-0.0167	-0.00632
		(0.00961)		(0.00639)	(0.0136)	(0.00590)	(0.0157)	(0.0139)
Plot Area Per Person		0.0951*		0.0899***	0.0980*	0.0842***	0.179***	0.213***
		(0.0535)		(0.0281)	(0.0520)	(0.0260)	(0.0525)	(0.0450)
Household Size		0.00494		-0.00112	0.000357	-0.00308	-0.00212	-0.00510
		(0.00548)		(0.00454)	(0.00494)	(0.00494)	(0.0107)	(0.00837)
Constant	0.370***	0.131***	0.386***	0.198***	0.00764	0.211***		-0.672***
	(0.0348)	(0.0390)	(0.0364)	(0.0434)	(0.139)	(0.0449)		(0.180)
Control Variables	No	Yes	No	Yes	Yes	Yes	Yes	Yes
District-Round F.E.	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Clustered S.E.	Yes	Yes	Yes	Yes	Yes	Yes	No	No
N	5615	5606	5615	5606	2301	3305	5606	5606
R^2	0.006	0.024	0.002	0.012	0.018	0.013		

Notes: 1. Bootstrapped standard errors are in parentheses.
*: $p < 0.1$, **: $p < 0.0.05$, ***: $p < 0.0.01$.
2. Coefficient estimates for Poisson and negative binomial regressions shown in this table are marginal effects.

Table 2.5: Falsification Test

Dependent Variable: Migrate (0 or 1)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
WTP	0.114***	0.0895***	0.113***		0.0961*	0.0955***	0.111***
	(0.0388)	(0.0316)	(0.0359)		(0.0525)	(0.0293)	(0.0277)
WTP Lag1		0.104**	0.110**				
		(0.0403)	(0.0547)				
WTP Lag2			0.0667				
			(0.0533)				
WTP Lead1				0.0651	0.0649		
				(0.0406)	(0.0422)		
Migrate Lag1						0.0789***	0.0833***
						(0.0164)	(0.0261)
Migrate Lag2							0.0486**
							(0.0196)
N	5,604	4,001	2,528	4,078	4,010	4,162	2,747
R^2	0.013	0.012	0.018	0.014	0.015	0.016	0.022

Notes:

1. Control variables included: access to loan, loan from friends and relatives, loan from bank, loan from NGO, loan for farming, loan for business, loan for food, loan for travel, income, non-farm income, business income, plot size per person, household size. 2. District-round fixed effects are included in all specifications.

3. Standard errors bootstrapped and clustered at the district level are in parentheses.

*: $p < 0.1$, **: $p < 0.0.05$, ***: $p < 0.0.01$.

Table 2.6: Village-specific Characteristics (1)

Dependent Variable: Migrate (0 or 1)

	Daily Market		Producer Co-op		Seasonal Migration	
	(1) No	(2) Yes	(3) No	(4) Yes	(5) No	(6) Yes
WTP	0.121***	0.0304***	0.112***	0.119	0.0706	0.142***
	(0.0421)	(0.00528)	(0.0398)	(0.0730)	(0.0461)	(0.0512)
Taken Loan	0.0178	-0.0320***	0.0291	-0.0260	0.0146	0.0144
	(0.0235)	(0.00295)	(0.0253)	(0.0205)	(0.0210)	(0.0274)
Loan from Friends and Rel.	-0.0323*	-0.0384*	-0.0379*	-0.0228	-0.0570*	-0.0218
	(0.0195)	(0.0226)	(0.0201)	(0.0170)	(0.0338)	(0.0187)
Loan from Bank	-0.134	-0.0105	-0.0766	-0.342***	-0.0659	-0.103
	(0.0925)	(0.0681)	(0.0613)	(0.0236)	(0.146)	(0.0742)
Loan from NGO	-0.0523**	-0.0328	-0.0598**	-0.0159	-0.0859***	-0.0297
	(0.0257)	(0.0956)	(0.0287)	(0.0145)	(0.0196)	(0.0252)
Loan for Farming	0.0287	-0.162***	-0.00619	0.114***	0.0822	-0.00629
	(0.0285)	(0.0491)	(0.0254)	(0.0390)	(0.0962)	(0.0279)
Loan for Business	0.0371	-0.0359	0.0137	-0.0548	-0.111***	0.0280
	(0.0570)	(0.0308)	(0.0433)	(0.0588)	(0.0323)	(0.0462)
Loan for Food	0.0366***	0.0458	0.0291*	0.0602***	0.0421*	0.0341**
	(0.0141)	(0.0279)	(0.0152)	(0.0146)	(0.0215)	(0.0152)
Loan for Travel	0.112	0.158	0.116	0.121	0.154*	0.106
	(0.0810)	(0.142)	(0.0986)	(0.0945)	(0.0837)	(0.0689)

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Table 2.6 (continued)

	Daily Market		Producer Co-op		Seasonal Migration	
	(1) No	(2) Yes	(3) No	(4) Yes	(5) No	(6) Yes
Logged Income	0.0116***	0.0174***	0.00970***	0.0196***	0.0181***	0.0107***
	(0.00216)	(0.00350)	(0.00241)	(0.00668)	(0.00529)	(0.00233)
Logged Nonfarm Income	-0.00486	-0.0117***	-0.00799***	0.00570	-0.00694***	-0.00507
	(0.00322)	(0.000902)	(0.00172)	(0.00744)	(0.00211)	(0.00359)
Logged Business Income	-0.00133	0.00750***	0.000648	-0.00283	0.00238	-0.000336
	(0.00287)	(0.000587)	(0.00378)	(0.00276)	(0.00336)	(0.00363)
Plot Area Per Person	0.0526*	0.421***	0.0683***	-0.00480	0.0437	0.0656*
	(0.0296)	(0.0534)	(0.0143)	(0.168)	(0.0689)	(0.0388)
Household Size	0.000470	-0.000131	0.00134	-0.00433	-0.000337	0.000477
	(0.00202)	(0.00121)	(0.00140)	(0.00673)	(0.00678)	(0.00139)
Constant	0.0945***	0.0838***	0.0858***	0.150***	0.0947	0.0890***
	(0.0186)	(0.0165)	(0.0183)	(0.0509)	(0.0622)	(0.0180)
N	5,073	531	4,443	1,161	1,636	3,968
R^2	0.013	0.033	0.015	0.020	0.019	0.012

Notes:
1. District-round fixed effects are included in all specifications.
2. Bootstrapped standard errors clustered at the district level are in parentheses.
*: $p < 0.1$, **: $p < 0.0.05$, ***: $p < 0.0.01$.

Table 2.7: Village-specific Characteristics (2)

Dependent Variable: Number of Migrants						
	Food Aid		Cash-for-work		Food-for-work	
	(1) No	(2) Yes	(3) No	(4) Yes	(5) No	(6) Yes
WTP	0.130***	0.0153	0.130***	0.0215	0.119***	0.0563**
	(0.0416)	(0.0268)	(0.0427)	(0.0413)	(0.0392)	(0.0271)
Taken Loan	0.0291	-0.0370	-0.00238	0.133	0.0169	-0.0340
	(0.0238)	(0.0285)	(0.0110)	(0.0823)	(0.0210)	(0.0347)
Loan from Friends and Rel.	-0.0381	-0.0166	-0.0157	-0.143***	-0.0365**	0.0265***
	(0.0233)	(0.0105)	(0.0118)	(0.0368)	(0.0186)	(0.00353)
Loan from Bank	-0.0802	-0.218***	-0.122	-0.0416*	-0.0807	-0.190***
	(0.0706)	(0.0659)	(0.0818)	(0.0229)	(0.0645)	(0.0593)
Loan from NGO	-0.0544*	-0.0425	-0.0324	-0.178***	-0.0502**	-0.0307
	(0.0278)	(0.0275)	(0.0204)	(0.0554)	(0.0239)	(0.0525)
Loan for Farming	0.0145	-0.0188	0.0283	-0.0201	0.0231	-0.0200
	(0.0385)	(0.0483)	(0.0403)	(0.0133)	(0.0321)	(0.0168)
Loan for Business	-0.00455	0.0709	-0.00846	0.127	-0.000683	0.324***
	(0.0449)	(0.0758)	(0.0298)	(0.103)	(0.0348)	(0.00205)
Loan for Food	0.0202	0.0818***	0.0375***	0.0363**	0.0381***	0.0307**
	(0.0156)	(0.00680)	(0.0121)	(0.0168)	(0.0144)	(0.0156)
Loan for Travel	0.137**	-0.0297	0.0591	0.697***	0.127	-0.00940
	(0.0698)	(0.142)	(0.0747)	(0.0990)	(0.0881)	(0.0559)

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Table 2.7 (continued)

	Food Aid		Cash-for-work		Food-for-work	
	(1) No	(2) Yes	(3) No	(4) Yes	(5) No	(6) Yes
Logged Income	0.0120***	0.0119***	0.0115***	0.0135***	0.0127***	0.0124***
	(0.00281)	(0.00317)	(0.00289)	(0.000573)	(0.00255)	(0.000380)
Logged Nonfarm Income	-0.00458	-0.00921***	-0.00533*	-0.0119***	-0.00438*	-0.0177***
	(0.00291)	(0.00233)	(0.00290)	(0.000963)	(0.00254)	(0.00199)
Logged Business Income	0.00176	-0.00927***	-0.000906	0.00953**	0.00140	-0.00744*
	(0.00315)	(0.00223)	(0.00283)	(0.00474)	(0.00303)	(0.00384)
Plot Area Per Person	0.0571	0.0354*	0.0527*	0.129	0.0551*	0.0355***
	(0.0387)	(0.0197)	(0.0271)	(0.194)	(0.0311)	(0.00119)
Household Size	0.000387	-0.00115	0.000413	0.00231**	-0.000320	0.00453**
	(0.00204)	(0.00267)	(0.00205)	(0.000925)	(0.00163)	(0.00219)
Constant	0.0862***	0.138***	0.106***	0.0168	0.0919***	0.0932***
	(0.0238)	(0.0108)	(0.0185)	(0.0203)	(0.0162)	(0.0326)
N	4,330	1,274	4,775	829	4,906	698
R^2	0.015	0.014	0.012	0.065	0.014	0.016

Notes:

1. District-round fixed effects are included in all specifications.
2. Bootstrapped standard errors clustered at the district level are in parentheses.

*: $p < 0.1$, **: $p < 0.0.05$, ***: $p < 0.0.01$.

Table 2.8: Price Volatility and Migration: Net Seller

Dependent Variable: Migrate (0 or 1)

	(1) Coffee	(2) Maize	(3) Beans	(4) Barley	(5) Wheat	(6) Teff	(7) Sorghum
Cv	0.231***	0.180	7.235**	-0.496	0.911	1.4365*	1.171
	(0.031)	(0.238)	(2.640)	(0.556)	(0.664)	(0.757)	(0.592)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	458	702	155	576	342	463	353
R^2	0.0889	0.0326	0.1090	0.0689	0.0542	0.0464	0.0545

Notes:

1. Control variables included: access to loan, loan from friends and relatives, loan from bank, loan from NGO, loan for farming, loan for business, loan for food, loan for travel, income, non-farm income, business income, plot size per person, household size

2. Standard errors clustered at the district level are in parentheses.

*: $p < 0.1$, **: $p < 0.0.05$, ***: $p < 0.0.01$.

Table 2.9: Price Volatility and Migration: Net Buyer

Dependent Variable: Migrate (0 or 1)

	(1) Coffee	(2) Maize	(3) Beans	(4) Barley	(5) Wheat	(6) Teff	(7) Sorghum
Cv	0.156*	-0.194	0.611	0.055	0.157	0.871***	0.151
	(0.085)	(0.151)	(0.379)	(0.188)	(0.235)	(0.243)	(0.406)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4,018	2,007	1,862	1,433	1,572	1,443	808
R^2	0.0257	0.0329	0.0341	0.0454	0.0278	0.0257	0.0386

Chapter 3

Producer Attitudes to Output Price Risk: Evidence from the Lab and from the Field[1] [2]

3.1 Introduction

How do producers respond to output price risk? In a seminal article, Sandmo (1971) showed that, starting from a situation of price certainty, an income risk-averse producer would respond to a mean-preserving spread of the output price distribution—that is, price risk at the extensive margin—by decreasing how much she produces in order to hedge against price risk. In follow-up work, Batra and Ullah (1974) showed that further mean-preserving spreads of the output price distribution—that is, price risk at the

[1]This chapter is a co-work with Marc Bellemare, Associate Professor in the Department of Applied Economics, University of Minnesota, and David Just, Professor in Charles H. Dyson School of Applied Economics and Management, Cornell University.

[2]We are grateful to the Office of the Vice President for Research as well as to the Center for International Food and Agricultural Policy at the University of Minnesota for respectively funding the lab and field components of this research project. We thank Linden McBride for useful comments on an earlier version of this paper. We also thank seminar audiences at Alberta, Georgia, Guelph, INRA-Rennes, Michigan State, New Mexico, and Western Michigan for useful comments and suggestions. All remaining errors are ours.

intensive margin—would lead to further decreases in output if the producer's income risk preferences exhibit decreasing absolute risk aversion (DARA).

In this paper, we apply experimental methods in the lab and in the field to both those predictions. Specifically, we study how experimental subjects who are put in the role of producers for whom storage and insurance are not available behave in the face of output price risk.[3] To do so, we use a two-stage randomized design to determine (i) whether our subjects face a certain or uncertain output price, and (ii) conditional on the price being uncertain, how much risk they face. The allows disentangling the effect of output price risk on production at both the extensive and intensive margins, i.e., the effect of output price risk relative to output price certainty, and the effect of more relative to less output price risk.

Our work is closest in spirit to recent work by Bellemare et al. (2013), who build on a theoretical literature studying the behavior of consumers (Turnovsky et al. 1980), producers (Baron 1970 and Sandmo 1971), and households (Finkelshtain and Chalfant 1991)in the face of price risk to develop an estimable matrix of price risk aversion. Using household-level data from rural Ethiopia, Bellemare et al. find that the average household in their data would be willing to give up almost 20 percent of its income to stabilize—that is, eliminate the variance of—the prices of the seven most traded commodities in the data. The findings in Bellemare et al. suffer from a few important shortcomings, however. First, they rely on structural estimation, which requires that a number of assumptions be made in order to generate price risk aversion estimates. Second, they rely on observational data, which means that the price risk aversion estimates in Bellemare et al. suffer almost surely from bias and imprecision.[4] Consequently, the findings in Bellemare et al. lack internal validity. More recently, Mattos and Zinn (2016) conducted lab experiments in

[3]This is similar to production conditions for the vast majority of agricultural producers in developing countries. On the lack of storage in developing countries, see Gouel (2013). See Platteau et al. (2017) for the extent to which insurance markets in the developing world are almost always missing.

[4]For instance, McBride (2015) shows that changing how the households reporting no income are treated overturns Bellemare et al.'s qualitative finding that household willingness to pay for price stabilization is increasing in income. Bellemare et al. (2015) identify many more instances where changing one their assumptions might change their findings.

which they study the marketing behavior of producers in response to uncertain prices, but their study focuses on reference-price formation in the face of price ambiguity or Knightian uncertainty, whereas our work focuses on price risk.[5]

Specifically, we develop an experimental protocol that exactly mimics the theoretical framework developed by Sandmo (1971) to study the behavior of individual producers in the face of price risk. This allows generating findings about producer behavior in the face of price risk that have more internal validity than the findings in Bellemare et al. (2013). We use this protocol to test the aforementioned theoretical predictions by Sandmo (1971) and Batra and Ullah (1974) in three distinct settings. In the first two settings, we ran our experiments with college students in the lab at research universities in the United States. In the third setting, we ran our experiments with farmers in the field in Peru. This allows generating findings about producer behavior in the face of price risk that have more external validity than the usual single-context experimental study.

Our results reject Sandmo's prediction that price risk at the extensive margin causes income risk-averse producers to decrease their production. In fact, we find the opposite: the presence of price risk leads our experimental subjects to produce significantly more relative to situations of price certainty. This is not inconsistent with expected utility theory if our subjects are risk-loving, but having elicited income risk preferences by way of the well-known Holt and Laury (2002) list experiment, we find no support for the hypothesis that our experimental subjects are indeed risk-loving, as most of them appear to be risk-averse. Moreover, although we find that our experimental subjects decrease their production in response to increases in price risk at the intensive margin, we find no evidence that their preferences exhibit DARA.

Exploring alternative theories of decision in the face of risk and uncertainty, we find no support for safety-first behavior or for expected revenue maximization, but we find strong support for prospect theory (Kahneman and Tversky 1979). Specifically, we find

[5] "Risk" refers to situations where the distribution of the uncertain variable is known. "Ambiguity" refers to situations where the distribution of the uncertain variable is unknown. Thus, the literature often distinguishes between risk and (Knightian) uncertainty.

evidence that expected losses make our subjects take on more risk but that expected gains have no effect on their risk-taking behavior and that our subjects react more strongly to small probability events (i.e., extreme prices, or tail risks) than to events that have a higher probability of happening. Lastly, we take our data to the structural framework developed in Bellemare et al. (2013) and find that our subjects have heterogeneous price risk preferences.

The contribution of this paper is threefold. First and foremost, it provides the first experimental test of the theory of producer behavior in the face of output price risk, and it brings both internal validity—via the use of experimental methods—as well as external validity—via lab experiments conducted with students at two US universities and lab-in-the-field experiments with farmers in Peru. Second, it brings credible evidence to a question of considerable importance for policy in that it reproduces the production conditions faced by most agricultural producers in rural areas of developing countries, who often lack access to storage technology and face missing insurance markets but who must nevertheless sink resources into production well ahead of the realization of price risk. Finally, having shown that the behavior of our experimental subjects is inconsistent with expected utility theory, we provide evidence that prospect theory provides a better description of producer behavior in the face of output price risk than expected utility theory.

The remainder of this paper is organized as follows. In Section 3.2, we present the simple theoretical framework on which we base our experimental protocols. Section 3.3 describes our experimental design, paying particular attention to how we ensured that we ran the same experiment in the lab as well as in the field. In Section 3.4, we discuss the empirical framework we rely on to test the predictions of the theory. Section 3.5 presents the data and briefly discusses some descriptive statistics. In Section 3.6, we present our core results, which aim at testing the theoretical model developed in Section 3.3. Because we reject the predictions of the theory, we next explore alternative theories of behavior in the face of price risk, and we conclude by taking our data to the structural model developed by Bellemare et al. (2013) to estimate the welfare effects of price risk. Section 3.7 summarizes our findings and concludes with directions for future research.

3.2 Theoretical Framework

Because we focus on reproducing the theoretical conditions in Sandmo (1971), we reproduce here Sandmo's original theoretical framework, which can be used to test both Sandmo's result that price risk at the extensive margin will lead a risk-averse producer to decrease her level of production as well as Batra and Ullah's result that price risk at the intensive margin will lead a producer to decrease her level of production if her preferences exhibit DARA. In the interest of brevity, this section establishes only the former result. The latter can be found in Batra and Ullah (1974).

Suppose that a firm manager's utility $u(\cdot)$ is defined over profit π, such that $u(\pi)$. Profit is such that $\pi = px - c(x) - F$, where output price $p > 0$ is uncertain, $E(p) = \mu$, and $Var(p) > 0$, and where $x > 0$ is the firm manager's choice of output, $c(x)$ is an increasing and convex function representing the firm's variable costs, i.e., $c'(x) > 0$ and $c''(x) > 0$, and F is a constant representing the firm's fixed costs.

The firm manager's objective is to maximize the utility she derives from his firm's profit by choosing how much to produce *ex ante* of the realization of the uncertain output price p. That is, the firm manager chooses her quantity produced x so as to

$$\max_x E\left\{u(px - c(x) - F)\right\}, \tag{3.1}$$

the first-order necessary and second-order sufficient conditions of which are such that

$$E\{u'(\pi)(p - c'(x))\} = 0, \tag{3.2}$$

and

$$E\{u''(\pi)(p - c'(x))^2 - u'(\pi)c''(x)\} < 0 \tag{3.3}$$

Given the foregoing, we can establish the following result.

Proposition 1 (Sandmo, 1971)**.** *Under the assumptions made so far, the presence of output price uncertainty causes an income risk-averse firm manager to underproduce relative to the case where output price is certain and equal to the mean of the price distribution.*

Proof. Equation 3.2 can be rewritten as

$$E\{u'(\pi)p\} = E\{u'(\pi)c'(x)\}. \tag{3.4}$$

Subtracting $E\{u'(\pi)\mu\}$ from both sides of equation 3.4 yields

$$E\{u'(\pi)(p-\mu)\} = E\{u'(\pi)(c'(x)-\mu)\}. \tag{3.5}$$

Expected profit $E(\pi) = \mu x - c(x) - F$, which can be rearranged to express profit as a function of expected profit and the difference between expected and realized prices such that $\pi = E(\pi) + (p-\mu)x$. Intuitively, this means that the difference between expected and realized profit is only due to the difference between the *ex post* realization of the stochastic output price p and the firm manager's expectation μ of that price.

The firm manager takes her decision on the basis of his expectation of what price will look like *ex post*; if that expectation is right, i.e., if $\mu = p$, then $E(\pi) = \pi$. But if $\mu \neq p$, there will be a discrepancy between expected and realized profit.

It follows from the foregoing that $u'(\pi) \leq u'(E(\pi))$ if $p > \mu$, so

$$u'(\pi)(p-\mu) \leq u'(E(\pi))(p-\mu), \tag{3.6}$$

an equality which holds for all values of p. Taking the expectations on both sides of equation 3.6 implies

$$E\left\{u'(\pi)(p-\mu)\right\} \leq u'(E(\pi))E(p-\mu), \tag{3.7}$$

where the right-hand side is equal to zero given that $E(p-\mu) = E(p) - \mu$, and $E(p) = \mu$, which means that the left-hand side is negative. This in turn means that $E\left\{u'(\pi)(c'(x)-\mu)\right\} \leq 0$, which means that $c'(x) < \mu$, or the firm manager's marginal cost of producing x is less than his marginal benefit of doing so. In other words, the firm manager produces less than she would when output price is certain, which establishes the result. □

The next section discusses the experimental protocol we develop in order to mimic the conditions just described in the lab as well as in the field.

3.3 Experimental Design

We design an experimental protocol that aims studying producer behavior in the face of price risk according to the theoretical conditions described in Section 3.2. In this section, we first describe the design of the experimental game we use to elicit behavior in the face of price risk. We then briefly discuss the design of the experimental game we use to elicit risk preferences, which was developed by Holt and Laury (2002). Finally, we describe the differences, wherever applicable, among the three contexts wherein we conducted our experiments, viz. in lab settings at Cornell and Minnesota, and a lab-in-the-field setting in Peru.[6]

3.3.1 Price Risk Game

In the output price risk game, each subject assumes the role of a producer (or the manager of a firm) producing a single commodity. To focus on the effect of output price risk, we assume away all uncertainty in production (e.g., uncertainty due to weather uncertainty, technological shocks, market conditions, etc.) We abstract from any strategic interactions

[6]The field component of our study was the subject of a pre-analysis plan filed with the American Economics Association's trial registry at `https://www.socialscienceregistry.org/trials/1497`. What we label our core analysis—that is, our tests of Sandmo and Batra and Ullah's predictions—is in the pre-analysis plan. Our exploration of alternatives to expected utility theory and the structural part of the work below is not in the pre-analysis plan.

in that a subject's behavior has no effect on other subjects' payoffs. Moreover, we abstract from general equilibrium effects in that every subject is a price taker, i.e., our subjects' production decisions have no effect on the price drawn.

To mimic the theoretical framework in Section 3.2, we choose simple cost and profit functions. We assume that the fixed cost F is such that $F = 15$ and the variable cost function $c(x)$ is such that $c(x) = 2x^{1.4}$, which is an increasing and convex function of output. Accordingly, the profit function $\pi = px - 2x^{1.4} - 15$ is a concave function of output. Our experimental subjects' monetary reward from this price risk game is directly tied their profits.

The level of output x that a subject can choose ranges from 0 to 20 and is expressed in thousands of units. It must be determined *ex ante* of the realization of output price. Once experimental subjects have made their production decisions, the price per unit is realized and is one of five values in the set $\{5, 6, 7, 8, 9\}$.

To facilitate decision-making, subjects are given charts that describe the relationship between output level, price, cost, and profit, along with graphs of the profit function under each of the five different possible prices in the set $\{5, 6, 7, 8, 9\}$. A combined chart summarizing the relationship between output and profit under all five price scenarios is also provided to facilitate comparisons and, ultimately, decision-making. Figures B.1 to B.6 in the appendix show those charts.

To determine the price of the output in each round, we follow the two-stage randomization strategy. This process is done publicly by showing subjects the method used to randomize the presence of price risk (i.e., the extensive margin of price risk) and, conditional on there being price risk, the price drawn from a bag filled with balls marked with prices (i.e., the intensive margin of price risk). Subjects are told explicitly that there are no strategic considerations or general equilibrium effects, i.e., their profit is not dependent on the behavior of other experimental subjects, nor is the price they face dependent on any subject's production decision.

In stage 1, we determine the extensive margin of the price uncertainty, i.e., whether there is any price uncertainty. In one third of the cases, subjects are presented with a certain price of $7 per unit, which is the mean of the five possible prices. We refer to this as experimental setting 1. In two thirds of the cases, subjects are presented with an uncertain price.[7] Conditional on facing an uncertain price, in stage two, the level of price risk is determined by randomly selecting one of four price distributions—we refer to these as experimental settings 2 to 5—which are all mean-preserving spreads of one another.[8,9] Figures B.7 to B.11 in the appendix show the histograms that were shown to our subjects before they made their output decision in every round.

In each round, once we determined the applicable setting from the two-stage randomization process, subjects are shown the shape of the price distribution of the corresponding setting.

Subjects choose how much to produce in each round *ex ante* of the realization of price uncertainty by looking at the picture of the randomly drawn price distribution and the profit charts they are given. Once all subjects have recorded their output choice, we draw a ball from the bag with the corresponding setting to determine the *ex post* market price and to give each subject a chance to figure out how she has done in terms of profit before moving on to the next round.

In each context, subjects played 10 practice rounds and 20 actual rounds of this price game.[10] Profits from the actual rounds were mapped into a monetary reward function. At the end of each experimental session, we randomly chose one of the 20 actual rounds

[7]This one third—two thirds breakdown of situations of price certainty versus price risk was decided upon in order to guarantee that we would have enough variation to study the effect of price risk at the extensive margin.

[8]In all settings, the mean value of the prices is $7. In setting 1 (price certainty), the standard deviation of the price distribution is zero. In settings 2 to 5, the standard deviation is respectively 0.8, 1.17, 1.45, and 1.58.

[9]An objection to the above design could be that the mean of the price distribution as well as the price drawn in certainty cases should also have been randomized. Though it would be interesting to also randomize the mean of each price distribution, we chose to keep the mean price across all settings the same in order to study the effect of mean-preserving spreads, which is what Sandmo (1971) focused on. Future iterations of this research design should certainly randomize over the mean price in order to study the effects of the skewness of output prices on production decisions.

[10]During the practice rounds, subjects were encouraged to ask questions to ensure that they properly understood the structure of the game.

for each subject using a 20-sided die thrown by the subject herself in order to determine which round we would base that subject's experimental payout on. The experimental payoff from the production game was determined by adding a $25-base payoff plus a half of the subject's profit or loss in the randomly selected price game round, her proceeds from the Holt-Laury list experiment, which we discuss below, and a $45 payment for participation in the experiment. Because our subjects do not know *ex ante* which of the 20 actual rounds will be chosen for their payoff, they are induced to truthfully reveal their preference in each round, and this allowed economizing on the substantial transactions costs involved with having to compile earnings over 20 rounds.

3.3.2 Holt-Laury List Experiment

Because it is well-known, we only briefly describe the Holt and Laury (2002) method we used to elicit our experimental subjects' risk preferences.[11]

Along with the price risk game, experimental subjects play the lottery game developed by Holt-Laury (2002). Some subjects played the price risk game first; others played it second; we discuss the order of games in the next sub-section. The list of choices used in the Holt-Laury game is shown in Figure B.12 in the appendix. We do this to make sure that we can control for risk preferences and to explore different behaviors for different degrees of risk aversion.

In the Holt-Laury game, subjects are shown a list with ten rows. Each row contains two options, A and B, which are different specifications of a lottery. Option A is always less risky than option B. The expected value of the payoff starts higher for option A than for option B in the top row, but the difference between the two decreases as the row number increases.

Subjects choose which option to take starting from the top row. The game is designed

[11] Although Drichoutis and Lusk (2017) show that the Holt and Laury (2002) method is better suited to elicit the shape of the probability weighting function than it is to measure the curvature of the utility function, the findings in Drichoutis and Lusk were not yet known when we developed our experimental protocol in 2014.

so that most subjects will eventually switch from A to B, and switching to B at higher row numbers means that a subject is more risk-averse. Once a subject switches to B, the game ends. In other words, in order to make sure that our setup satisfies the axioms of expected utility theory, we enforce monotonic switching. This is common practice in list experiments (Liu, 2013).

To determine the payoff in the Holt-Laury lottery game, each subject rolled a 10-sided die twice: once to randomly select the row number on which we based that subject's experimental payout on, and another time to play the lottery in that row to determine the subject's payoff for this part of the experiment. The monetary payoff in this case was identical to the dollar amount shown in the table.

3.3.3 Differences across Contexts

Recall that we conducted our experiments in three contexts. In the first two contexts, we conducted our experiments in lab settings in the Dyson School of Applied Economics and Management at Cornell University and in the Department of Applied Economics at the University of Minnesota. In the third context, we conducted our experiments in lab-in-the-field settings with farmers in Peru.

The Cornell lab experiments were conducted in December 2014 and March 2015. The Minnesota lab experiments were conducted in October 2015. The Peruvian lab-in-the-field experiments were conducted in August and September 2016. The lab experiments at both Cornell and Minnesota were conducted by the authors; the lab-in-the-field experiments in Peru were contracted out to Innovations for Poverty Action (IPA), a New Haven, CT-based organization with offices throughout the developing world whose expertise lies in implementing field and lab-in-the-field experiments. Prior to IPA conducting the lab-in-the-field experiments in Peru, the authors spent three days training IPA staff on the proper implementation of the experimental design.

At Cornell and Minnesota, experimental subjects were undergraduate students. At Cornell, subjects were recruited via the lab listserv from the general undergraduate population. At Minnesota, subjects were recruited via undergraduate listserv from the population of undergraduates enrolled in the two majors offered by the Department of Applied Economics. In Peru, subjects were recruited by IPA staff from among a population of farmers in rural Lima province who were numerate and literate enough to take part in the experimental games discussed above.

An important difference between the lab experiments conducted at Cornell and Minnesota and the lab-in-the-field experiments conducted in Peru lies in the variation across observations. At both Cornell and Minnesota, where the costs of conducting experiments are relatively high, prices vary within each subject across rounds, but not across subjects within a round, i.e., we draw a single round for all subjects in each round. In Peru, where the cost of conducting the experiments are relatively lower, we had the luxury of doing the experiments one-on-one with each subject, and so each subject faces her own price in each round, i.e., prices vary across subjects within each round and within subject across all rounds. In either case, we have the necessary statistical power to detect the effects we are interested in.

Another important difference between contexts is the order in which the price risk and the Holt-Laury games were played. At Cornell in December 2014, the price risk game was played first and the Holt-Laury game was played second. At Cornell in March 2015 and at Minnesota in October 2015, the Holt-Laury game was played first and the price risk game was played second. In Peru, the order of games was randomly determined by the throw of a die. Across all contexts, this provides us with enough variation to determine whether the order in which the games are played matters.

Finally, one last difference across contexts has to do with the randomization method. At both Cornell and Minnesota, we determined both the extensive and intensive price risk margins by means of public randomization via an Excel spreadsheet projected on a screen for all to see. In Peru, the extensive and intensive price risk margins were respectively determined by throwing a six- and a four-sided dice. Across all contexts, prices were drawn for settings 2 to 5 from bags containing 20 balls marked with prices in the relevant proportions for each setting.

3.4 Empirical Framework

To test the predictions of Sandmo (1971) and Batra and Ullah (1974), we estimate the following equation

$$y_{it} = \alpha + \beta_1 I(\sigma_t > 0) + \gamma_1 \sigma_t + \delta_1 R_i + \tau_1 t_t + \theta_1 x_i + \nu_{1i} + \epsilon_{1it}, \tag{3.8}$$

where y_{1it} denotes the subject i's output choice in round $t \in \{1, ..., 20\}$, $I(\sigma_t > 0)$ is an indicator variable equal to one if subjects have to make their output choice in the face of price risk and equal to zero otherwise, σ_t denotes the standard deviation of the price distribution used in round t, R_i denotes subject i's Arrow-Pratt coefficient of relative risk aversion obtained from the Holt-Laury lottery game,[12] x_i is a vector of controls specific to subject i, ν_{1i} is an effect specific to subject i, and ϵ_{it} is an error term with mean zero.

To test Sandmo's hypothesis that output price risk at the extensive margin causes producers to decrease their level of output, we test the null hypothesis $H_0 : \beta_1 = 0$. Rejecting the null in favor of the alternative hypothesis that $\beta_1 < 0$ would constitute evidence in favor of Sandmo's hypothesis, although strictly speaking, this would only really need to hold in cases where our subjects are risk-averse, i.e., for subjects for whom $R > 0$.

To test Batra and Ullah's hypothesis that output price risk at the intensive margin causes producers to decrease their level of output, we estimate a second version of

[12]Following Holt and Laury's recommendations (2002), we assume constant relative risk aversion (CRRA) and ascribe $R = -0.95$ to subjects who switch in the first line of the Holt-Laury list experiment; $R = -0.49$ to subjects who switch in the second line; $R = -0.15$ to subjects who switch in the third; $R = 0.15$ to subjects who switch in the fourth line; $R = 0.41$ to subjects who switch in the fifth line; $R = 0.68$ to subjects who switch in the sixth line; $R = 0.97$ to subjects who switch in the seventh line; $R = 1.37$ to subjects who switch in the eighth line; $R = 1.50$ to subjects who switch in the ninth or tenth line. Note that the assumption of CRRA is not inconsistent with the test of DARA we conduct in relation to our test of Batra and Ullah's (1974) prediction.

equation 3.8 such that

$$y_{it} = \alpha + \beta_2 I(\sigma_t > 0) + \gamma_2 \sigma_t + \delta_2 A_{it} + \theta_2(\sigma_t \times A_{it}) + \tau_2 t_t + \theta_2 x_i + \nu_{2i} + \epsilon_{2it}, \quad (3.9)$$

where all variables are defined as in equation 3.8 save for A, which denotes a subject's coefficient of absolute risk aversion.[13] We then test the null hypothesis $H_0 : \theta_2 = 0$. Rejecting the null in favor of the alternative hypothesis that $\theta_2 < 0$ would constitute evidence in favor of Batra and Ullah's hypothesis, since it would indicate that as our subjects get more risk averse, i.e., as R increases, an increase in risk causes our subjects to decrease their production level.

Although the dependent variable in equations 3.8 and 3.9 is a nonnegative integer and therefore lends itself in principle to the estimation of count data models such as Poisson or negative binomial regressions, we present throughout the results of ordinary least squares (OLS) regressions as our preferred specifications. We favor OLS results because with likelihood-based procedures like Poisson or negative binomial regressions, there is a small possibility that a coefficient is identified off of the specific functional form imposed on the error term. Though this is less of an issue with the estimated coefficients for those variable which we assign experimentally—that is, for β and γ—it could be an issue for those variables which are not randomly assigned by us. Moreover, the coefficients from a least squares regression are directly interpretable as marginal effects.

Moreover, because our data are longitudinal and we follow each subject over the course of 20 rounds, we cluster standard errors everywhere below at the subject level.

Lastly, there remains to discuss the use of random over fixed effects. We estimate random effects regressions for two reasons. First, because when considering fixed versus random effects, the latter are superior to the former when dealing with experimental data given that the variables of interest are clearly orthogonal to the error term and because the fixed effects estimator is inefficient. Second, we do so based on the result of

[13] We explain below how we recover absolute risk aversion from the available data.

a Hausman test which we discuss in Section 3.6, and which fails to reject the null that the coefficients from random and fixed effects specifications are equal.

3.5 Data and Descriptive Statistics

The experiments for this paper were conducted at the Lab for Experimental Economics and Decision Research in the Dyson School of Applied Economics and Management at Cornell University in December 2014 and March 2015, in the Department of Applied Economics at the University of Minnesota in October 2015, and rural areas of Peru's Lima province in August and September 2016. Cornell's LEEDR lab does not allow deceiving subjects, the Minnesota subjects were recruited on an ad hoc basis from the Department of Applied Economics' undergraduate listserv, and the subjects in Peru had never been part of an economic experiment before they took part in our experiments. Subjects in the US were undergraduate students at the respective universities where we ran our experiments; subjects in Peru were farmers who were literate and numerate enough to understand the experimental materials used as part of our experiments.

Our sample consists of 24 subjects at Cornell in December 2014, 24 subjects at Cornell in March 2015, 23 subjects at Minnesota in October 2015, and 48 subjects in Peru in August and September 2016, for a total of 119 subjects across all three contexts. Because each subject played 20 actual rounds (after playing 10 practice rounds) of the price game, our pooled sample size consists of 2,380 subject-round observations for the price risk game. Obviously, because we only have as many Holt-Laury switch points as we have experimental subjects, our pooled sample size consists of 119 such observations, i.e., one for each of our experimental subjects. In some cases, we lose a subject-round or all or q subject's rounds altogether due to missing data.

Table 3.1 presents summary statistics for our pooled sample of experimental subjects, and tables 3.2, 3.3, and 3.4 respectively present summary statistics for Cornell, Minnesota, and Peru. We skip the discussion of the summary statistics in Table 3.1 to discuss summary statistics in our three sub-samples. Across all three contexts, the mean price drawn does not differ significantly from the mean price of 7 in all distributions, nor does the mean output chosen differ significantly from 10, the profit-maximizing output choice when the price is equal to 7. Likewise, across all three contexts, subjects face an uncertain—that is, risky—output price in about two thirds of cases, as one would expect given our randomization strategy.

Because the proportion of rounds in which setting 1 (i.e., price certainty) is equal to one minus the uncertainty dummy, the mean of the uncertainty dummy and the mean of the setting 1 dummy necessarily sum up to one. As regards settings 2 to 5, although those are uniformly distributed across subject-rounds in Peru given that each subject play each round on her own, they are not uniformly distributed across subject rounds at Cornell and Minnesota given that a setting is drawn for all subjects in each round. In other words, we would expected asymptotic results to be more likely to hold in Peru given that a different setting is drawn for each subject-round observation in Peru, but a different setting is only drawn in each round for all subjects at Cornell and Minnesota.

Lastly, it is interesting to note that subjects at Cornell and Minnesota—undergraduate students all—are almost identical in how risk-averse they are, but that Peruvian farmers are markedly less risk-averse. Indeed, Cornell and Minnesota subjects switch from column A to column B of the Holt-Laury list experiment around the seventh line of the list, but Peruvian farmers switch much earlier, around the third line. This contradicts the conventional wisdom that smallholder farmers in developing countries tend to be more risk-averse than average.

3.6 Experimental Results

This section proceeds in three parts. In the first part, we discuss the results of our core results (i.e., the estimation results for equation 3.8) for our entire sample, for Cornell, for Minnesota, and for Peru. In doing so, we also report the results of hypothesis tests aimed at evaluating the testable predictions of Sandmo (1971) and Batra and Ullah (1974). Then, finding little to no support for those testable predictions, we test three alternative theories which we believe might explain the patterns we observe in the data, viz. safety-first behavior, expected revenue maximization, and prospect theory, finding no support for the former two and strong support for the latter. Finally, we use our experimental data to estimate price risk preferences structurally, as in Bellemare et al. (2013).

3.6.1 Core Results and Tests of the Theory

Table 3.5 presents estimation results for equation 3.8.[14] The results in Table 3.5 are rather damning for the expected utility-based predictions of Sandmo (1971). Indeed, the former, Table 3.5 shows that price risk at the extensive margin—the dummy for whether the price is uncertain—causes our subjects to significantly raise their output by an entire unit of production. Table 3.5 further shows that price risk at the intensive margin—the standard deviation of the price distribution—causes decreases in output.

Tables B.1 to B.3 in the appendix show results similar to those in Table 3.5 for the subsamples of Cornell, Minnesota, and Peruvian subjects. These results indicate that the results in Table 3.5 are driven entirely by US subjects. Indeed, both the Cornell and Minnesota subjects respond positively to price risk at the extensive margin and negatively to price at the intensive margin, whereas Peruvian subjects do not respond to either.[15]

Taking the results in table 5 at face value, these results are not necessarily inconsistent

[14] A Hausman test pitting the specification in Table 3.5 against the same specification but with subject-specific fixed effects failed to reject the null with a p-value of 0.99. This constitutes strong evidence that random effects are to be preferred in this context, and so the remainder of this paper proceeds with random effects regressions, except in one specific case.

[15] With $n = 959$ subject-round observations in Peru and with both production and price varying across subjects and across rounds, it seems unlikely that the Peruvian findings are underpowered relative to the Cornell and Minnesota findings. In other words, it seems likely that the Peruvian results in Table B.3 constitute evidence of absence of any significant effect rather than absence of evidence regarding such effects.

with expected utility (EU) theory. Indeed, if our subjects were risk-loving and their preferences exhibited DARA, it would be possible to witness this kind of behavior under EU. The simultaneous occurrence of risk-loving and DARA preferences, however, seems unlikely to hold.

Indeed, Table B.4 in the appendix shows that the counterintuitive result for price risk at the extensive margin holds even more strongly in the subset of subjects for whom $R > 0$. Recall that in that subset of subjects, we would expect price risk at the extensive margin to significantly decrease—not increase—how much they choose to produce. Moreover, the results in Tables 3.5 and B.3 hold whether we include R on the RHS of equation 1 or not.[16]

What of Batra and Ullah's EU-based prediction for price risk at the intensive margin? To test this, we need to interact price risk at the intensive margin with each respondent's Arrow-Pratt coefficient of absolute risk aversion. Recall, however, that from the Holt-Laury list experiment, we can only derive each respondent's Arrow-Pratt coefficient of relative risk aversion.

To recover absolute risk aversion, and because relative risk aversion is equal to absolute risk aversion multiplied by reference income, we divide each respondent's time-invariant coefficient of relative risk aversion by the income he or she would has in every round. Estimating equation 3.9 that way, we fail to reject the null that the interaction between absolute risk aversion and price risk at the intensive margin is not significantly different from zero. In other words, as absolute risk aversion decreases, we do not see subjects decreasing how much they produce.[17]

3.6.2 Alternative Theories

Taken together, our core results constitute an outright rejection of the predictions in Sandmo (1971) and Batra and Ullah (1974). More generally, and given that our

[16]These results are not shown for brevity, but are available upon request from the authors.

[17]Again, these results are not shown for brevity, but are available upon request from the authors.

experimental setup exactly mimics the theoretical conditions laid out by Sandmo (1971), our core results suggest that EU theory is likely to be poorly suited to our subjects' behavior in the face of price risk. In the next few sections, we explore three alternative theories which we feel might explain behavior in our data.

Safety First

One possible explanation for why the average subject in our data chooses to expose herself to more risk in response to price risk at the extensive margin is that she might exhibit safety-first behavior. Recall that under safety first, individuals attempt to avoid experiencing a disaster (Telser 1995; Bigman 1996). In this context, we choose to define "disaster" as any negative profit, though we are fully aware that the decision of what counts as a disaster is arbitrary in safety-first models, which is one of their weakness.

In other words, in our estimations, any loss counts as a disaster, and we thus regress a dummy variable equal to one if, in a given round, a given subject makes a choice that minimizes the likelihood of experiencing a loss and equal to zero otherwise on the variables on the RHS of equation 3.8.

The results of this regression are shown in Table 3.6. Here, note that price risk at the extensive margin has no statistically significant effect on whether our subjects minimize the probability of experiencing a loss. Moreover, price risk at the intensive margin makes them less—not more—likely to minimize the probability of experiencing a loss. The only variable that appears roughly consistent with safety-first behavior in Table 3.6 is the Arrow-Pratt coefficient of relative risk aversion, and this result suggests that as our subjects are more relatively risk-averse, they are more likely to choose their output level so as to minimize the probability of experiencing a loss. This result is not causal, however, given that our subjects' Holt-Laury switch point cannot be argued to be strictly exogenous to their output choice.

Appendix Tables B.5 to B.7 show results similar to those in Table 3.6 for the subsamples of Cornell, Minnesota, and Peruvian subjects. All in all, the results in this section leave us with little to no faith that a safety-first approach accurately represents how our subjects are making their decisions in the face of price risk.

Expected Revenue Maximization

Another possible explanation for why the average subject in our data chooses to expose herself to more risk in response to price risk at the extensive margin is that she might an expected revenue (here, profit) maximizer. Under expected revenue maximization, subjects seek to maximize $E\left\{px - c(x) - F\right\}$ instead of maximizing $E\left\{u(px - c(x) - F)\right\}$.

To test this decision-making framework, we regress a measure of the expected revenue (or profit) in each round for each subject on the variables on the RHS of equation of equation 3.8. Simply, our measure of expected revenue captures, for a subject's output choice in a given round, the likelihood of observing each price times the subject's payoff under that price.

The results of this regression are shown in Table 3.7. Similarly to the results for safety-first behavior in Table 3.6, we find that price risk at the extensive margin has no statistically significant effect on expected revenue, and that price risk at the intensive margin causes our subjects to minimize—not maximize—their expected revenue. The only variable that appears somewhat consistent with expected revenue maximization in Table 3.7 is the Arrow-Pratt coefficient of relative risk aversion, a result which suggests that as our subjects become more relatively risk-averse, they are more likely to choose their output level so as to maximize their expected revenue. Again, this result is not causal given that our subjects' Holt-Laury switch point is almost surely endogenous to output choice.

Appendix Tables B.8 to B.10 show results similar to those in Table 3.7 for the subsamples of Cornell, Minnesota, and Peruvian subjects. All in all, the results in this section provide no support for expected revenue maximization as an alternative explanation for our subjects' behavior in the face of price risk.

Prospect Theory

One last possible explanation why the behavior of the average subject in our data is at odds with the predictions of the canonical model is that prospect theory (Kahneman and Tversky, 1979) might be better suited than EU theory to explain their behavior.

Recall that prospect theory differs from EU theory in three important ways. First, subjects have a reference point above which they are risk-averse and below which they are risk-loving. Second, subjects are loss-averse, so that a loss is felt more sharply than an equivalent gain. Finally, subjects tend to overweight small-probability events.

Given that we fully expected to find support for the canonical predictions of Sandmo (1971) and Batra and Ullah (1974), our experimental protocol was not designed to test prospect theory. Yet, we can conduct a credible test of prospect theory with what we have. Specifically, we can look at whether subjects are risk-averse over gains and risk-averse over losses, and we can look at how they respond to small-probability prospects relative to other prospects. The only implication we cannot test directly is loss aversion, but we can test for it indirectly by comparing the respective magnitudes of the coefficients associated with expected gains and losses. Finding that the latter is significantly great than the former in absolute value would constitute support for loss aversion in that it would suggest that subjects are more responsive to a loss than to a gain

Table 3.8 shows the results of a regression of our subjects' output choice on (i) the probability that the price drawn will be equal to 5 or 9, (ii) the probability that the price drawn will be equal to 6 or 8, (iii) the probability that the price drawn will be 7, (iv) their expected gain, and (v) their expected loss.

Note that (i), (ii), and (iii) are mutually exclusive but not collectively exhaustive, i.e., the probability of drawing a price of 5 (6) is always equal to the probability of drawing a price of 9 (8) given that we take mean-preserving spreads, and so adding up the probabilities that we draw prices of 5, 6, or 7 sums up to less than one, as would summing up the probability that we draw prices of 7, 8, or 9. What matters here is that we can measure the likelihood of small-probability events (i.e., a price of 5 or 9) relative to other events (i.e., a price of 6, 7, or 8). Moreover, note that in cases where a subject faces a positive expected gain, her expected loss is coded as equal to zero, and in cases where she faces a positive expected loss, her expected gain is coded as equal to zero. Finally, expected losses are expressed in absolute value.

The results in Table 3.8 strongly suggest that prospect theory can explain the behavior of our experimental subjects. Indeed, our subjects react much more strongly to small probability events (i.e., the likelihood that the price will be equal to 5, which equals the likelihood that it will be equal to 9) than they do to intermediate probability events (i.e., the likelihood that the price will be equal to 6, which equals the likelihood that it will be equal to 6) and than they do to the most likely event (i.e., the likelihood that the price will be equal to 6). Because these results hold both the expected gain and loss constant, this suggests that our subjects overweight small probability events. Indeed, the coefficient on the probability that the price will be 5 (or that it will be 9) is equal to -28.36, whereas the coefficient on the probability that the price will be 6 (or that it will be 8) is equal to -23.88, and the coefficient on the probability that the price will be 7 is equal to -12.43. The coefficient on the probability of small probability events (i.e., the probability that the price will be 5 or that it will be 9) is statistically significantly different from the other two probability coefficients.

Before proceeding with the remainder of the results in Table 3.8, recall that the more a subject produces, the more she exposes herself to risk. Conversely, the less she produces, the more she hedges against risk. In Table 3.8 then, although the coefficient on expected gain is not statistically significant, which suggests that our subjects are risk-neutral over gains (i.e., they neither expose themselves to more or less price risk in response to expected gains), the coefficient on expected losses is positive and statistically significant, which suggests that they are risk-loving over losses given that they expose themselves to more risk in response to greater expected losses. In the limit, one might even interpret the fact that the coefficient on expected losses being greater in magnitude than the absolute value of the coefficient on expected gains as evidence of loss aversion, since it suggests that our subject respond more sharply to a loss than to an equivalent gain.[18]

Appendix Tables B.11 to B.13 show results similar to those in Table 3.8 for the subsamples of Cornell, Minnesota, and Peruvian subjects. Here, it looks as though the overweighting of small probability events is driven by Minnesota subjects, but that subjects act as if risk-loving over losses across all contexts. All in all, the results in Table 3.8 and in Tables B.11 to B.13 offer robust support for prospect theory as the relevant decision model used by our subjects when deciding how much to produce in the face of price risk.

3.6.3 Structural Estimation of Price Risk Preferences

The findings just discussed are interesting in and of themselves, but our experimental data allow going one step further. Specifically, they allow structurally estimating the coefficient of price risk aversion developed by Barrett (1996) for the single-commodity case and expanded to the case of multiple commodities by Bellemare, Barrett, and Just (2013).

From Barrett (1996), we know that in the single-commodity case, an individual i's coefficient of price risk aversion in round t, A_{it}, is such that

$$A_{it} = -\frac{x_{it}}{p_t}[\phi_{it}(\eta - R_i) + \xi], \tag{3.10}$$

where x denotes individual i's marketable surplus of the commodity under consideration (i.e., how much she produces in round t); p denotes the price in round t, ϕ denotes individual i's budget share of marketable surplus in round t, i.e., the value of her marketable surplus divided by her income if that round were to be chosen as the paying round; η is the income elasticity of marketable surplus; R_i is individual i's Arrow-Pratt

[18] A test of the null hypothesis that the coefficient on expected losses is equal to the absolute value of the coefficient on expected gains rejects the null at less than the 5 percent level of significance.

coefficient of relative risk aversion; and ξ is the price elasticity of marketable surplus.

As it turns out, all those components of equation 3.10 are either available in, computable from, or estimable from our experimental data. Specifically:

1. x_{it} is a subject's output choice in each round.
2. p_t is the price drawn at random in each round.
3. ϕ_{it} is computed by multiplying the previous two variables to obtain the value of subject i's marketable surplus in round t and dividing that value by subject i's income if round t were chosen as the round on which that subject's compensation is based.
4. η is estimable from a regression of marketable surplus on income and other variables, as shown below.
5. R is determined from the results of the Holt-Laury list experiment. As with our core results above, we follow Holt and Laury (2002) in assuming that $u(\pi) = \frac{\pi^{1-r}}{1-r}$, and by using the values of a subject's coefficient of relative risk-aversion in Table 3 of Holt and Laury, as explained in footnote 10 above.
6. ξ is estimable from a regression of marketable surplus on price and other variables, as shown below.

Specifically, the marketable surplus regression from which η and ξ are obtained is such that

$$\ln x_{it} = \alpha + \xi \ln p_t + \eta \ln m_{it} + \tau t + \delta d_i + \omega_{it}, \tag{3.11}$$

where, in a slight abuse of notation, and as in Bellemare, Barrett, and Just (2013), $\ln(\cdot)$ denotes an inverse hyperbolic sine (IHS) transformation of a variable (Burbidge et al. 1988; MacKinnon and Magee, 1990; Moss and Shonkwiler 1993), a log-like transformation commonly used in applied microeconomics, and which allows keeping zero-valued and negative observations, x denotes output choice, p denotes the price drawn, m denotes the subject's income in the current round, t denotes the round, d is a vector of subject-specific fixed effects,[19] and ω is an error term with mean zero. Given that equation 3.11 regresses a log-like transformation on log-like transformations, the coefficients ξ and η can be treated as elasticities.

Equation 3.11 is estimated by ordinary least squares with standard errors clustered at the subject level, and those results can be found in Table 3.9. From those results, we note that for a 1 percent increase in price, there is an associated increase in output of 0.76 percent, i.e., supply is relatively price-inelastic. Likewise, for a 1 percent increase in income, there is an associated 0.89 percent decrease in output.[20]

We use the results in Table 3.9 to calculate A above. Then, following the derivations in Bellemare, Barrett, and Just (2013), we multiply each A_{it} by $0.5 \times \sigma_t$ to recover the willingness to pay (WTP) of individual i to stabilize the price in round t (i.e., her WTP to set price equal to its mean of 7 and set its standard deviation equal to zero).

The average WTP is -0.10 and is significant at less than the 5 percent level, i.e., the average subject-round would require a payment of \$0.10 to be compensate for the disutility incurred by price stabilization. In other words, the average subject in the average round is estimated to be price risk-loving, and WTP ranges from $-\$3.52$ to \$2.52. Note that, in absolute value, those numbers are well below the average profit made by our experimental subjects in those rounds. When expressed as a proportion of "income," this WTP ranges from about -16 to 12 percent of a subject-round's income. Forty-two percent of subject-rounds (i.e., 984 out of 2,338) are estimated to be price risk-loving, 30 percent (i.e., 707 out of 2,338) to be price risk-neutral, and 28 percent (i.e., 647 out of 2,338) to be price risk-averse.

[19]We use fixed effects here because income is not assigned at random, and it is thus not orthogonal to the error term.

[20]The reader might wonder why, if price is randomly drawn in each round, there is a statistically significant relationship between price and output. Here, this statistical significance arises from the fact that in rounds where the price is known with certainty, subjects almost always pick the profit-maximizing quantity of output, i.e., $x = 10$.

The high proportion of estimated price risk-loving subject-rounds—over 40 percent of all observations—is consistent with our core results. Indeed, recall that the introduction of output price risk caused the average respondent to produce more rather than less, in contrast with Sandmo's (1971) theoretical result. This correspondence between our core, reduced-form findings and the structural estimates in this section are encouraging for the pursuit of structural work in this area of research.

Finally, following Bellemare et al. (2013), we plot the WTP of each subject against her income for every round. Following an initial drop, WTP as a proportion of income increases with income. This is similar to Bellemare et al.'s finding for rural Ethiopian households, whose WTP to stabilize the prices of the top seven most trade commodities in rural Ethiopia is increasing in their income.

3.7 Summary and Concluding Remarks

We have conducted the first experimental test of the theory of producers behavior in the face of output price risk. Specifically, we have developed an experimental protocol that exactly mimics the theoretical framework in Sandmo (1971) to test the prediction that risk-averse producers respond to the presence of price risk at the extensive margin by hedging against price risk by decreasing the quantity they choose to produce. Our experimental protocol also allows testing Batra and Ullah's (1974) prediction that producers respond to the presence of price risk at the intensive margin by decreasing the quantity they choose to produce when their preferences exhibit DARA.

Our core results offer no support for either prediction, although our results for price risk at the extensive margin (i.e., Sandmo's prediction) are arguably cleaner than our results for price risk at the intensive margin (i.e., Batra and Ullah's prediction) given that the experimental game we use to elicit our subjects' risk preferences tell us about their relative risk aversion and that we have to deduce their absolute risk aversion therefrom.

Because the canonical predictions of Sandmo and Batra and Ullah are rooted in expected utility theory, we then explored whether alternative models of decision-making in the face of risk could explain our subjects' behavior. When testing whether safety first, expected revenue maximization, or prospect theory explain our subjects' behavior, we find no support for either safety first or expected revenue maximization, but we find strong support for prospect theory.

Finally, we take the method developed by Barrett (1996) and extended by Bellemare et al. (2013) to estimate price risk preferences to our experimental data. Our finding that our average subject is price risk-loving is consistent with our core results. Similarly, our finding that WTP to stabilize prices is generally increasing in income is consistent with the findings of Bellemare et al. (2013), who find that as they get wealthier, households are willing to give up an increasing proportion of their income for price stabilization in rural Ethiopia.

Moreover, because we conducted the same experiments in the lab with US college students and in the field with Peruvian farmers, our results have more external validity than the usual experiment. If one were to take our results at face value, one would need to rethink a number of policies aimed at stabilizing prices. Indeed, a number of such programs are based on the belief that producers respond to the presence of price risk by decreasing how much they produce, whereas our findings show that price risk at the extensive margin causes producers to produce more rather than less.

Our work suggests that the theory of producer behavior in the face of output price risk as well as the policies used to protect producers from price risk need to be rethought along the lines of prospect theory. Likewise, our experiments only considered producers facing output price risk in situations without storage or insurance. This suggests similar experiments aimed at studying consumer choice in the face of price risk, producer behavior in the face of input price risk, or producer behavior in the face of price risk with storage or insurance. For now, we leave both these endeavors to future research.

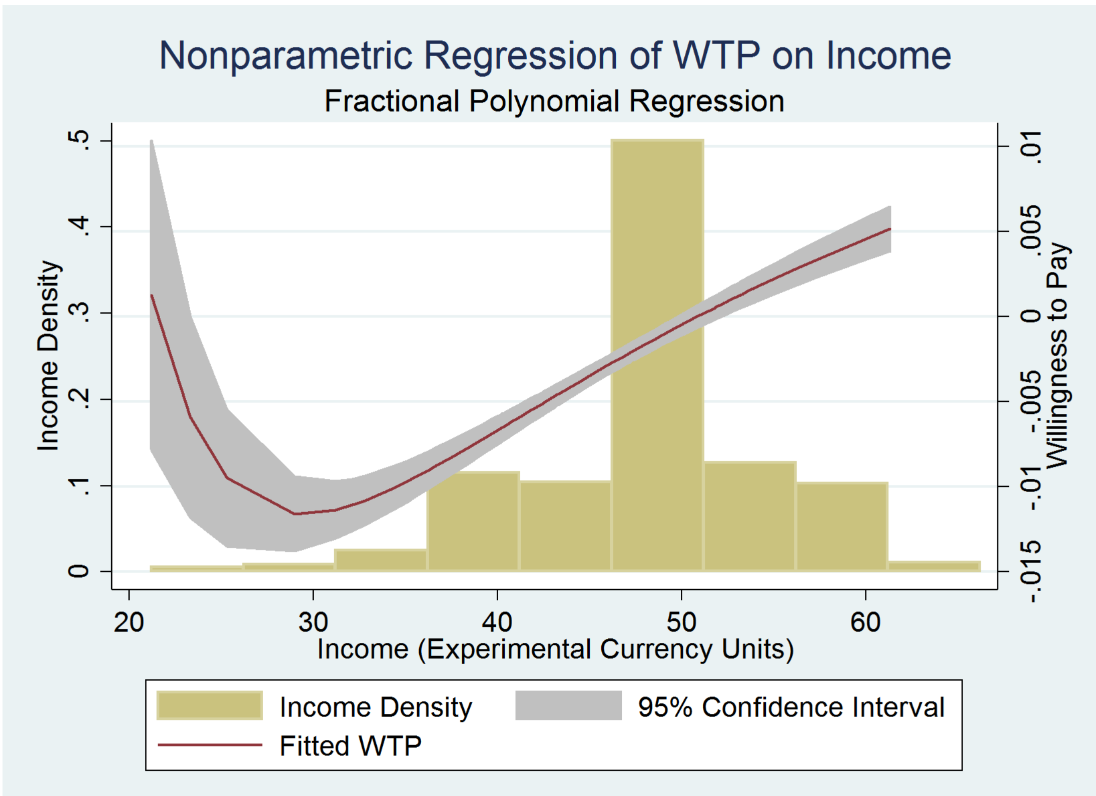

Figure 3.1: WTP for Price Stabilization as a Function of Income.

Table 3.1: Summary Statistics for the Pooled Sample

Variable	Coefficient	(Std. Err.)
Output	10.235	(0.056)
Price	6.946	(0.023)
Uncertainty Dummy	0.698	(0.009)
Setting 1 Dummy	0.302	(0.009)
Setting 2 Dummy	0.152	(0.007)
Setting 3 Dummy	0.110	(0.006)
Setting 4 Dummy	0.234	(0.009)
Setting 5 Dummy	0.203	(0.008)
Holt-Laury Switch Point	5.717	(0.056)
N	2378	

Table 3.2: Summary Statistics for the Cornell Sample

Variable	Coefficient	(Std. Err.)
Output	10.012	(0.072)
Price	6.875	(0.035)
Uncertainty Dummy	0.675	(0.015)
Setting 1 Dummy	0.325	(0.015)
Setting 2 Dummy	0.125	(0.011)
Setting 3 Dummy	0.075	(0.009)
Setting 4 Dummy	0.200	(0.013)
Setting 5 Dummy	0.275	(0.014)
Holt-Laury Switch Point	7.083	(0.048)
N	960	

Table 3.3: Summary Statistics for the Minnesota Sample

Variable	Coefficient	(Std. Err.)
Output	10.159	(0.105)
Price	6.902	(0.069)
Uncertainty Dummy	0.850	(0.017)
Setting 1 Dummy	0.150	(0.017)
Setting 2 Dummy	0.148	(0.017)
Setting 3 Dummy	0.100	(0.014)
Setting 4v	0.451	(0.023)
Setting 5 Dummy	0.150	(0.017)
Holt-Laury Switch Point	7.353	(0.071)
N	459	

Table 3.4: Summary Statistics for the Peru Sample

Variable	Coefficient	(Std. Err.)
Output	10.495	(0.106)
Price	7.038	(0.033)
Uncertainty Dummy	0.650	(0.015)
Setting 1 Dummy	0.350	(0.015)
Setting 2 Dummy	0.181	(0.012)
Setting 3 Dummy	0.149	(0.012)
Setting 4 Dummy	0.164	(0.012)
Setting 5 Dummy	0.155	(0.012)
Holt-Laury Switch Point	3.565	(0.089)
N	959	

Table 3.5: OLS Estimation Results for Production with Subject-Specific Random Effects

Variable	**Coefficient** (Std. Err.)
Uncertainty	0.982** (0.354)
Standard Deviation	-0.563† (0.291)
Arrow-Pratt Coefficient of RRA	-0.308 (0.189)
Holt-Laury First Dummy	0.394 (0.265)
Female	-0.262 (0.264)
Round	-0.021* (0.010)
Intercept	10.595** (0.313)
N	2319
$\chi^2_{(6)}$	17.855

Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

Table 3.6: OLS Estimation Results for Whether Subjects Minimize the Probability of Loss with Subject-Specific Random Effects

Variable	**Coefficient** (Std. Err.)
Uncertainty	0.014
	(0.036)
Standard Deviation	-0.078**
	(0.029)
Arrow-Pratt Coefficient of RRA	0.048**
	(0.014)
Holt-Laury First	0.014
	(0.019)
Female	0.005
	(0.018)
Round	0.001
	(0.001)
Intercept	0.947**
	(0.023)
N	2320
$\chi^2_{(6)}$	40.639

Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

Table 3.7: OLS Estimation Results for Expected Revenue with Subject-Specific Random Effects

Variable	**Coefficient** (Std. Err.)
Uncertainty	-0.079
	(0.258)
Standard Deviation	-0.985**
	(0.227)
Arrow-Pratt Coefficient of RRA	0.445**
	(0.113)
Holt-Laury First	0.121
	(0.165)
Female	0.137
	(0.164)
Round	0.009
	(0.008)
Intercept	4.067**
	(0.191)
N	2319
$\chi^2_{(6)}$	120.486

Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

Table 3.8: OLS Estimation Results for Production with Subject-Specific Random Effects

Variable	**Coefficient** (Std. Err.)
$P(p = 5)$ or $P(p = 9)$	-28.359*
	(12.847)
$P(p = 6)$ or $P(p = 8)$	-23.876*
	(11.906)
$P(p = 7)$	-12.434*
	(6.073)
Expected Gain	-0.235
	(0.154)
Expected Loss	0.936**
	(0.250)
Arrow-Pratt Coefficient of RRA	-0.098
	(0.148)
Holt-Laury First	0.415†
	(0.227)
Female	-0.215
	(0.228)
Round	-0.017†
	(0.010)
Intercept	23.883**
	(6.049)
N	2319
$\chi^2_{(9)}$	50.663

Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

Table 3.9: Production Function OLS Results with Subject-Specific Fixed Effects

Variable	**Coefficient** (Std. Err.)
Log of Price	0.756**
	(0.121)
Log of Income	-0.895**
	(0.128)
Round	-0.001
	(0.001)
Intercept	5.083**
	(0.300)
N	2378
R^2	0.044
$F_{(2,118)}$	17.362

Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

Chapter 4

Production under Output Price Ambiguity: An Experimental Evidence[1]

4.1 Introduction

How do producers make production decisions under output price ambiguity? Previous researchers (Sandmo, 1971; Batra and Ullah, 1974) developed theories of production under price uncertainty. Sandmo's theory famously predicted that, under price uncertainty, a risk-averse producer produces at a level lower than the optimal level of production under price certainty, failing to maximize profits (Sandmo, 1971). Batra and Ullah (1974) predicted that a producer who exhibits DARA (decreasing absolute risk aversion) would monotonically decrease the level of production according to a mean preserving spread of an output price distribution. These theories were developed under an assumption that producers know the distribution of output prices. We lack both theoretical and

[1]This chapter is a co-work with Marc Bellemare, Associate Professor in the Department of Applied Economics, University of Minnesota, and David Just, Professor in Charles H. Dyson School of Applied Economics and Management, Cornell University.

empirical evidence, however, on how production decisions are made when probability distributions of prices are unknown. Hereafter, we call price uncertainty with an unknown probability distribution *price ambiguity*, and distinguish this concept from *price risk*−price uncertainty with a known probability distribution.[2] Understanding how production decisions are made under price ambiguity is very relevant to the context of agriculture in developing economies in which farmers often face challenges in accessing market information due to various middlemen that create barriers for information flows (Sodhi and Tang 2014), incomplete insurance and credit markets, and significant information asymmetry between market participants (Chen and Tang, 2015).

In this paper, we first examine how production decisions are made under output price ambiguity. Do producers increase or decrease production levels under price ambiguity compared to the situation of price certainty? How do producers incorporate price information when making production decisions? Secondly, given that individuals are provided with only a limited amount of information on prices, we are interested in figuring out whether any behavioral anomalies are observed in decision making. Specifically, we examine whether producers show patterns of behavior consistent with gambler's fallacy (Tversky and Kahneman, 1971), framing (Meredith and Salant, 2011), prospect theory (Kahneman and Tversky, 1979), and safety-first decision making (Telser 1995; Bigman 1996). Lastly, we investigate if there are any systematic differences in decision making patterns across contexts. Thus, we generate unique experimental data based on a simple decision-making game designed to study how producers make production decisions facing output price ambiguity, i.e., knowing only the range, not distribution, of possible prices.

Empirical studies on decision making under price ambiguity have focused on the formation of reference prices of financial commodities (Arkes et al., 2008; Baucells et al, 2011; Chen and Rao, 2002) and how references prices affect investment and selling decisions in financial markets (Gneezy, 2005; Lee et al., 2008). Another strand of empirical

[2]Uncertainty of unmeasurable nature is called Knightian risk following the name of economist Frank Knight (1885-1972) who distinguished measurable uncertainty and unmeasurable uncertainty in his work (Knight, 1921).

literature on decision making under price ambiguity investigates producers' marketing decisions under price uncertainty. A recent study by Mattos and Zinn (2016) conducted a set of experiments on price information and marketing decisions with Canadian grain producers and find that producers form reference prices based on the current market price, the highest price to date, and the expected price (Mattos and Zinn, 2016). Another paper related to our study is an experimental work by Warnick et al. (2011). They conducted experiments to measure farmers' risk and ambiguity aversion in rural Peru to examine their relationships with crop diversification. They find that farmers' ambiguity aversion is negatively associated with crop diversification, while risk aversion has no measurable association with crop diversification (Warnick et al., 2011).

This study contributes to the literature in the following ways: First, to the best of our knowledge, this is the first study to examine production decision making under output price ambiguity. Previous studies focused on farmers' marketing decisions (Mattos and Zinn, 2016) or crop diversification (Warnick et al., 2011), but not production. From a policy perspective, understanding the effect of price ambiguity on production can inform policies to alleviate food insecurity in developing countries. For example, if price ambiguity contributes to decreases in production, efforts to provide a better access to price information on agricultural commodities to farmers might be helpful in increasing production. In conjunction with findings in Bellemare et al. (2017) in which producer decision making under price risk is examined, this paper contributes to a broader literature on producer decision making under uncertainty. Second, unique data set is generated based on unique lab experiments designed specifically to examine how producers make production decision under price ambiguity. Given the charts that show relationships between production decision, costs, and profits under different price scenarios, subjects are asked to make production decisions in subsequent rounds.[3] For internal validity, in every round, we randomize between situations of output price certainty and price

[3]Cost and profit functions used in this experiment are convex and concave in the level of output, respectively, and follow the functional forms used in Sandmo's (1971) theoretical model of production decision making under output price uncertainty.

ambiguity. With our experimental subjects, we also elicit risk attitudes using the list design by Holt and Laury (2002). For external validity, we conduct our experiments in the lab with student subjects in the U.S., and we take our lab experiments to the field and conduct the same experiments with minimal necessary adjustments with farmers in rural Peru.

The paper proceeds as follows: Sections 4.2 and 4.2 describe the experimental design and the data, respectively. Sections 4.4 discusses the empirical strategy, and Section 4.5 presents the results, robustness checks, and limitations. The paper is summarized and future directions are discussed in Section 4.6.

4.2 Experimental Design

In every session, each subject played two types of experiments−price ambiguity experiment and Holt-Laury list experiment. After finishing both experiments, subjects were asked to fill out basic demographic information. Then, each participant received cash payoffs at the end of the session. Subjects spent about 90 to 120 minutes for the experiments and remuneration. Four sessions are conducted in total. First three sessions were conducted in the U.S. with undergraduate students, and the last session was conducted in Peru with smallholder farmers.

4.2.1 Price Ambiguity Experiment

In the price ambiguity experiment, each subject hypothetically played a role of a wheat producer and was asked to decide how many units of wheat to under price certainty or price ambiguity. There were five possibilities for the selling price of wheat−$\$5, \$6, \$7, \$8,$ and \$9 per bushel. Subjects could choose any integer from 0 to 20 as levels of production x (in 1,000 bushels). A simple cost function convex in x with a fixed cost of 15 (in $\$1,000$), $c(x) = 2x^{1.4} + 15$, was used. Accordingly, a simple profit function $\pi = p \cdot x - c(x) = p \cdot x - 2x^{1.4} - 15$ that is concave in x was used. Each subject was given charts that describe, the amount of costs to be incurred according to production levels 0 through 20 (in 1,000 bushels), and corresponding profits (in $\$1,000$). Each subject was also given a summary chart that shows only the relationship between the production level and the profit under the five price scenarios. See Appendix I for the charts.

The structure of the game is described in Figure 4.1. In each round, subjects were randomly given one of the two situations: (1) Selling price of wheat will be exactly \$7 (price certainty); (2) Selling price of wheat will be one of the five values$-\$5, \$6, \$7, \$8,$ or \$9 per bushel (price ambiguity). Under each given situation, subjects were asked to determine how much wheat to produce by choosing any integer between 0 and 20 as their production level. After every subject has made her own production decision, a real ping pong ball was randomly drawn from a bag containing 80 balls described in Figure 4.2. The bag was shown to the subjects, but the distribution was not shown. In each round, randomization was conducted to determine the situations of price certainty and price ambiguity. In the lab, experimenters drew a random integer between 1 and 3. Number 1 (2 or 3) corresponded to the situation of price certainty (ambiguity). This randomization procedure was made public to all participants in each session using an excel spreadsheet and a beam projector in the lab. Therefore, this experimental design allows within-subject variation in prices over rounds, but no between-subjects variation in prices in each given round.

Ten practice rounds were played in the beginning to help subjects understand the experiment. Subjects were allowed to freely ask questions to facilitate their decisions during the practice rounds. Ample time was given between rounds to make sure that subjects understand the relationship between the decisions and the profits that they made. Then, twenty real rounds were played in which remunerations were directly related to the profits subjects make. Subjects were allowed to look at the charts and take notes throughout the session.

4.2.2 Holt-Laury List Experiment

The list experiment developed by Holt and Laury (2002) was conducted to elicit subjects' attitudes to income risk. Each subject was presented a table of ten paired lotteries, A and B, from which she was asked to choose one that she preferred. Lottery B is always riskier than lottery A. In the first row, expected value of lottery A is greater than that of B, and as row number proceeds, the difference in the expected values decreases. Eventually, the expected value of B exceeds that of A. If a subject chooses option A, then she proceeds to the next row. If she chooses option B, she was asked to stop. Thus, we enforced monotonic switching. For example, if a subject switched from option A to B in row 5, it was assumed that she would have chosen option B from row 5 and on. A higher row number in which a subject switched from lottery A to lottery B corresponds to a greater degree of income risk aversion.

4.2.3 Payoff Scheme

In the price ambiguity experiment, each subject started from an endowment of \$25. In a given round, profit ranges between $-\$47.58$ and \$32.61. At the end of the session, for each subject, one round was randomly selected among the 20 actual rounds by making the subject roll a 20-sided die. The payoff from the price ambiguity experiment was determined by summing up the \$25 endowment and a half of the profit in the randomly selected round. For example, if a subject made a loss of 30 in the selected round, her final payoff was determined as $\$25 + (-\$30 \times 0.5) = \$10$. The final payoff from the price ambiguity game ranged between \$1.21 and \$41.31.

The payoff from the Holt-Laury list experiment was determined in the following way: A random number between 1 to 10 was drawn by each subject using a ten-sided die to determine a row number. Then, according to the choice of A or B made by the subject and the probabilities given in lotteries A and B, payoff was determined by rolling a ten-sided die again. For example, suppose that the first random number drawn was 7 and also that the subject switched from lottery A to B in the fifth row. Then, according to the choice made by the subject, lottery B in the row 7 is played by rolling a ten-sided die. If the number drawn from the second roll of a die was 7 or less, then the subject receives $3.85. If the number was 8 or higher, then the subject receives $0.1. The payoff from the Holt-Laury List Experiment ranged between $0.1 and $3.85.

Subjects received $45 for compensation for their time and for filling out demographic information, and in addition earned a sum of payoffs between $1.31 and $45.16 from the price ambiguity and Holt-Laury experiments depending on their performance and luck. Experimenters explained the payment scheme in the beginning of each experiment, but actual cash payments were made after all the experiments were finished.

4.2.4 Experiments with Peruvian Farmers

For experiments in rural Peru with smallholder farmers, the experimental protocol was translated from English to Spanish, making only minimal necessary changes. The crop was changed from wheat to potato, the crop produced more commonly in Peru. Numbers for the range of production levels (0-20), range of prices (5-9), and cost and profit functions remained unchanged and only units were changed, making sure that the numbers are reasonable in the context of recent prices. For example, the unit of production was changed from 1,000 bushels to 10 kilos; the unit of prices was changed from USD ($) per bushel to Nuevos Soles (PEN, or *S/.*) per 10 kilos. To facilitate understanding of randomization during the price ambiguity experiment, enumerators carried a panel of randomization chart (See Appendix IV) and showed it to subjects. For Holt-Laury list experiment, both pictures (See Appendix V) and the original list were presented to subjects to facilitate understanding. Proportion of the participation fee and endowments for the price ambiguity game remained unchanged.[4]

[4]For experiments in the U.S., the participation fee and the endowments (from which a subject can lose almost all or can gain more depending on the results of the price ambiguity experiment) were 45 USD and 25 USD, respectively. For experiments in Peru, these amounts were 45 PEN and 25 PEN, respectively.

4.3 Data and Summary Statistics

Experiments were conducted in three locations over four sessions. Sessions 1 and 2 were conducted in December 2014 and March 2015, respectively, in the Lab for Experimental Economics and Decision Research (LEEDR) at the Dyson School of Applied Economics and Management at Cornell University. Cornell's LEEDER lab has a rule that does not allow deceiving subjects. For each session, 24 subjects were recruited via LEEDR lab's listserv, and the subjects were undergraduate students enrolled in the Dyson School. Session 3 was conducted at the University of Minnesota in October 2015. Subjects were recruited via undergraduate listserv of the Department of Applied Economics at the University of Minnesota. 24 subjects were recruited, but only 19 showed up due to weather. Session 4 was conducted in rural Peru in collaboration with the Innovations for Poverty Action (IPA) in Lima, Peru in August and September 2016. Farmers were contacted and recruited by two enumerators in the rural vicinity of Lima, and efforts were made to make sure that farmers are literate and numerate. Several screening questions were asked to make sure that they understand basic concepts of probability, and 48 farmers participated in experiments. Therefore, throughout all sessions, 115 subjects participated.

There are several notable differences across sessions and locations. First, for sessions 1, 2, and 3 conducted in the U.S., experiments were conducted in a group setting in the lab (Cornell) or in a classroom (Minnesota) by authors. On the other hand, for session 4 conducted in rural Peru, two enumerators who speak Spanish conducted experiments one-on-one with each participant. Therefore, in sessions 1, 2, and 3, there is only within-subject variations in the prices drawn in each round and no between-subjects variations. In session 4, however, there are both between-subjects and within-subject variations in prices. Secondly, we were interested in figuring out whether the order of the games conducted affects production choices. Thus, in session 1, we conducted the price ambiguity game first, and the Holt-Laury list experiment was conducted later. In sessions 2 and 3, the Holt-Laury list experiment was conducted first. In session 4 in which experiments were conducted one-on-one with subjects, the order was randomized for each subject using a throw of die. Table 4.1 summarizes the date, location, number of subjects, and order of games of each session.

Table 4.2 presents summary statistics for the pooled sample from all sessions. Because there are a total of 115 subjects and each subject plays 10 practice and 20 actual rounds of the price ambiguity game, there are $115 \times 30 = 3,450$ subject-round observations. Mean value of production level was about 10.76 units, and the situation of price uncertainty was drawn 68% of all rounds. On average, during the Holt-Laury list experiments, subjects switched from option A (safe option) to option B (risky option) between rows 5 and 6, indicating that an average subject is slightly risk-averse. Figure reffig:production-allsessions is a histogram of production levels chosen in the real rounds (11-30) under the situation of uncertainty.

Tables 4.3, 4.4, 4.5, and 4.6 present summary statistics for the sub-samples corresponding to the sessions 1, 2, 3, and 4, respectively. The average Peruvian farmer is significantly older than the average student in the U.S. Another noticeable difference between the student subjects in the U.S. and farmer subjects in Peru is their risk attitudes. During the Holt-Laury list experiment, subjects who participated in sessions 1 through 3 on average switched from the option A to option B either in row 6 or 7, indicating risk aversion. On the other hand, Peruvian farmers switched either in row 3 or 4 on average, indicating risk loving or risk neutrality.

Figure 4.4 shows histograms of the prices drawn during the practice rounds (rounds 1-10) in each session. Interestingly, in session 1, only prices of 5 and 7 were randomly drawn during the practice rounds. On the other hand, in session 2, only high prices (7, 8, and 9) were randomly drawn. Given the concern that the price drawn during the practice rounds may significantly affect priors for the prices during the real rounds, in session 3, authors intentionally drew prices from a uniform distribution without replacements. In session 4, prices were drawn randomly for each subjects in each round, and the histogram looks like a normal distribution.

Figure 4.5 shows histograms of the production levels chosen under uncertainty in real rounds (rounds 11-30) in each session. From inspection, it is noteworthy that the levels of production chosen in session 2 tend to be higher than those in session 1. In session 3 in which prices were drawn from a uniform distribution without replacements, in surprisingly many times (about 60% of all subject-round observations), subjects chose to produce at 10, the optimal level of production when price is 7. In session 4, we see greater variations in the production levels.

4.4 Empirical Strategy

For empirical analysis, we estimate the following panel regression:

$$Y_{i,t} = \beta_0 + \beta_1 U_{i,t} + \beta_2 \overline{P}_{i,t-1} + \beta_3 \overline{V}_{i,t-1} + \beta_4 Z_i + C_i + t + \epsilon_{i,t} \tag{4.1}$$

$Y_{i,t}$ is subject i's choice of production level in round t. $U_{i,t}$ is 1 if price is uncertain in round t and 0 otherwise. $\overline{P}_{i,t-1}$ is a cumulative average of prices from round 1 to round $t-1$ for subject i, and $\overline{V}_{i,t-1}$ is a variance of prices drawn drawn from round 1 to round $t-1$ for subject i. Z_i is a vector of observed individual-specific characteristics, such as the row number of switch in the Holt-Laury game that indicates risk attitudes, gender, and age, and C_i is an effect specific to individual i. t is a linear time trend for round. Lastly, ϵ_{it} is an error term with an expected value of zero, with standard errors clustered in subject level.

We estimate an OLS with random effects model, because our experimentally-assigned variables of interest (namely, $U_{i,t}$, $P_{i,t-1}$, and $V_{i,t-1}$) are orthogonal to the error term. Hausman specification test indicates that random effects and fixed effects models are not significantly different. Given that random effects models are more efficient than fixed effects models, we estimate random effects model.

4.5 Results

4.5.1 Main Results

Table 4.7 shows the main results. Throughout columns (1)-(5), we can see that individuals increased their production level by about half unit on average when faced with price ambiguity as opposed to price certainty, and that the coefficient is statistically significant. Columns (2)-(5) show that a dollar (or a Peruvian Sole) increase in the cumulative average of the prices drawn up to a previous round significantly increases production level by 1.2-1.7 units. Cumulative variance of the prices drawn up to a previous round does not have a significant impact on production, implying that levels of past prices may matter more than the volatility of prices. Individual's switch point during the Holt-Laury game has a negative and significant coefficient estimate, indicating that a greater degree of income risk aversion is significantly associated with lower levels of production. We can also observe that, as rounds proceed, individuals tend to choose higher levels of production. Being a female does not have a significant effect on the choices of production level.

Table 4.8 presents how individuals incorporate price information from various windows of time horizon in making production decisions, displaying the coefficient estimates on the cumulative average price from all previous rounds (column (1)), 4-periods (column (2)), 3-periods (column (3)), and 2-periods moving average prices (column (4)), and one-period lagged prices (column (5)). Going from the results in columns (1) to (4), we can see that the magnitude of the coefficient estimates monotonically decreases, indicating that individuals tend to use full information when making the production decisions. However, from column (5), we can see that the magnitude of the coefficient estimate on one-period lagged prices is greater than the those of the moving averages, suggesting that the most current price information matters more than older information. This is consistent with 'recency effects' in which last event in a series has a disproportionate impact on overall effect (Chen and Rao, 2002) and also with findings from the study by Mattos and Zinn

(2016) on producers' reference prices.

4.5.2 Behavioral Anomalies

In this subsection, we investigate if we can find some evidence of behavioral anomalies or uses of heuristics when subjects are faced with price ambiguity.

Gambler's Fallacy

People's tendency to view small sample as representative has been called the law of small numbers (Tversky and Kahneman, 1971), and gambler's fallacy is a famous example. The gambler's fallacy is the mistaken expectation that "any deviation in one direction will soon be canceled by a corresponding deviation in the other (Tversky and Kahneman, 1971)," or, one's belief that sampling is a "self-correcting process (Tversky and Kahneman, 1971)." In other words, it describes a tendency to think that "early draws of one signal increase the odds of next drawing other signals (Rabin, 2002)"

The variable 'underestimation' is the difference between the actual price drawn in the previous round and the expected price in the previous round estimated from the choice of production level. This difference is positive (or negative) when the actual price drawn was greater (less) than the expected price, i.e., when the subject underestimated (or overestimated) the price in the previous round. Coefficient estimates on 'underestimation' in Tables 4.7 and 4.8 show that underestimating the price in the previous round significantly decreases the level of production in the current round. In other words, having seen a greater-than-expected price being drawn in the previous round, a subject decreases her production level, expecting to see a lower price in the current round. Therefore, our subjects display behavior consistent with gambler's fallacy.

Order Effect

Literature in behavioral economics demonstrate that the order in which options are presented affects choices of individuals. For example, the order in which candidates are listed on a ballot can affect the result of an election (Meredith and Salant, 2011). In the context of our experimental setting, for example, a subject who completed the Holt-Laury list experiment before the price ambiguity experiment may feel that she has earned some money to gamble on the price ambiguity experiment and thus make riskier choices, if the order effect was present.[5]

To test whether the order of the experiments affects production decisions, we mixed up the order of the price ambiguity experiment and the Holt-Laury list experiment. In session 1, price ambiguity experiment was conducted first; In sessions 2 and 3, the Holt-Laury list experiment was conducted first; In session 4, the order was randomized for each subjects. Enumerators rolled a six-sided die in the beginning of each session to determine which of the two games the subject would play first. If the number was either 1, 2, or 3, the price ambiguity experiment was conducted first; If the number was 4, 5, or 6, then the Holt-Laury list experiment was conducted first.

The variable 'Holt-Laury First' is an indicator variable equal to 1 if the Holt-Laury list experiment was played first; 0 otherwise. In Table 4.7, the coefficient estimate on the 'Holt-Laury First' is not statistically significant from zero. Thus, evidence is not strong enough to support the existence of order effects in any direction in our experimental setting.

Prospect theory

Kahneman and Tversky (1979) developed the prospect theory as an alternative to the expected utility theory in order to explain decision making under uncertainty. According to the prospect theory, people interpret outcomes as gains and losses relative to some reference point. We are interested in testing whether individuals behave according to the predictions of the prospect theory. Specific predictions to be tested are the following:

[5] In our experiments, payoffs were summed up and paid at the end of the session, after both experiments were conducted. Therefore, having completed only the first part of the session, subjects were not paid cash yet. But the mere idea of having earned some money in the first part of the session may affect choices in the latter part of the session.

First, the value function is steeper for losses than for gains, i.e., individuals get hurt more by losses than they gain from gains. Second, the value function is concave for gains and convex for losses, i.e., individuals are risk-averse over gains and risk-seeking over losses. Third, individuals tend to overweigh outcomes with low probabilities.

As there is no way of testing where the reference point is, we would like to first use a reference point of zero profit in the previous round, i.e., a positive (negative) profit in the previous round is considered as a gain (loss). Table 4.9 shows the result. Column 1 only contains the magnitudes of lagged gains and losses, and column 2 contains both the magnitudes and the squared magnitudes of lagged gains and losses. Both the columns 1 and 2 in Table 4.9 indicate that individuals produce more (less) after making a positive (negative) profit in the previous round. First, we can observe that individuals who made a positive (negative) profit in the previous round tend to increase (decrease) production. Given that the size of the coefficient estimate is greater for the magnitude of the gain than for the magnitude of the loss, we cannot find evidence of the prediction that the value function is steeper for losses than for gains. Looking at the squared terms of the gains and losses that are negative and positive, respectively, we can see that the second prediction can be supported by our results−the value function seems to be concave for gains and convex for losses.

Table 4.10 shows how subjects react to moderate and extreme outcomes. In columns 1 and 2, a lagged profit of ±4.76 was picked as thresholds.[6] In column 1, the base case is having had a negative profit in the previous round. Dummy variables are created for having a profit greater than 4.76 (extreme outcome) and a profit between 0 and 4.76 (moderate outcome). Column 1 shows that having had a positive profit in the previous round increases the production level compared to the situation of having had a negative profit. It is also shown that subjects increase the production level by a greater degree after having a profit greater than 4.76 compared to having a profit between 0 and 4.76.

[6] In a given round, a profit can range from -47.58 to 32.61. 4.76 was naturally picked as a threshold for a high profit given that 4.76 is the amount of profit when price is $7 and production level is 10 which is the optimal level of production when price is $7.

In column 2, the base case is having had a positive profit in the previous round. We can see that having had a negative profit decreases production level, and having had a profit less than -4.76 (extreme outcome) decreases production level by a greater amount than having had a profit between -4.76 and 0 (moderate outcome). In columns 3 and 4, a lagged profit of ± 15 was picked as threshold values. We can again see that subjects react more to extreme outcomes than to moderate outcomes in the previous round. Especially, having had a previous profit greater than 15 increases the level of production by more than 3 units compared to the case of making a loss.

All in all, our results support some predictions of the prospect theory while rejecting some others. Based on our results, subjects tend to behave consistently with the prospect theory by overweighing events with low probabilities and being risk-averse over gains and risk-seeking over losses. However, subjects tend to react more to gains than to losses, which is inconsistent with the prospect theory.

Safety-First

Under safety-first rule, individuals make decisions in order to avoid disaster (Telser 1995; Bigman 1996). In this paper, we are interested in figuring out: (1) whether price ambiguity makes individuals to make safety-first choices; and (2) what makes individuals to follow (or deviate from) the safety-first decision-making rule.

We define safety-first decision making as choosing a production level in order to minimize the possibility of making a loss. Following this definition, choosing a production level between 5 and 15 is equivalent to making a safety-first choice in our setup. Table 4.11 shows regression results with an indicator for safety-first choices as a dependent variable. The dependent variable is 1 if a subject made a safety-first choice, and 0 if not. From both columns 1 and 2, we can see that price ambiguity causes individuals to deviate from safety-first choices. Column 1 shows that making a loss in the previous round induces individuals to make safety-first choices, but it is not significant in column 2 where session dummies are included. On the other hand, making a positive profit (gain) in the previous round causes individuals to deviate from making safety-first choices. The coefficient estimate on 'underestimation' is positive and significant, which means that, having seen a price that is greater than what was expected in the previous round, subjects make safe choices in the current round, which is also consistent with gambler's fallacy. Greater degree of income risk aversion (switch) is significantly related with making safer choices in column 1, but it is not significant in column 2. Lastly, subjects in Peru (session 4) significantly deviated from making safe choices.

4.5.3 Differences across Contexts

Recall that different sessions were conducted in different dates and locations. Sessions 1 and 2 were conducted at Cornell University in December 2014 and March 2015, respectively, and session 3 was conducted at the University of Minnesota in October 2015. Session 4 was conducted in rural Peru during August-September 2016. Subjects in sessions 1 through 3 were undergraduate students, and subjects in session 4 were smallholder farmers in rural Peru.

Table 4.12 shows whether there is any differential effect of price ambiguity and cumulative average prices by session, using interaction terms. In column 1, the base case is session 4 conducted in Peru. We can see that, given price uncertainty, subjects in session 1 decreased production level, whereas subjects in session 2 increased it. There was no differential effect of session 3 participants given uncertainty. In column 2, the base case is sessions 1-3 in which students in the U.S. participated as subjects. Column 2 shows that, farmers in rural Peru tend to produce more under uncertainty compared to students in the U.S. Comparing the coefficients on uncertainty in columns 1 and 2, we can see that positive and significant impact of uncertainty on production was driven by participants in sessions 2 and 4. Cumulative average price has positive and significant coefficient in both columns 1 and 2, and we do not observe differential effect of sessions.

Table 4.13 shows results by each session. Again, subjects in session 1 decreased production under uncertainty, but subjects in sessions 2 and 4 increased production under uncertainty. Participants in session 3 neither significantly increased nor decreased production under uncertainty. Negative coefficient on underestimation, which suggests a gambler's fallacy, is consistent across all sessions, although not significant in session 3.

Why do we observe different patterns of production choices under price ambiguity according to sessions? Comparing the prices drawn in sessions 1-4 shown in Tables 4.3–4.6, we can see that the average price was higher for session 2, but the difference is not statistically significant. Figure 4.4 shows histograms of only the prices drawn under uncertainty during practice rounds (rounds 1-10) by session. We can see that only low prices (5 or 7) were drawn in session 1 and only high prices (7, 8, or 9) were drawn in session 2. Suspecting that the different prices drawn might have affected the priors formed by subjects in sessions 1 and 2, we intentionally drew prices from a uniform distribution without replacements in session 3 during practice rounds. In session 4 in which prices in all rounds were randomly drawn for each subject, the distribution resembles a normal distribution in Figure 4.2 which ping pong balls were drawn from.

Figure 4.5 compares production choices during real rounds (rounds 11-30) under uncertainty by session. We can see that in session 3 in which prices were drawn from a uniform distribution during practice rounds, subjects chose to produce at 10 (optimal production level when price is 7) in 39% of all subject-round observations. We can also see that the distribution of production choices is a lot more spread out for session 4. Figure 4.6 shows scatter plots of cumulative average prices by session, and Figure 4.7 shows the difference between actual and optimal production level by session. A positive (negative) difference indicates that subjects on average produced more (less) than the optimal level based on the cumulative average price. According to the cumulative average prices that increases (decreases) over time in session 1 (session 2), we can see that subjects adjust their production levels from above (below) in session 1 (session 2). In sessions 3 and 4, subjects tend to produce more than the optimal level throughout the rounds. Figures 4.8 through 4.11 show the plots of the difference between actual and optimal production level by each individual for sessions 1 through 4.

Another notable difference across context is the switch point during the Holt-Laury list experiment. Subjects in sessions 1-3 switched from option A to option B in row 7 on average, 6 safe choices. This corresponds to having the coefficient of relative risk aversion between 0.41 and 0.68, or being risk averse (Holt and Laury, 2002). This is very similar to the degree of risk aversion Holt and Laury (2002) finds for students in the U.S. using the same amount of payoffs. From Table 4.6, we can see that subjects in session 4 switched in row 3 on average. This corresponds to having the coefficient of relative risk aversion between -0.95 and -0.49 (very risk loving). Thus, we find that farmer subjects who participated in session 4 are much more risk loving than what was found by Warnick et al. (2011) for Peruvian farmers[7] and what Cardenas and Carpenter (2008) summarized as findings for subjects in developing countries.

Again, subjects in sessions 2 and 4 significantly increased production levels under price ambiguity. We conjecture that the behavior of subjects in sessions 2 is associated with unusually high prices drawn during the practice round in session 2, and also that the results in session 4 is largely driven by subjects' risk-loving attitudes.

4.5.4 Risk Attitudes and Production Decisions

Sandmo (1971) predicted that, under price risk, risk-averse producers would decrease the level of production compared to the situation of price certainty. How would risk-averse producers behave under price ambiguity? Table 4.14 shows regression results with interaction terms for risk attitudes. Column 1 includes results with interaction terms involving an indicator for risk-aversion,[8] and column 2 includes interaction terms involving the row number in which a subjects switched from a safe to a risky choice. We do not see a differential effect of price ambiguity or cumulative average price on the level of production when the indicator for risk aversion was used. However, column 2

[7] Warnick et al. (2011) used a measure to elicit risk aversion inspired by Eckel and Grossman (2008), and found that the corresponding range of risk aversion of Peruvian farmers is between 0.27 and 0.48.

[8] The indicator for risk-aversion was created following Holt-Laury's (2002) range of relative risk aversion. The value is 1 if a subject has made 5 or more safe choices in the list experiment; 0 otherwise.

shows that, given price ambiguity, a greater degree of risk aversion significantly decreases production levels. Or, given one's risk attitude, price ambiguity significantly decreases production. We can also see that, given a cumulative average price, greater risk aversion significantly decreases production level.

Table 4.15 shows the results for risk-averse (column 1) and risk-neutral to risk-loving (column 2) subsamples separately. We can see that the increased production level under price ambiguity is driven by risk-neutral and risk-loving subjects. Risk-averse subjects tend to slightly decrease production under price ambiguity although it is not statistically significant. Both risk-averse and risk-neutral to risk-loving subjects update production levels according to cumulative average prices and significantly increase production level as rounds proceed. We see evidence of gambler's fallacy from both subsamples.

4.5.5 Robustness Checks

In the lab-in-the-field experiments in Peru, we included a set of survey questions asking whether subjects could understand the experiments. Among 48 subjects participated in session 4 (experiments in Peru), 5 individuals and 3 individuals reported that they could not understand the price ambiguity game and Holt-Laury list game, respectively.[9] Columns 1 and 2 of Table 4.16 report results from excluding the 8 individuals who self-reported that they could not understand either the price ambiguity experiment or the Holt-Laury list experiment, without and with session dummies. Our basic results are robust to the exclusion of the subjects who admitted lack of understanding.

From the charts provided to the subjects, we can see that producing at 1, 2, 3, or 20 units are not rational given any price scenario.[10] There are 4 individuals among the U.S. student subjects and 17 among the Peruvian farmer subjects who produced at these levels during real rounds. Columns 3 and 4 show the results excluding the 8

[9] The groups of individuals that self-reported their lack of understanding of the two games do not overlap.

[10] For example, at any given price level, producing at 4 yields a higher profit than producing at 1, 2, or 3; Likewise, producing at 19 always yields a higher profit than producing at 20 at any given price.

subjects who self-reported their lack of understanding and the 21 subjects who made the irrational choices,[11] without and with session dummies. We can see that the effect of price ambiguity, although still positive in sign, become insignificant. Cumulative average price is still positive, although it becomes insignificant due to a high standard error when session dummies are included.[12]

All in all, when the subjects who self-reported their lack of understanding of the experiments are excluded, our basic results are robust. When we exclude the subjects who made irrational choices during real rounds of the price ambiguity game as well, uncertainty becomes insignificant and cumulative average price becomes marginally significant. Our findings on gambler's fallacy is robust, and greater degree of risk aversion consistently decreases production.

4.5.6 Limitations

This study is not without its limitations. Our results indicate that production level is increased under price ambiguity. There might be a possibility that this result was driven by the 'house-money effect,' a tendency that investors buy riskier assets after making a profitable trade (Thaler and Johnson, 1990). We had to guarantee some fixed amount of remunerations to our participants in order to compensate for their time. Thus, student subjects received 45 USD and 45 PEN for participation. These are the amounts of money that participants received regardless of their performance in price ambiguity experiment and the Holt-Laury List experiment. To minimize the possibility that subjects think that they have earned some positive profits to gamble during the experiments and take high risks, we mentioned during the instructions that subjects receive the fixed payments "for their time for participation and also for filling out demographic questions." But with our experimental design, we could neither eliminate nor test the possibility of the house money effect.

[11]There are two subjects who both self-reported their lack of understanding and were spotted as irrational. Thus, a total of 27 subjects were excluded.

[12]The p-value on the cumulative average price is 0.147.

4.6 Concluding Remarks

We generate experimental data from unique production game designed to study decision making under price ambiguity. Our results from the pooled sample indicate that subjects increase production levels under price ambiguity, but when we examine the subsamples, we find that the results were driven by two factors: information on past prices and risk attitudes. First, priors on prices formed during practice sessions seem to matter. In sessions 1 and 2 in which experimenters accidentally drove low and high prices during practice sessions, respectively, subjects decreased and increased production levels under price ambiguity. In session 3 where prices were drawn from a uniform distribution without replacements, price ambiguity had no significant impact on production. Second, this result is also driven by risk-loving subjects based on the risk attitude elicitation from Holt-Laury list experiments. Also, participants in our lab-in-the-field experiments in Peru exhibited risk-loving tendency and produced significantly high levels of output during price ambiguity. Thus, we find that subjects' risk attitudes play an important role in making production decisions.

How do subjects incorporate price information when making production decisions? We observe that subjects rationally incorporate and update price informations following the cumulative average of past prices. We find evidence that subjects incorporate all the past price information, but most current price information matters more than older information which is similar to what Mattos and Zinn (2016) find for producers' marketing decisions in Canada.

We examine whether people resort to heuristics when making production decisions with very limited information. We find very consistent and strong evidence of gambler's fallacy. We also find some behavior consistent with prospect theory−subjects react more to extreme values of profits in the previous rounds.

What can we learn from the findings in this paper in conjunction with the findings in Bellemare et al. (2017)? Bellemare et al. (2017) conducts experiments that are almost identical to the experiments in this study. But in Bellemare et al. (2017) subjects know price distributions. Under the situation of price risk not price ambiguity, subjects significantly increase production at an extensive margin but decrease production in response to price risk at the intensive margin. In our experimental setup in which subjects do not know price distributions, contexts matter and past price information form expectations for future prices. Also, law of small numbers and producer's risk attitudes dictate production decisions.

There is a possibility that subjects may have increased their production levels under price ambiguity due to the fixed payoffs that they received for participation, which is a limitation of this study. In that spirit, making the following changes to the price ambiguity experiments conducted in this paper can be interesting to pursue for future studies: First, with a varying amounts of participation payoffs, we could test whether there is a house money effect. Second, introducing an opportunity to purchase insurance products or a requirement to satisfy a subsistence level of profits (below which, for example, subjects "die" and should drop out of the session) and investigating how production decisions are affected might be topics worth exploring.

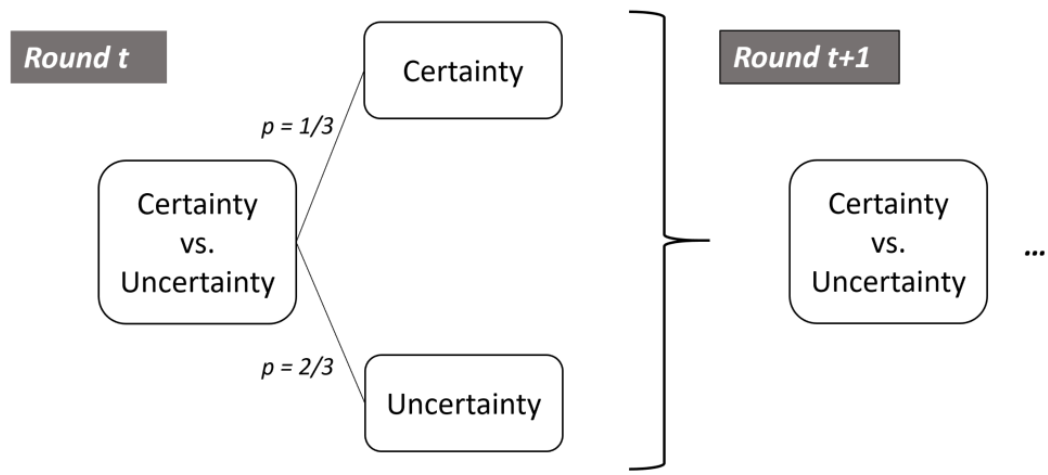

Figure 4.1: Structure of the Production Game

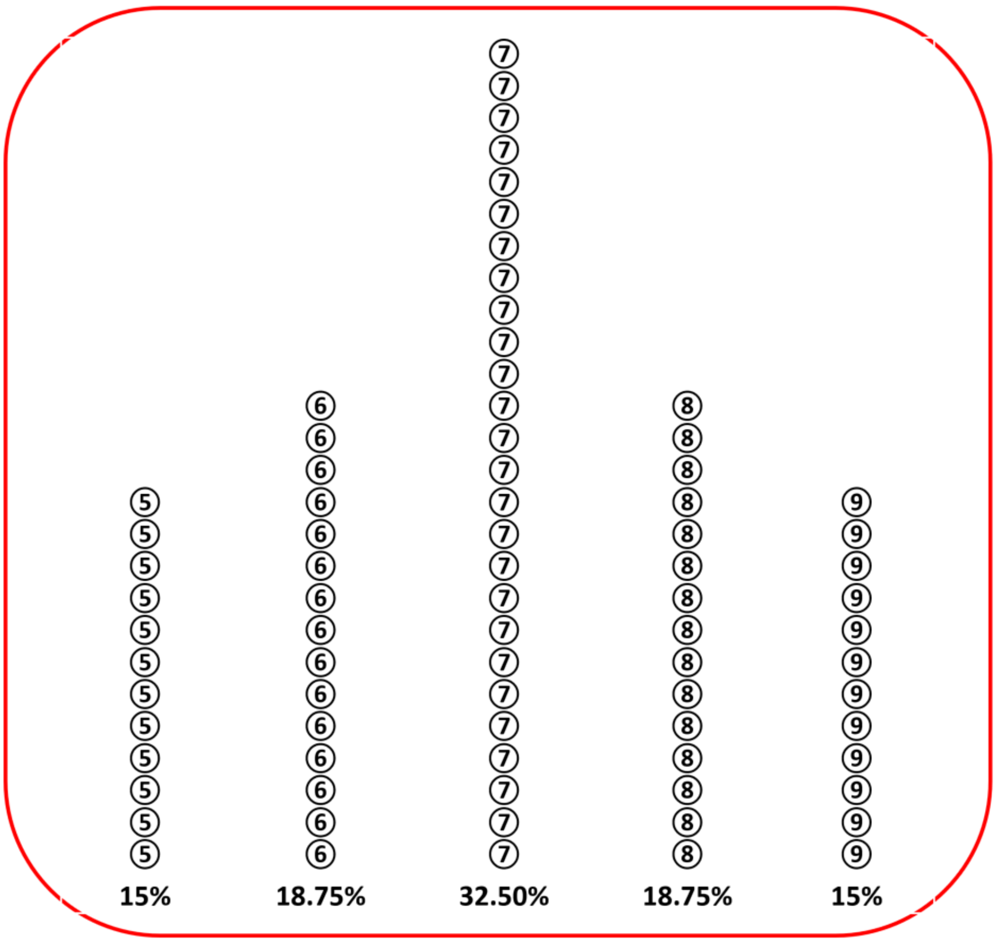

Figure 4.2: Bag of 80 Balls

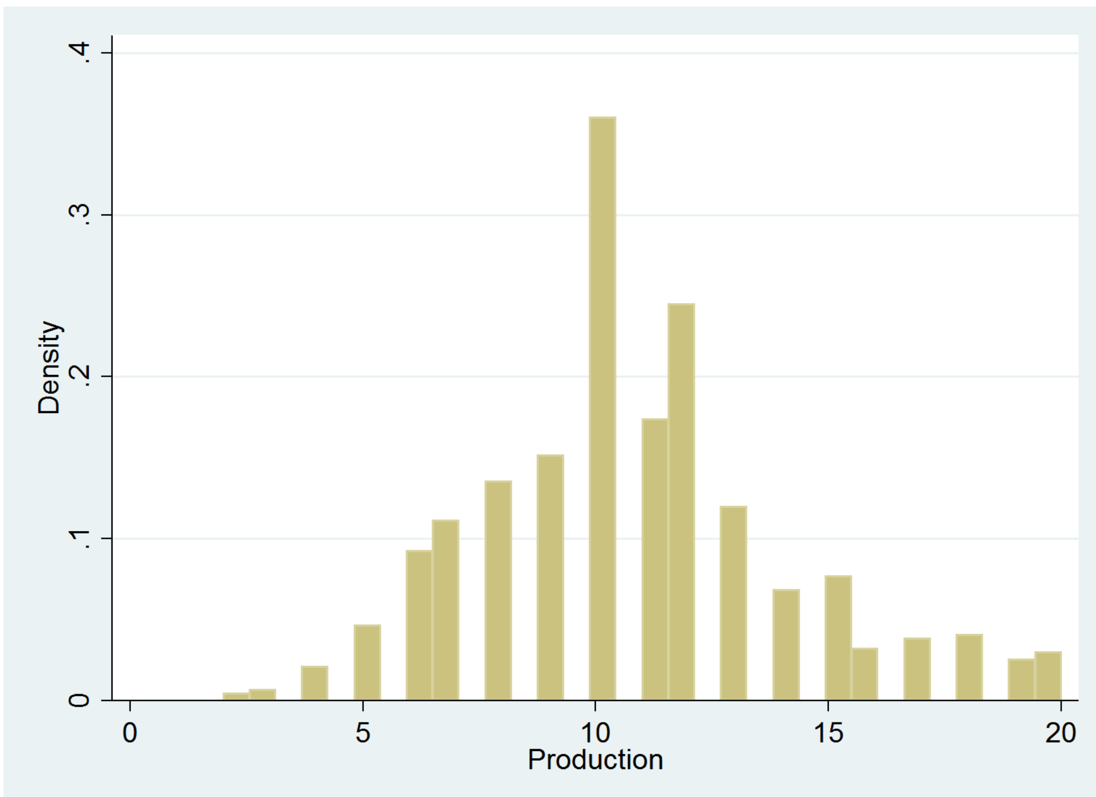

Figure 4.3: Production under Uncertainty, All Sessions, Real Rounds (Rounds 11-30)

Figure 4.4: Prices Drawn under Uncertainty During Practice Rounds (Rounds 1-10), by Session

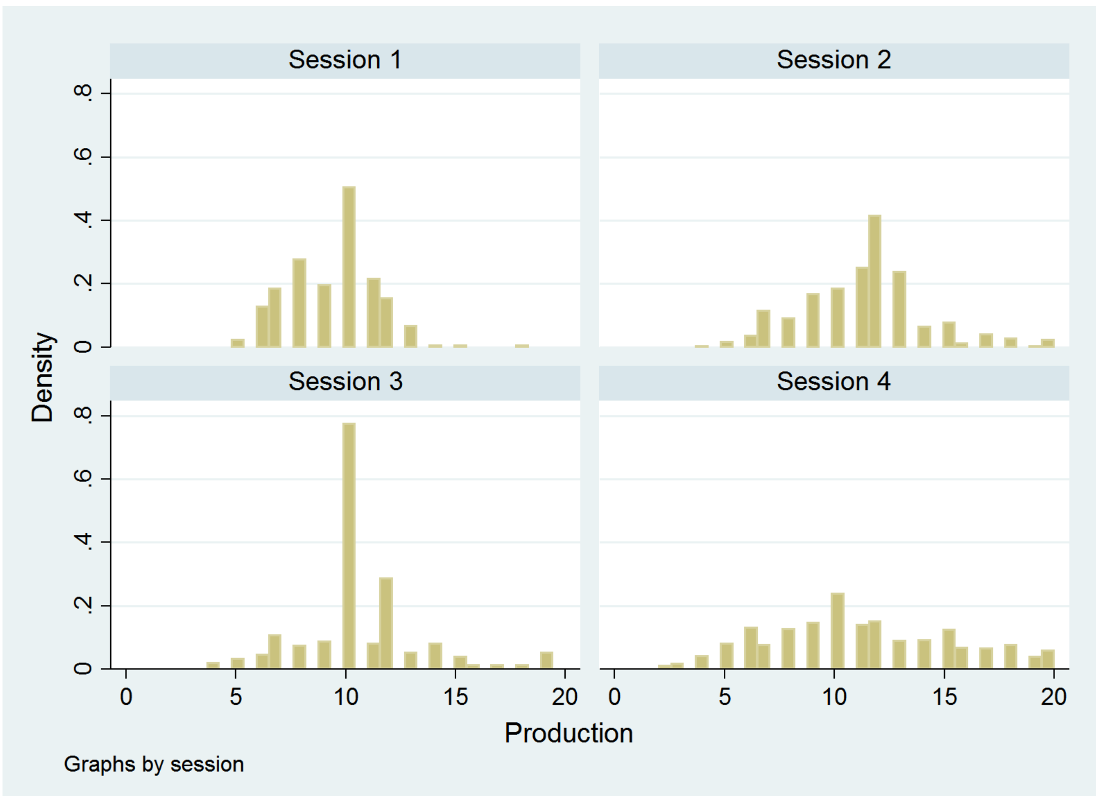

Figure 4.5: Production under Uncertainty During Real Rounds (Rounds 11-30), by Session

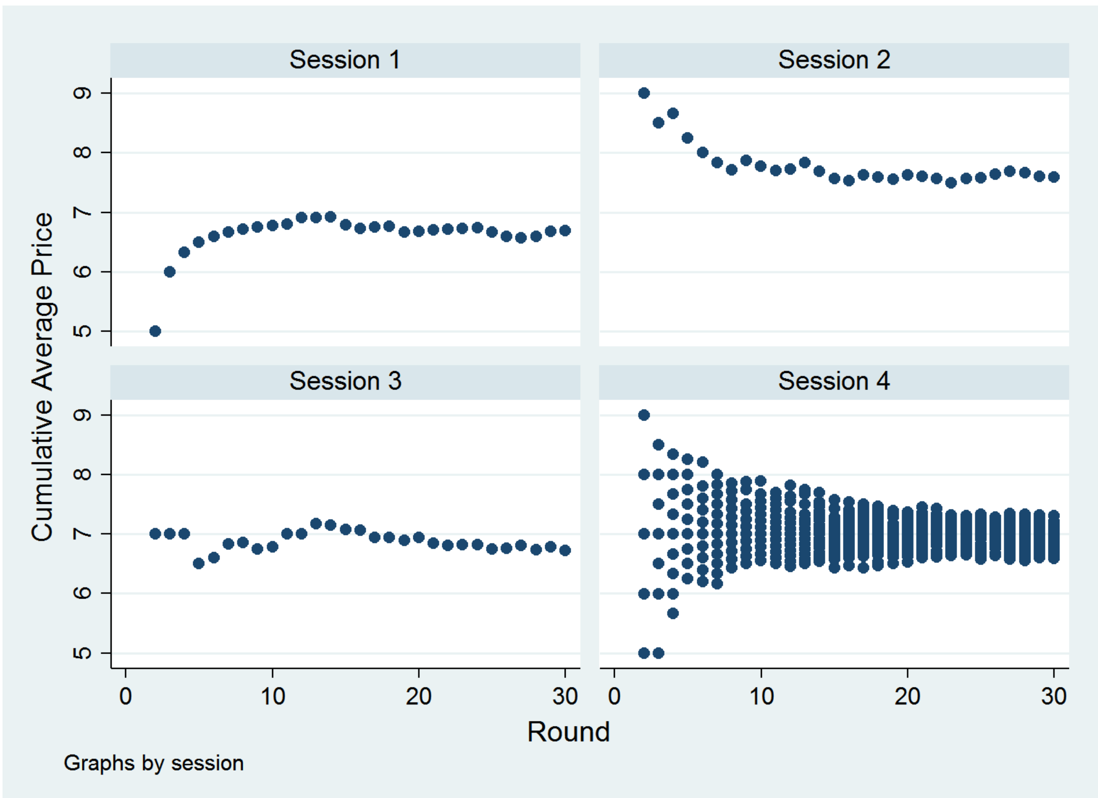

Figure 4.6: Cumulative Average Price, by Session

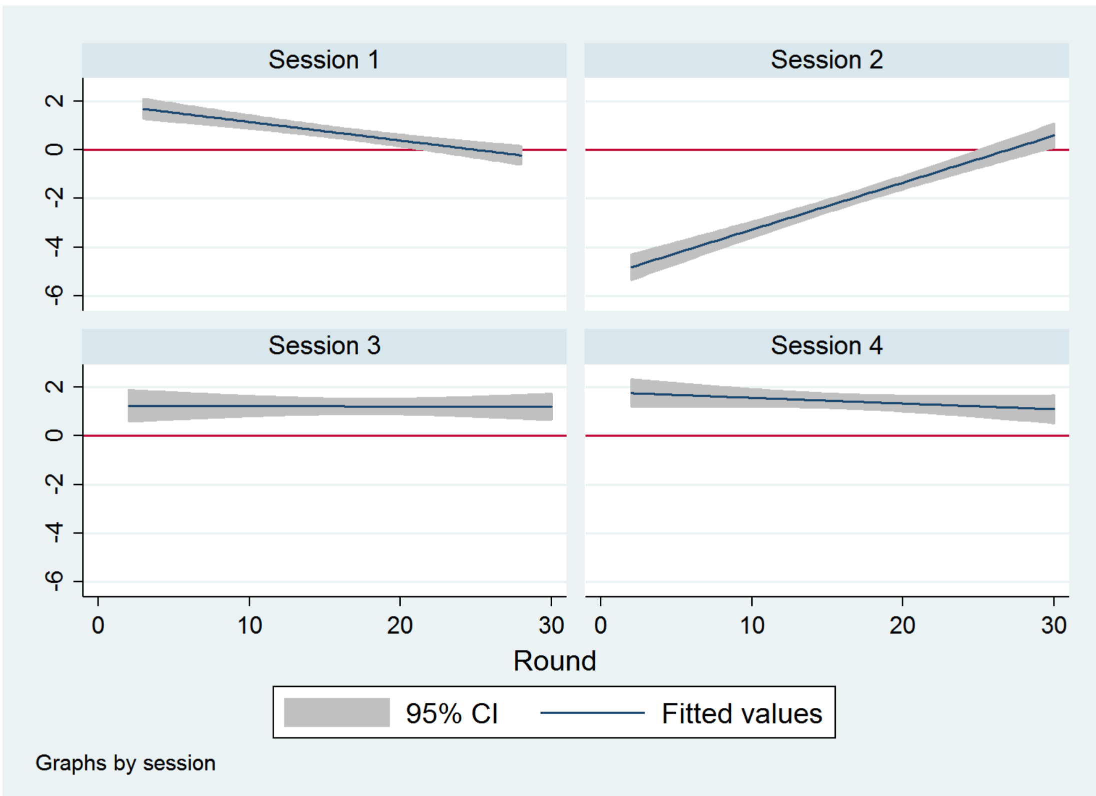

Figure 4.7: Actual vs. Optimal Production under Uncertainty, by Session

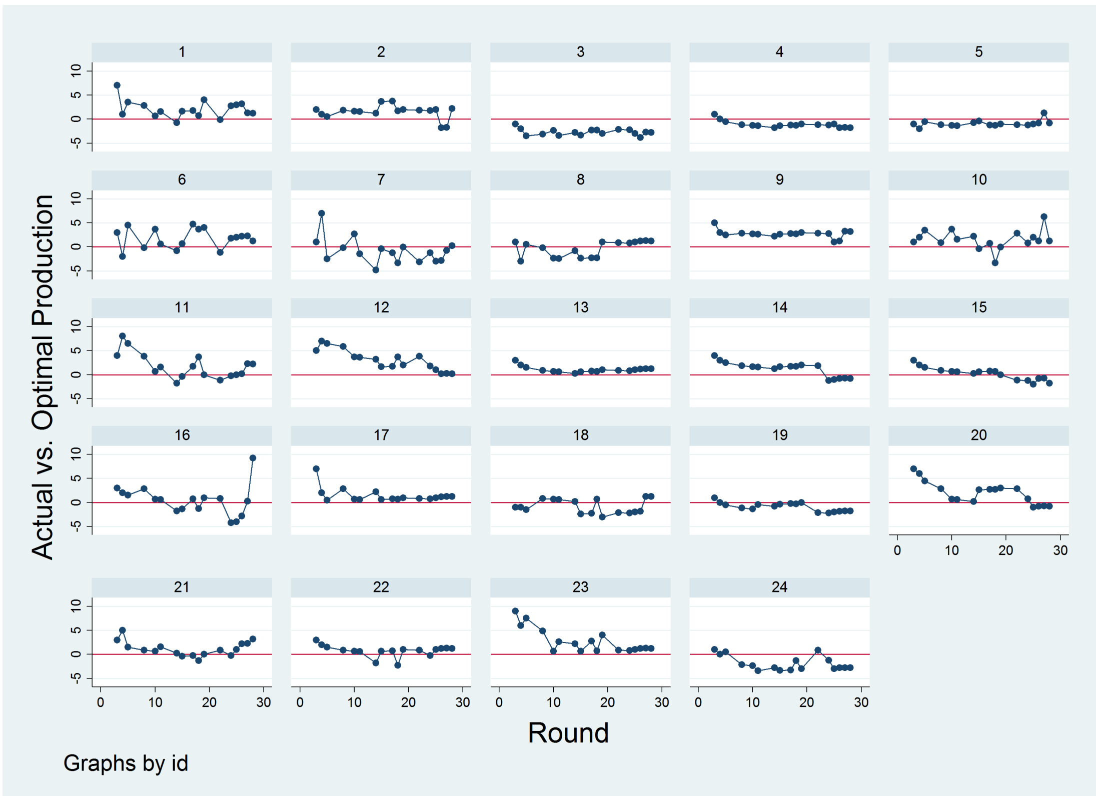

Figure 4.8: Actual vs. Optimal Production under Uncertainty, by ID: Session 1

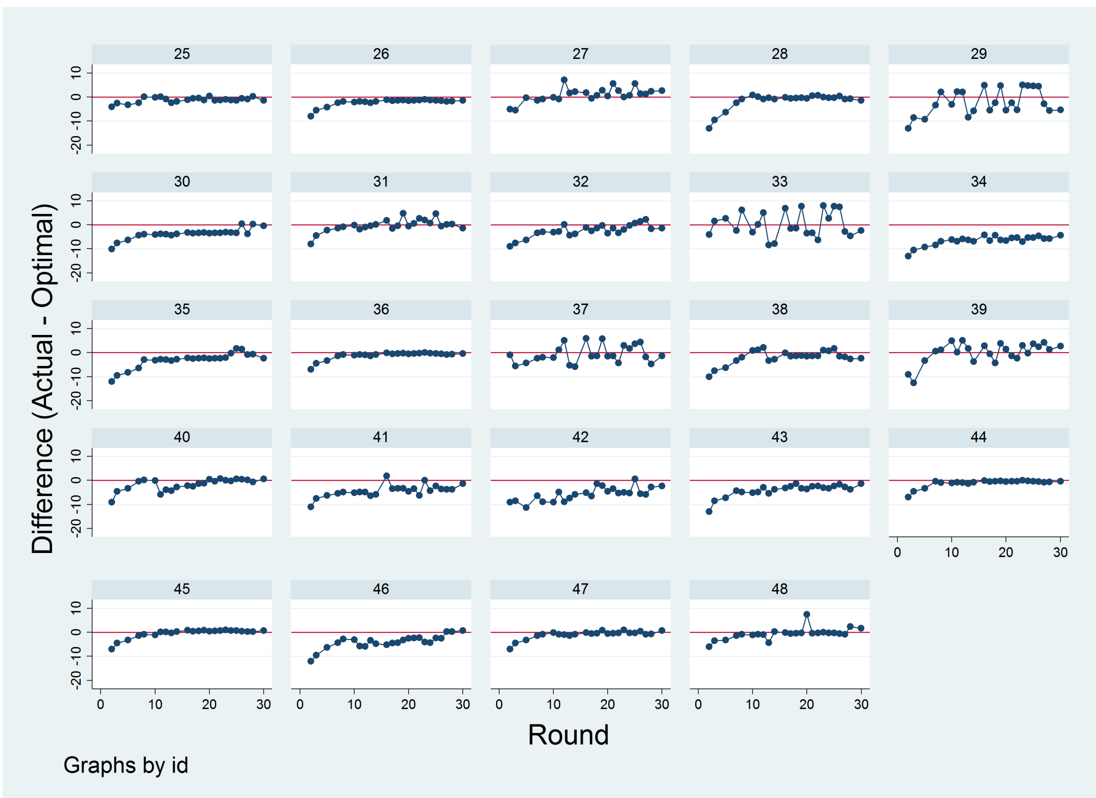

Figure 4.9: Actual vs. Optimal Production under Uncertainty, by ID: Session 2

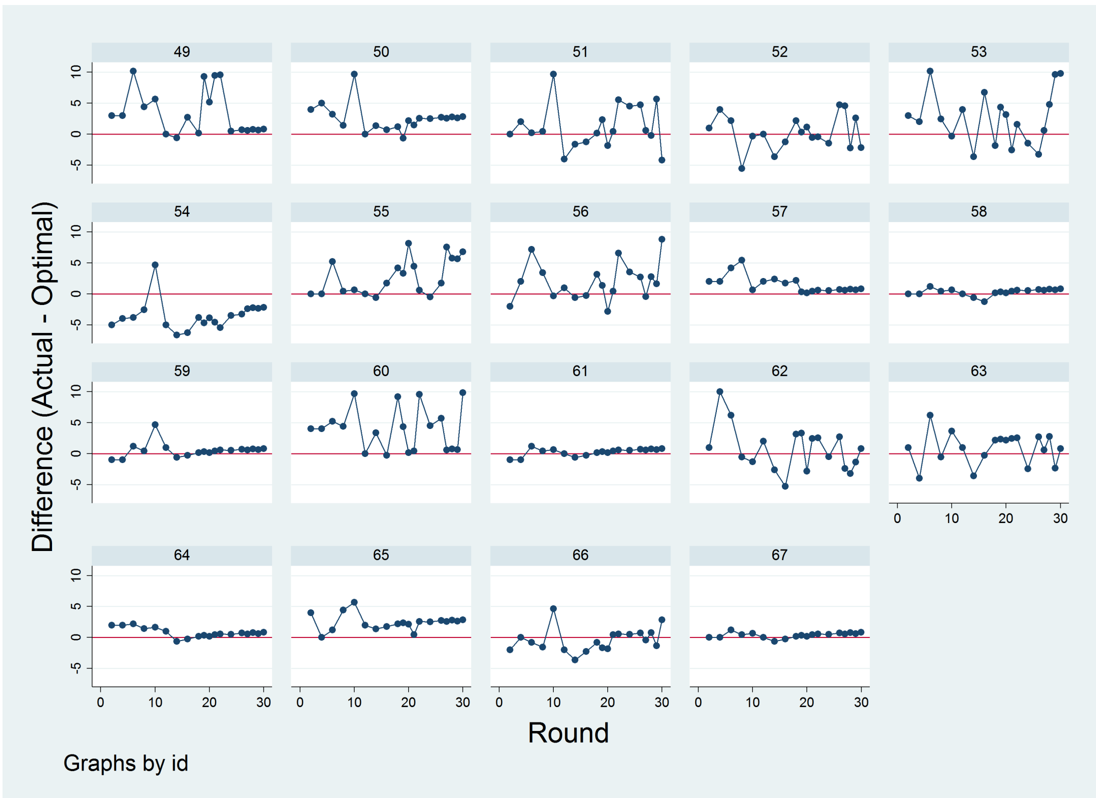

Figure 4.10: Actual vs. Optimal Production under Uncertainty, by ID: Session 3

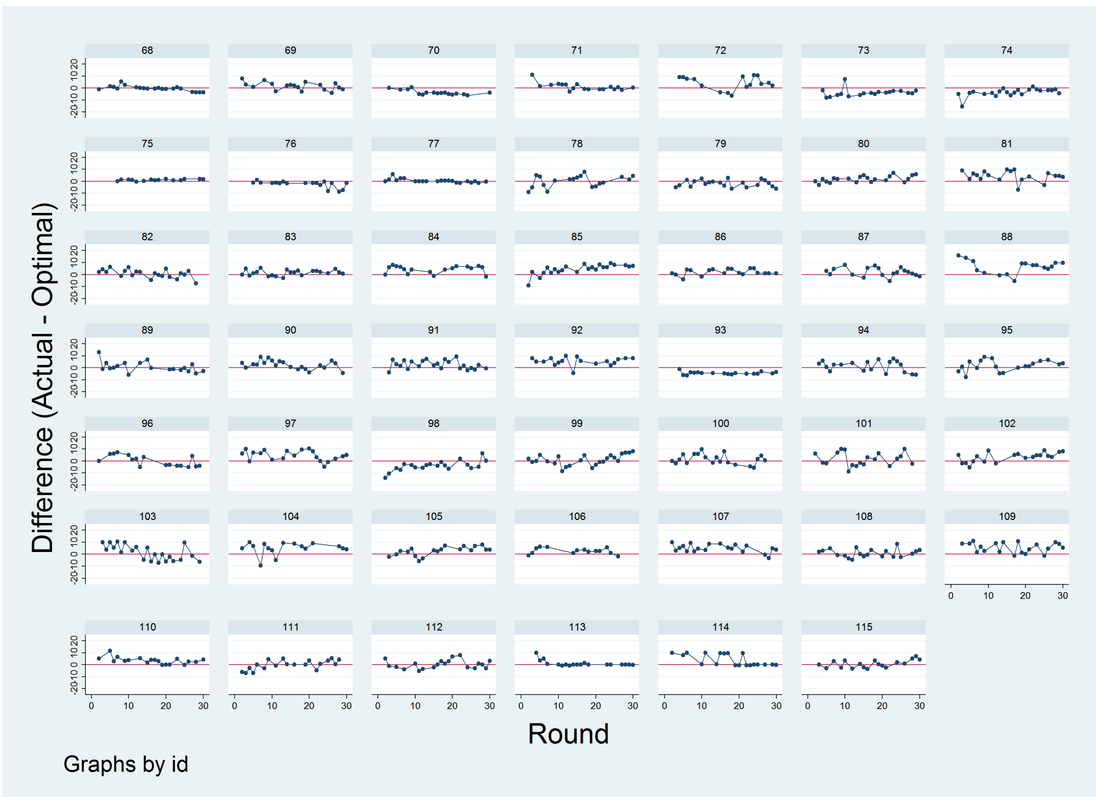

Figure 4.11: Actual vs. Optimal Production under Uncertainty, by ID: Session 4

Table 4.1: Experimental Setup

Session	**Date**	**Location**	**N. of Subjects**	**Order of Games**
1	Dec. 2014	Cornell LEEDR Lab	24	Production - HL
2	Mar. 2015	Cornell LEEDR Lab	24	HL - Production
3	Oct. 2015	Univ. of Minnesota	19	HL - Production
4	Aug.-Sep. 2016	Peru	48	Random

Table 4.2: Summary Statistics for the Pooled Sample (N =3,450)

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Production (0 to 20)	10.762	3.099	1	20
Uncertainty (0 or 1)	0.680	0.467	0	1
Price (5,6,7,8,9)	7.009	1.075	5	9
Holt-Laury Switch Point (1 to 10)	5.304	2.589	1	10
Age (years)	31.991	16.503	18	73
Female (0 or 1)	0.456	0.498	0	1
Holt-Laury First (0 or 1)	0.557	0.497	0	1
Profit (-47.58 to 32.61)	3.831	12.55	-47.578	32.609

Table 4.3: Summary Statistics for Session 1 (N =720)

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Production (0 to 20)	9.693	1.766	3	18
Uncertainty (0 or 1)	0.6	0.49	0	1
Price (5,6,7,8,9)	6.7	0.901	5	9
Holt-Laury Switch Point (1 to 10)	6.792	1.959	4	10
Age (years)	20.652	0.915	19	23
Female (0 or 1)	0.609	0.488	0	1
Profit (-47.58 to 32.61)	1.633	8.588	-22.536	32.604

Table 4.4: Summary Statistics for Session 2 (N =720)

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Production (0 to 20)	10.922	2.63	4	20
Uncertainty (0 or 1)	0.833	0.373	0	1
Price (5,6,7,8,9)	7.567	1.055	6	9
Holt-Laury Switch Point (1 to 10)	7.083	1.802	4	10
Age (years)	20.792	1.684	18	25
Female (0 or 1)	0.583	0.493	0	1
Profit (-47.58 to 32.61)	10.411	12.032	-13.625	32.609

Table 4.5: Summary Statistics for Session 3 (N =570)

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Production (0 to 20)	10.521	2.336	4	20
Uncertainty (0 or 1)	0.633	0.482	0	1
Price (5,6,7,8,9)	6.733	1.124	5	9
Holt-Laury Switch Point (1 to 10)	6.158	1.388	4	9
Age (years)	19.895	1.295	18	23
Female (0 or 1)	0.158	0.365	0	1
Profit (-47.58 to 32.61)	1.379	12.673	-47.578	32.609

Table 4.6: Summary Statistics for Session 4 (N =1440)

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Production (0 to 20)	11.313	3.864	1	20
Uncertainty (0 or 1)	0.662	0.473	0	1
Price (5,6,7,8,9)	6.994	1.038	5	9
Holt-Laury Switch Point (1 to 10)	3.333	2.212	1	9
Age (years)	47.813	14.552	20	73
Female (0 or 1)	0.438	0.496	0	1
Holt-Laury First (0 or 1)	0.438	0.496	0	1
Profit (-47.58 to 32.61)	2.609	13.3	-47.578	32.609

Table 4.7: Main Results

Dependent Variable: Level of Production (0-20)

	(1)	(2)	(3)	(4)	(5)
Uncertainty	0.571***	0.556***	0.568***	0.494**	0.467**
	(0.215)	(0.214)	(0.214)	(0.217)	(0.224)
Cumulative Avg. Price		1.192***	1.166***	1.710***	1.683*
		(0.394)	(0.405)	(0.390)	(0.889)
Cumulative Variance			0.301	0.0700	-0.131
			(0.418)	(0.514)	(0.537)
Underestimation				-0.316***	-0.391***
				(0.0592)	(0.0654)
Switch		-0.169***	-0.167***	-0.166***	-0.134*
		(0.0548)	(0.0555)	(0.0507)	(0.0800)
Round		0.0346**	0.0312*	0.0364***	0.0378**
		(0.0142)	(0.0170)	(0.0141)	(0.0162)
Female		-0.402	-0.395	-0.360	-0.335
		(0.285)	(0.285)	(0.262)	(0.280)
Holt-Laury First				0.00796	-0.0792
				(0.374)	(0.541)
Session 2					0.310
					(1.135)
Session 3					0.333
					(0.756)
Session 4					0.403
					(0.626)
Constant	10.21***	2.180	2.121	-1.608	-1.665
	(0.0925)	(2.746)	(2.709)	(2.640)	(6.118)
N	2300	2280	2280	2280	2280
R^2	0.0103	0.0604	0.0607	0.0866	0.0883

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4.8: Moving Average Prices

Dependent Variable: Level of Production (0-20)

	(1)	(2)	(3)	(4)	(5)
Uncertainty	0.494**	0.648***	0.656***	0.612***	0.625***
	(0.212)	(0.201)	(0.201)	(0.198)	(0.204)
Cumulative Avg. Price	1.715***				
	(0.356)				
4-rounds M.A.		1.097***			
		(0.147)			
3-rounds M.A.			0.965***		
			(0.128)		
2-rounds M.A.				0.935***	
				(0.121)	
Price L.1					1.428***
					(0.133)
Cumulative Variance	0.0746	0.356	0.424	0.471	0.429
	(0.417)	(0.381)	(0.376)	(0.365)	(0.295)
Underestimation	-0.317***	-0.471***	-0.515***	-0.624***	-1.304***
	(0.0588)	(0.0677)	(0.0715)	(0.0859)	(0.124)
Switch	-0.166***	-0.139***	-0.133***	-0.125***	-0.103***
	(0.0508)	(0.0454)	(0.0446)	(0.0431)	(0.0336)
Round	0.0363***	0.0268**	0.0248**	0.0206*	0.0200**
	(0.0140)	(0.0125)	(0.0125)	(0.0121)	(0.0101)
Female	-0.361	-0.309	-0.305	-0.282	-0.186
	(0.266)	(0.248)	(0.246)	(0.241)	(0.194)
Constant	-1.642	2.438**	3.299***	3.515***	-0.111
	(2.351)	(1.102)	(0.998)	(0.964)	(1.015)
N	2280	2280	2279	2279	2280
R^2	0.0866	0.0946	0.0931	0.0998	0.1609

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4.9: Gains and Losses

Dependent Variable: Level of Production (0-20)

	(1)	(2)
Uncertainty	0.459**	0.427*
	(0.222)	(0.222)
Cumulative Avg. Price	0.808	0.760
	(0.727)	(0.705)
Cumulative Variance	-0.0320	0.0628
	(0.459)	(0.446)
Loss Magnitude L.1	-0.0904***	-0.132***
	(0.0163)	(0.0289)
Loss Magnitude L.1 Squared		0.00186**
		(0.000860)
Gain Magnitude L.1	0.109***	0.193***
	(0.0121)	(0.0358)
Gain Magnitude L.1 Squared		-0.00283**
		(0.00112)
Underestimation	-1.143***	-1.235***
	(0.114)	(0.120)
Switch	-0.0973	-0.0965
	(0.0630)	(0.0610)
Round	0.0276**	0.0277**
	(0.0138)	(0.0135)
Female	-0.206	-0.211
	(0.225)	(0.218)
Holt-Laury First	-0.0774	-0.0658
	(0.441)	(0.427)
Session 2	0.454	0.502
	(0.907)	(0.873)
Session 3	0.336	0.278
	(0.614)	(0.585)
Session 4	0.595	0.545
	(0.506)	(0.488)
Constant	3.713	3.795
	(4.966)	(4.826)
N	2280	2280
R^2	0.1587	0.1666

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4.10: Extreme Outcomes

Dependent Variable: Level of Production (0-20)

	Threshold ±4.76		Threshold ±15	
	(1)	(2)	(3)	(4)
Uncertainty	0.366*	0.395*	0.412*	0.387*
	(0.220)	(0.219)	(0.223)	(0.222)
Cumulative Avg. Price	1.280	1.422*	1.044	1.422*
	(0.821)	(0.818)	(0.756)	(0.826)
Cumulative Variance	0.103	0.227	-0.0295	0.192
	(0.497)	(0.508)	(0.459)	(0.515)
4.76 <Profit L.1	1.696***			
	(0.212)			
0 < Profit L.1 < 4.76	0.994***			
	(0.191)			
-4.76 < Profit L.1 < 0		-1.021***		
		(0.225)		
Profit L.1 < -4.76		-1.601***		
		(0.241)		
15 <Profit L.1			3.189***	
			(0.307)	
0 < Profit L.1 < 15			1.342***	
			(0.175)	
-15 < Profit L.1 < 0				-1.357***
				(0.177)
Profit L.1 < -15				-1.547***
				(0.342)
Underestimation	-0.766***	-0.751***	-0.917***	-0.721***
	(0.0870)	(0.0930)	(0.0896)	(0.0926)
Switch	-0.122*	-0.125*	-0.106*	-0.122*
	(0.0708)	(0.0732)	(0.0636)	(0.0728)
Round	0.0335**	0.0355**	0.0293**	0.0357**
	(0.0151)	(0.0154)	(0.0142)	(0.0155)
Female	-0.267	-0.295	-0.238	-0.287
	(0.254)	(0.257)	(0.230)	(0.258)
Holt-Laury First	-0.0739	-0.0687	-0.0146	-0.0814
	(0.492)	(0.498)	(0.457)	(0.501)
Constant	-0.201	0.261	1.376	0.239
	(5.642)	(5.634)	(5.183)	(5.692)
Session Dummies	Yes	Yes	Yes	Yes
N	2280	2280	2280	2280
R^2	0.1201	0.1145	0.1528	0.1130

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4.11: Safety First

Dependent Variable: Safety First Production (0 or 1)

	(1)	(2)
Uncertainty	-0.108***	-0.109***
	(0.0166)	(0.0168)
Cumulative Avg. Price	0.00254	-0.0439
	(0.0297)	(0.0642)
Cumulative Variance	-0.0394	-0.00848
	(0.0348)	(0.0370)
Loss Magnitude L.1	0.00246*	0.00239
	(0.00146)	(0.00146)
Gain Magnitude L.1	-0.00334***	-0.00364***
	(0.000955)	(0.000942)
Underestimation	0.0293***	0.0326***
	(0.00927)	(0.00929)
Switch	0.0127***	-0.00387
	(0.00379)	(0.00431)
Round	-0.000469	-0.00117
	(0.00122)	(0.00135)
Female	-0.0340*	-0.0305
	(0.0204)	(0.0199)
Holt-Laury First	0.00646	-0.00809
	(0.0283)	(0.0407)
Session 2		0.0449
		(0.0878)
Session 3		-0.0174
		(0.0557)
Session 4		-0.132***
		(0.0418)
Constant	0.986***	1.446***
	(0.208)	(0.447)
N	2280	2280
R^2	0.0635	0.0980

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4.12: Results by Contexts

Dependent Variable: Level of Production (0-20)

	(1)	(2)
Uncertainty	0.863**	0.130
	(0.365)	(0.244)
Uncertainty × Session 1	-1.801***	
	(0.476)	
Uncertainty × Session 2	1.176**	
	(0.499)	
Uncertainty × Session 3	-0.385	
	(0.548)	
Uncertainty × Session 4		0.734*
		(0.439)
Cumulative Avg. Price	1.657*	1.861***
	(0.875)	(0.395)
Cumulative Avg. Price × Session 1	0.102	
	(0.0862)	
Cumulative Avg. Price × Session 2	-0.159	
	(0.0998)	
Cumulative Avg. Price × Session 3	0.0231	
	(0.0568)	
Cumulative Avg. Price × Session 4		-0.0451
		(0.0500)
Cumulative Variance	-0.114	-0.0101
	(0.536)	(0.526)
Underestimation	-0.460***	-0.389***
	(0.0644)	(0.0620)
Holt-Laury First	-0.0840	0.0477
	(0.535)	(0.372)
Switch	-0.132*	-0.144*
	(0.0787)	(0.0778)
Round	0.0382**	0.0390***
	(0.0160)	(0.0139)
Female	-0.325	-0.360
	(0.276)	(0.259)
Constant	-1.394	-2.613
	(6.270)	(2.715)
N	2280	2280
R^2	0.1051	0.0909

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4.13: Results by Contexts

Dependent Variable: Level of Production (0-20)

	(1) Session 1	(2) Session 2	(3) Session 3	(4) Session 4
Uncertainty	-0.752**	1.641***	0.639	0.883**
	(0.331)	(0.242)	(0.473)	(0.365)
Cumulative Avg. Price	1.739	-4.311	-1.997	1.477
	(1.290)	(3.165)	(2.312)	(1.045)
Cumulative Variance	0.446	-3.286	2.462	-0.246
	(0.985)	(2.156)	(2.223)	(0.530)
Underestimation	-0.287***	-0.242**	-0.173	-0.423***
	(0.0880)	(0.106)	(0.130)	(0.0996)
Holt-Laury First	-	-	-	-0.269
	-	-	-	(0.582)
Switch	-0.0309	-0.558***	-0.198	-0.0181
	(0.0974)	(0.138)	(0.146)	(0.128)
Round	-0.000896	0.0818***	-0.0582	0.0402
	(0.0293)	(0.0203)	(0.0806)	(0.0270)
Female	-0.428	-0.569	-0.973	0.0890
	(0.287)	(0.372)	(1.058)	(0.512)
Constant	-1.504	48.67*	23.48	-0.524
	(9.126)	(25.48)	(15.54)	(7.279)
N	460	480	380	960
R^2	0.0831	0.2677	0.0805	0.0554

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4.14: Results by Income Risk Attitudes

Dependent Variable: Level of Production (0-20)

	(1)	(2)
Uncertainty	0.827**	1.522***
	(0.351)	(0.470)
Cumulative Avg. Price	1.805*	2.899***
	(1.007)	(1.081)
Uncertainty × Risk Averse	-0.611	
	(0.441)	
Uncertainty × Switch		-0.212***
		(0.0811)
Cumulative Avg. Price × Risk Averse	-0.907	
	(0.966)	
Cumulative Avg. Price × Switch		-0.394**
		(0.165)
Cumulative Variance	-0.227	-0.282
	(0.523)	(0.546)
Risk Averse	6.528	
	(6.753)	
Switch		2.790**
		(1.147)
Underestimation	-0.390***	-0.357***
	(0.0669)	(0.0653)
Round	0.0343**	0.0302*
	(0.0167)	(0.0167)
Female	-0.399	-0.301
	(0.285)	(0.278)
Holt-Laury First	-0.180	-0.106
	(0.552)	(0.548)
Session 2	1.118	1.903
	(1.225)	(1.201)
Session 3	0.701	0.805
	(0.748)	(0.765)
Session 4	1.040	1.045
	(0.644)	(0.637)
Constant	-3.520	-11.27
	(6.893)	(7.497)
N	2280	2280
R^2	0.0858	0.1044

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4.15: Results by Income Risk Attitudes

Dependent Variable: Level of Production (0-20)

	(1) Risk Averse	(2) Risk Neutral, Risk Loving
Uncertainty	-0.0996	0.977***
	(0.297)	(0.284)
Cumulative Avg. Price	1.724**	2.057***
	(0.724)	(0.539)
Cumulative Variance	-1.058	0.324
	(1.014)	(0.532)
Underestimation	-0.385***	-0.293***
	(0.0893)	(0.0831)
Switch	-0.274	-0.0668
	(0.167)	(0.136)
Round	0.0404**	0.0477**
	(0.0181)	(0.0217)
Female	-0.437	-0.126
	(0.365)	(0.374)
Holt-Laury First	0.278	0.0475
	(0.873)	(0.471)
Constant	0.331	-5.233
	(5.363)	(3.787)
N	1120	1160
R^2	0.0863	0.0881

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4.16: Robustness Checks

Dependent Variable: Level of Production (0-20)

	(1)	(2)	(3)	(4)
	Self-reported		Irrational Decisions	
Uncertainty	0.446**	0.420*	0.114	0.0595
	(0.214)	(0.225)	(0.213)	(0.228)
Cumulative Avg. Price	1.768***	1.651*	1.539***	1.166
	(0.420)	(0.916)	(0.439)	(0.804)
Cumulative Variance	-0.145	-0.428	-0.172	-0.391
	(0.451)	(0.559)	(0.417)	(0.597)
Underestimation	-0.316***	-0.347***	-0.305***	-0.305***
	(0.0587)	(0.0605)	(0.0630)	(0.0625)
Switch	-0.138***	-0.112	-0.104**	-0.158*
	(0.0529)	(0.0822)	(0.0519)	(0.0833)
Female	-0.443*	-0.377	-0.379	-0.330
	(0.259)	(0.294)	(0.279)	(0.291)
Round	0.0389***	0.0408**	0.0371***	0.0362**
	(0.0141)	(0.0168)	(0.0114)	(0.0155)
Holt-Laury First	0.0319	-0.181	0.141	-0.301
	(0.345)	(0.536)	(0.354)	(0.597)
Session 2		0.561		0.971
		(1.116)		(1.118)
Session 3		0.609		0.776
		(0.818)		(0.872)
Session 4		0.498		-0.0943
		(0.651)		(0.646)
Constant	-2.029	-1.430	-0.585	2.465
	(2.845)	(6.322)	(2.955)	(5.745)
N	2120	2120	1740	1740
R^2	0.0836	0.0853	0.0783	0.0877

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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Appendix A

A.1 Derivation of Expression (4)

Case 1 ($L^F > 0$, $L^U > 0$)**.** *For both L^F and L^U to have interior solutions, the following conditions must be both satisfied.*

$$\begin{aligned} E\left[V_y(w^U - c)\right] &= E\left[V_y w^R\right] \\ E\left[V_y p F_{L^F}\right] &= E\left[V_y w^R\right] \end{aligned} \tag{A.1}$$

Therefore,

$$\begin{aligned} E\left[V_y(w^U - c)\right] &= E\left[V_y p F_{L^F}\right] \\ \Leftrightarrow\ Cov[V_y,(w^U - c)] + E[V_y]\,E[w^U - c] &= Cov[V_y, pF_{L^F}] + E[V_y]\,E[pF_{L^F}] \\ \Leftrightarrow\ E[V_y]E[w^U - c - pF_{L^F}] &= Cov[V_y, pF_{L^F}] - Cov[V_y, w^U - c] \\ \Leftrightarrow\ E[w^U - c - pF_{L^F}] &= \frac{F_{L^F}Cov[V_y, p] - Cov[V_y, w^U - c]}{E[V_y]} \end{aligned} \tag{A.2}$$

The second line follows from the identity $Cov(X,Y) = E(XY) - E(X)E(Y)$, and the last line follows from the assumption that utility is strictly increasing in income.

Case 2 ($L^F = 0$, $L^U > 0$)**.** *For L^U to have an interior solution,*

$$E\left[V_y w^R\right] = E\left[V_y(w^U - c)\right] \tag{A.3}$$

From the first order condition for L^F and the complementary slackness condition, if the following inequality holds, $L^F = 0$.

$$E\left[V_y p F_{L^F}\right] < E\left[V_y w^R\right] \tag{A.4}$$

From the above two conditions, the following is a sufficient condition to have $L^U = 0$.

$$\begin{aligned} E\left[V_y(w^U - c)\right] &> E\left[V_y p F_{L^F}\right] \\ \Leftrightarrow\ Cov[V_y, (w^U - c)] + E[V_y]\, E[w^U - c] &> Cov[V_y, pF_{L^F}] + E[V_y]\, E[pF_{L^F}] \\ \Leftrightarrow\ E[V_y]E[w^U - c - pF_{L^F}] &> Cov[V_y, pF_{L^F}] - Cov[V_y, w^U - c] \\ \Leftrightarrow\ E[w^U - c - pF_{L^F}] &> \frac{F_{L^F} Cov[V_y, p] - Cov[V_y, w^U - c]}{E[V_y]} \end{aligned} \tag{A.5}$$

The second line follows from the identity $Cov(X,Y) = E(XY) - E(X)E(Y)$, and the last line follows from the assumption that utility is strictly increasing in income.

Case 3 (L^F>0, $L^U = 0$)**.** *A farming household allocates positive labor hours to household farming. For L^F to have an interior solution,*

$$E\left[V_y w^R\right] = E\left[V_y p F_{L^F}\right] \tag{A.6}$$

From the first order condition for L^U and the complementary slackness condition, if the following inequality holds, $L^U = 0$.

$$E\left[V_y(w^U - c)\right] < E\left[V_y w^R\right] \tag{A.7}$$

From the above two conditions, the following is a sufficient condition to have $L^U = 0$.

$$\begin{aligned} & E\left[V_y(w^U - c)\right] < E\left[V_y p F_{L^F}\right] \\ \Leftrightarrow\ & Cov[V_y,(w^U - c)] + E[V_y]\,E[w^U - c] < Cov[V_y, pF_{L^F}] + E[V_y]\,E[pF_{L^F}] \\ \Leftrightarrow\ & E[V_y]E[w^U - c - pF_{L^F}] < Cov[V_y, pF_{L^F}] - Cov[V_y, w^U - c] \\ \Leftrightarrow\ & E[w^U - c - pF_{L^F}] < \frac{F_{L^F}Cov[V_y,p] - Cov[V_y, w^U - c]}{E[V_y]} \end{aligned} \tag{A.8}$$

The second line follows from the identity $Cov(X, Y) = E(XY) - E(X)E(Y)$, and the last line follows from the assumption that utility is strictly increasing in income.

From the cases 1–3, the following condition must hold if $L^U \geq 0$.

$$E[\underbrace{w^U - c}_{\substack{\text{Gains from}\\\text{Migration}}} - \underbrace{pF_{L^F}}_{\substack{\text{Gains from}\\\text{Agriculture}}}] \geq \frac{F_{L^F}\cdot \overbrace{Cov[V_y,p]}^{\substack{\text{Price Risk}\\\text{Attitude}}} - \overbrace{Cov[V_y, w^U - c]}^{\substack{\text{Income Risk}\\\text{Attitude}}}}{E[V_y]} \tag{A.9}$$

A.2 How ($Cov[V_y, p]$) and ($Cov[V_y, w^U - c]$) are related to risk attitudes towards price and income, respectively

To see why the terms ($Cov[V_y, p]$) and ($Cov[V_y, w^U - c]$) are associated with attitudes towards price and income risks, respectively, consider ($Cov[V_y, w^U - c]$) first. Given that c is a fixed parameter, sign($Cov[V_y, w^U - c]$) = sign($Cov[V_y, w^U]$) = sign($Cov[V_y, y]$) = sign(V_{yy}) < 0 given income risk aversion. The term $Cov[V_y, p]$ depends on attitudes towards price risk.[1] To see why, first note that sign($Cov[V_y, p]$) = sign(V_{yp}). By Roy's Identity,

$$M = \frac{V_p}{V_y} \quad \Leftrightarrow V_y = \frac{V_p}{M} \tag{A.10}$$

[1]This is shown in Barrett (1996) and is reproduced here.

where marketable surplus, denoted as M, is the difference between production and consumption of the staple commodity $(F - S)$. Therefore,

$$V_{yp} = \frac{V_{pp}}{M} - \frac{V_p}{M^2}\frac{\partial M}{\partial p} = \frac{V_{pp}}{M} - \frac{V_y}{M}\frac{\partial M}{\partial p} = \frac{V_{pp}}{M} - \frac{\epsilon V_y}{p} \tag{A.11}$$

where ϵ is the own-price elasticity of the marketable surplus. The sign of $Cov[V_y, p]$ thus depends on $M, p, V_y, \frac{\partial M}{\partial p}$, ϵ, and the household's attitudes towards price risk represented by V_{pp}.

A.3 Derivation of the Coefficient of Absolute Price Risk Aversion

This is shown in Barrett (1996) and is reproduced here. From expression (27) in A.2, $V_{pp} = V_{yp}M + V_y\frac{\partial M}{\partial p}$. From expression (26), $V_{py} = V_{yy}M + V_y\frac{\partial M}{\partial y} = V_{yp}$ (by symmetry). Therefore, $V_{pp} = M\left[V_{yy}M + V_y\frac{\partial M}{\partial y}\right] + V_y\frac{\partial M}{\partial p}$.

V_{pp} and V_{yp} can then be expressed as the following.

$$V_{pp} = \frac{MV_y}{p}\{\epsilon + \beta(\eta - R)\} \qquad V_{yp} = \frac{V_y}{p}\{\beta(\eta - R)\} \tag{A.12}$$

where β is a budget share of the marketable surplus of the commodity $(\frac{pM}{y})$, η is the income elasticity of the marketable surplus $(\frac{\partial M}{\partial y}\frac{y}{M})$, R is the Arrow-Pratt coefficient of relative risk aversion of households, and ϵ is the own-price elasticity of the marketable surplus $(\frac{\partial M}{\partial p}\frac{p}{M})$.

Therefore,

$$A \equiv -\frac{V_{pp}}{V_y} = -\frac{M}{p}\cdot\{\beta(\eta - R) + \epsilon\} \tag{A.13}$$

A.4 Necessary and Sufficient Condition for Price Risk Aversion

Claim. *Both net sellers and net buyers are averse to price risk ($A > 0$) if and only if* $R > \eta + \frac{\epsilon}{\beta}$.

Proof. This is shown in Barrett (1996) and is reproduced here. For both sellers and net buyers, $A > 0$ if and only if $\frac{M}{p} \cdot \{\beta(\eta - R) + \epsilon\} < 0$ by expression (5).

For net sellers, $M, \beta >0$.

$\frac{M}{p}\{\epsilon + \beta(\eta - R)\} < 0$

$\Leftrightarrow \epsilon + \beta(\eta - R) < 0$

$\Leftrightarrow \beta(\eta - R) < -\epsilon$

$\Leftrightarrow \eta - R < -\frac{\epsilon}{\beta}$

$\Leftrightarrow R > \eta + \frac{\epsilon}{\beta}$

For net buyers, $M, \beta <0$.

$\frac{M}{p}\{\epsilon + \beta(\eta - R)\} < 0$

$\Leftrightarrow \epsilon + \beta(\eta - R) > 0$

$\Leftrightarrow \beta(\eta - R) > -\epsilon$

$\Leftrightarrow \eta - R < -\frac{\epsilon}{\beta}$

$\Leftrightarrow R > \eta + \frac{\epsilon}{\beta}$ □

A.5 Proof of Claim I

Claim 1. *If a household is a net seller of a normal good S, aversion to price risk ($V_{pp} < 0$) is a sufficient condition for $Cov[V_y, p] < 0$.*[2]

Proof. $V_{pp} < 0$

$\Rightarrow R > \eta + \frac{\epsilon}{\beta}$ by A.4.

[2]The same result was shown by Barrett (1996) to show that a price risk-averse net seller will underemploy labor.

$\Rightarrow \beta R - \beta\eta > \epsilon \quad \because \beta > 0$ for net sellers.

$\Rightarrow \beta R - \beta\eta > 0 \quad \because \epsilon > 0$ for net sellers.

$\Rightarrow \beta(\eta - R) < 0$

$\Rightarrow \frac{V_y}{p}\{\beta(\eta - R)\} = V_{yp} < 0$

$\Rightarrow Cov[V_y, p] < 0$ □

A.6 Proof of Claim II

Claim 2. *If a household is a net buyer of a normal good S, aversion to price risk ($V_{pp} < 0$) is a sufficient condition for $Cov[V_y, p] > 0$.*[3]

Proof. $V_{pp} < 0$

$\Rightarrow R > \eta + \frac{\epsilon}{\beta}$ by A.4.

$\Rightarrow \beta R - \beta\eta < \epsilon \quad \because \beta < 0$ for net buyers.

$\Rightarrow \beta R - \beta\eta < 0 \quad \because \epsilon < 0$ for net buyers.

$\Rightarrow \frac{V_y}{p}\{\beta(\eta - R)\} = V_{yp} > 0$

$\Rightarrow Cov[V_y, p] > 0$ □

[3]The same result was derived by Barrett (1996) to show that a price risk-averse net buyer will overemploy labor.

Table A.1: Variable Descriptions

Variable	**Descriptions**
Dependent Variables	
Migrate	1 if there is a household member who left the household since the previous round of the survey. 0 otherwise. Excludes leaving a household due to the following reasons: death; parents were too sick to care for; divorced/out of family; returned home; to look after other relatives; conscripted into the army; sick, went for treatment.
Migrate for Work	1 if there is a household member who left the household for the following reasons: to look for work; to take up jobs; to be near to the place of work; to run own farm or enterprise. 0 otherwise.
Migrate to Urban Areas	1 if there is a household member whose current residence is an urban area in this district; Addis Ababa; or other urban areas. 0 otherwise.
Migrate to Urban Areas for Work	Interaction of "Migrate for work" and "Migrate to urban areas"
Migrate for Marriage	1 if there is a household member who migrated to live with spouse or for marriage. 0 otherwise.
Number of Migrants	Number of household members who left their households since the previous round of the survey.
Independent Variables	
WTP	Household-level willingness-to-pay to stabilize prices of the seven most important commodities (coffee, maize, beans, barley, wheat, teff, sorghum) at their means, expressed as a proportion of household income, estimated by BBJ (2013). Ranges from -1 to 1.

Continued on next page

Table A.1 (continued)

Variable	**Descriptions**
Taken Loan	1 if anyone in a household has ever taken a loan during the previous 5 years. 0 otherwise. Includes both cash and in-kind.
Loan from Friends and Relatives	1 if anyone in a household has ever taken a loan from friends and relatives during the previous 5 years. 0 otherwise. Includes both cash and in-kind.
Loan from Bank	1 if anyone in a household has ever taken a loan from banks during the previous 5 years. 0 otherwise. Includes both cash and in-kind.
Loan from NGO	1 if anyone in a household has ever taken a loan from NGOs during the previous 5 years. 0 otherwise. Includes both cash and in-kind.
Loan for Farming	1 if anyone in a household has ever taken loan during the previous 5 years: in order to buy a farm; to buy inputs such as seeds and fertilizer; to buy livestock. 0 otherwise. Includes both cash and in-kind.
Loan for Business	1 if anyone in a household has ever taken loan during the previous 5 years: in order to start an off-farm business. 0 otherwise. Includes both cash and in-kind.
Loan for Food	1 if anyone in a household has ever taken loan during the previous 5 years: in order to buy food and goods. 0 otherwise. Includes both cash and in-kind.
Loan for Travel	1 if anyone in a household has ever taken loan during the previous 5 years: in order to pay for travels. 0 otherwise. Includes both cash and in-kind.
Logged Income	Inverse hyperbolic sine (IHS) transformation of household income, (in Birr, including in-kind) during the last four months as of the date of survey
Logged Nonfarm Income	Inverse hyperbolic sine (IHS) transformation of household income, (in Birr, including in-kind) from nonfarm activities during the last four months as of the date of survey

Continued on next page

Table A.1 (continued)

Variable	**Descriptions**
Logged Business Income	Inverse hyperbolic sine (IHS) transformation of household income, (in Birr, including in-kind) from running businesses during the last four months as of the date of survey
Plot Area per Person	Household plot area (in ha) divided by the number of household members
Household Size	Number of household members
MS_k	Household marketable Surplus (in kg) of commodity k, or quantity supplied minus quantity demanded of commodity k. $k \in \{1, 2, ...7\}$
P_k	Price (in Birr/kg) of commodity k. $k \in \{1, 2, ...7\}$

Table A.2: Reasons for Migration (Frequency)

	Round 1	Round 2	Round 3	Round 4	Total
1. To be with parent	22	90	74	179	365
2. To be near to school / For education	9	34	27	45	115
3. Parents were to sick to care for	3	4	3	11	21
4. Sent to relatives/friends	29	49	40	53	171
5. To live with spouse/marriage	363	63	67	387	880
6. Divorced / Out of family	36	37	28	55	156
7. Returned home	9	39	55	85	188
8. To look for work	49	49	49	129	276
9. To take up a job	24	36	21	50	131
10. To be near to their places of work	7	3	1	17	28
11. To run own farm or enterprise	2	1	2	8	13
12. Contract ended	2	14	12	27	55
13. Land shortage	1	1	1	2	5
14. Drought	5	-	-	-	5
15. To look after other relatives	10	34	29	25	98
16. Conscripted into the army	6	14	3	8	31
17. Sick, went for treatment	1	3	3	4	11
18. Migrated, intentions unknown	3	12	8	20	43
20. Other	31	8	14	16	69
Total	612	491	437	1,121	2,661

Notes: This table presents reasons for leaving households reported in the rounds 1-4 of the survey. The most common reasons for household members to leave home are family-related reasons (to be with parents and spouse, marriage, divorce, and to look after relatives). On average, labor migration (migration aiming to look for work, to take up a job, to be near to their places of work, to run own farm or enterprise) happens in about 16 percent of all cases.

Table A.3: Destinations for Migration (Frequency)

Destination	Round 1	Round 2	Round 3	Round 4	Total
1. This village	236	116	112	433	897
2. Rural area, this district	127	102	95	211	535
3. Rural area, neighboring district	65	51	50	85	251
4. Other rural area	36	69	62	137	304
5. Urban area, this district	22	35	23	40	120
6. Addis Ababa	50	31	40	68	189
7. Other urban area	68	68	44	99	279
8. Other/ Don't know	12	13	6	20	51
Total	616	485	432	1,093	2,626

Notes: This table is constructed from the survey question that asks current residences of the household members who had left their households. It is notable that migration to rural areas (destinations 1-4) happens more frequently than migration to urban areas (destinations 5-7). On average, in about 75 percent of all cases, migrants ended up in rural areas (destinations 1-5). This is consistent with the fact that Ethiopia is one of the least urbanized countries in the world. Also, in about 60 percent of all cases, migrants end up in some places within the district (destinations 1, 2, and 5).

Table A.4: Robustness Check (1): Alternative Definitions of Migration

	(1) Urban	(2) Outside Distr.	(3) Within Distr.	(4) Work	(5) Marriage
WTP	0.0512**	0.0515**	0.0795**	0.00252	0.0856**
	(0.0240)	(0.0218)	(0.0393)	(0.0172)	(0.0342)
Taken Loan	0.000459	0.00798	0.0258	0.00387	0.0481***
	(0.0111)	(0.0126)	(0.0224)	(0.00856)	(0.0162)
Loan from Friends and Rel.	-0.00147	-0.00739	-0.0440***	0.0108	-0.0497***
	(0.00794)	(0.0149)	(0.0141)	(0.00735)	(0.0143)
Loan from Bank	-0.0758***	0.0199	-0.138***	-0.0486	-0.136***
	(0.0170)	(0.0445)	(0.0327)	(0.0299)	(0.0188)
Loan from NGO	-0.0252**	-0.0233*	-0.0436**	-0.00651	-0.0542***
	(0.0112)	(0.0141)	(0.0189)	(0.00951)	(0.0137)
Loan for Farming	0.00829	0.0217	-0.00434	0.00978	-0.0290**
	(0.0169)	(0.0234)	(0.0208)	(0.0233)	(0.0127)
Loan for Business	0.0319	-0.00207	0.00244	0.0367	-0.0100
	(0.0321)	(0.0367)	(0.0210)	(0.0362)	(0.0221)
Loan for Food	-0.000169	0.0129	0.0290**	0.00166	-0.00000793
	(0.00694)	(0.00929)	(0.0138)	(0.0112)	(0.0104)
Loan for Travel	0.00612	0.0392	0.0678	-0.00786	0.0459
	(0.0353)	(0.0593)	(0.0575)	(0.0366)	(0.0626)

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Table A.4 (continued)

	(1) Urban	(2) Outside Distr.	(3) Within Distr.	(4) Work	(5) Marriage
Logged Income	0.00179	0.00403**	0.00850***	0.00196	0.00775***
	(0.00131)	(0.00160)	(0.00202)	(0.00158)	(0.00236)
Logged Nonfarm Income	0.00131	-0.00150	-0.00368	0.00119	-0.00399*
	(0.00120)	(0.00125)	(0.00247)	(0.00170)	(0.00211)
Logged Business Income	0.00175*	0.00306**	-0.00158	0.00183	-0.00252
	(0.000912)	(0.00151)	(0.00202)	(0.00155)	(0.00214)
Plot Area Per Person	0.0146	0.0168*	0.0415**	0.0209***	0.0181
	(0.0105)	(0.00999)	(0.0191)	(0.00808)	(0.0140)
Household Size	0.000200	0.000178	0.00141	0.000754	0.000966
	(0.000743)	(0.000684)	(0.00113)	(0.00127)	(0.00138)
Constant	0.0242**	0.0329**	0.0505***	0.0293***	0.0527***
	(0.00973)	(0.0134)	(0.00880)	(0.00918)	(0.0141)
N	5,604	5,610	5,610	5,606	5,606
R^2	0.006	0.005	0.011	0.004	0.009

Notes:
1. District-round fixed effects are included in all specifications.
2. Bootstrapped standard errors clustered at the district level are in parentheses.
*: $p < 0.1$, **: $p < 0.0.05$, ***: $p < 0.0.01$.

Table A.5: Robustness Check (2): Alternative Definition of WTP

	Dependent Variable: Migrate (0 or 1)					
	(1)	(2)	(3)	(4)	(5)	(6)
	LPM	FE LPM	FE LPM	FE LPM	Net Sellers	Net Buyers
Alternative WTP	0.0697	0.0774*	0.0731	0.110***	0.116**	0.125**
	(0.0484)	(0.0447)	(0.0472)	(0.0390)	(0.0466)	(0.0513)
Taken Loan			0.0153	0.0130	-0.0137	0.0345
			(0.0247)	(0.0235)	(0.0286)	(0.0393)
Loan from Friends and Rel.			-0.0403**	-0.0429**	-0.00930	-0.0708**
			(0.0203)	(0.0193)	(0.0346)	(0.0352)
Loan from Bank			-0.0747	-0.0725	-0.0743	-0.0728
			(0.0572)	(0.0639)	(0.102)	(0.0568)
Loan from NGO			-0.0598***	-0.0638***	-0.0353	-0.0942***
			(0.0227)	(0.0235)	(0.0404)	(0.0307)
Loan for Farming			0.0302	0.0271	0.0198	0.0551
			(0.0297)	(0.0341)	(0.0541)	(0.0588)
Loan for Business			0.0273	0.0205	-0.0485	0.0584
			(0.0282)	(0.0347)	(0.0596)	(0.0487)
Loan for Food			0.0532***	0.0580***	0.0640**	0.0570**
			(0.0149)	(0.0140)	(0.0258)	(0.0249)
Loan for Travel			0.131*	0.126	0.137	0.130**
			(0.0698)	(0.0853)	(0.0974)	(0.0578)

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Table A.5 (continued)

	(1) LPM	(2) FE LPM	(3) FE LPM	(4) FE LPM	(5) Net Sellers	(6) Net Buyers
Logged Income				0.0212***	0.0229***	0.0257***
				(0.00316)	(0.00763)	(0.00482)
Logged Nonfarm Income				-0.00447	-0.00674*	-0.00304
				(0.00303)	(0.00394)	(0.00443)
Logged Business Income				0.0000755	-0.000665	-0.00160
				(0.00287)	(0.00453)	(0.00442)
Plot Area Per Person				0.0464	0.0558*	0.0325
				(0.0347)	(0.0296)	(0.0492)
Household Size				0.00127	0.00169	0.000433
				(0.00188)	(0.00277)	(0.00323)
Constant	0.176***	0.180***	0.179***	0.0235	0.0144	-0.00266
	(0.0150)	(0.0145)	(0.0200)	(0.0232)	(0.0612)	(0.0346)
Control Variables	No	No	Yes	Yes	Yes	Yes
District-Round F.E.	No	Yes	Yes	Yes	Yes	Yes
N	4,253	4,253	4,248	4,248	2,163	,2085
R^2	0.001	0.002	0.006	0.015	0.014	0.023

Notes: Bootstrapped standard errors clustered at the district level are in parentheses.
*: $p < 0.1$, **: $p < 0.0.05$, ***: $p < 0.0.01$.

Table A.6: Robustness Check (3): Various Fixed Effects and Clustered S.E.

Dependent Variable: Migrate (0 or 1)						
	(1)	(2)	(3)	(4)	(5)	(6)
WTP	0.114***	0.0945**	0.112***	0.0940**	0.107***	0.0891*
	(0.0388)	(0.0461)	(0.0407)	(0.0442)	(0.0395)	(0.0515)
Taken Loan	0.0146	0.0151	0.0112	0.0118	0.0188	0.0114
	(0.0212)	(0.0192)	(0.0234)	(0.0218)	(0.0249)	(0.0227)
Loan from Friends and Rel.	-0.0329*	-0.0280*	-0.0305	-0.0249	-0.0313*	-0.0250
	(0.0176)	(0.0154)	(0.0194)	(0.0181)	(0.0182)	(0.0188)
Loan from Bank	-0.0904	-0.0490	-0.0837	-0.0457	-0.0867	-0.0529
	(0.0680)	(0.0603)	(0.0741)	(0.0784)	(0.0731)	(0.0716)
Loan from NGO	-0.0485**	-0.0365*	-0.0455**	-0.0336	-0.0458*	-0.0254
	(0.0226)	(0.0220)	(0.0219)	(0.0214)	(0.0263)	(0.0269)
Loan for Farming	0.0135	0.00403	0.0103	0.00149	0.0105	0.00207
	(0.0239)	(0.0280)	(0.0254)	(0.0268)	(0.0262)	(0.0218)
Loan for Business	0.00827	-0.0106	0.00781	-0.00950	-0.00186	-0.0125
	(0.0377)	(0.0511)	(0.0435)	(0.0482)	(0.0453)	(0.0530)
Loan for Food	0.0364***	0.0368***	0.0382***	0.0392**	0.0270**	0.0310***
	(0.0112)	(0.0143)	(0.0135)	(0.0157)	(0.0114)	(0.0104)
Loan for Travel	0.117*	0.108*	0.118*	0.109	0.119	0.110
	(0.0683)	(0.0623)	(0.0646)	(0.0744)	(0.0860)	(0.0755)
Logged Income	0.0121***	0.0126***	0.0119***	0.0128***	0.00979***	0.0123***

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Table A.6 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)
	(0.00203)	(0.00242)	(0.00225)	(0.00272)	(0.00289)	(0.00244)
Logged Nonfarm Income	-0.00575**	-0.00397*	-0.00548**	-0.00378	-0.00462*	-0.00376
	(0.00260)	(0.00231)	(0.00271)	(0.00264)	(0.00263)	(0.00236)
Logged Business Income	0.0000974	-0.000111	0.000492	-0.0000283	0.00251	0.00121
	(0.00235)	(0.00276)	(0.00294)	(0.00324)	(0.00288)	(0.00307)
Plot Area Per Person	0.0527**	0.0545**	0.0500**	0.0518**	0.0506*	0.0526*
	(0.0262)	(0.0274)	(0.0215)	(0.0255)	(0.0286)	(0.0304)
Household Size	0.000225	0.000965	0.000411	0.00106	0.000512	0.00117
	(0.00140)	(0.00190)	(0.00201)	(0.00190)	(0.00195)	(0.00208)
Time Trend		-0.0114**		-0.0111*		-0.0106
		(0.00543)		(0.00581)		(0.00761)
Constant	0.0957***	0.115***	0.0950***	0.112***	0.101***	0.112***
	(0.0154)	(0.0260)	(0.0180)	(0.0221)	(0.0245)	(0.0359)
Fixed Effects	Dist.-Round	District	Village-Round	Village	Region-Round	Region
Number of Groups	60	15	72	18	24	6
Clustered S.E.	District	District	Village	Village	Region	Region
Time Trend	No	Yes	No	Yes	No	Yes
N	5,604	5,604	5,576	5,576	5,576	5,576
R^2	0.013	0.015	0.012	0.015	0.012	0.015

Notes: Standard errors are in parentheses. *: $p < 0.1$, **: $p < 0.0.05$, ***: $p < 0.0.01$.

Table A.7: Robustness Check (4): Conditional Logit Model with Fixed Effects

	Dependent Variable: Migrate (0 or 1)					
	(1)	(2)	(3)	(4)	(5)	(6)
WTP	0.756***	0.611***	0.745***	0.608**	0.713***	0.578*
	(0.178)	(0.226)	(0.214)	(0.240)	(0.185)	(0.322)
Taken Loan	0.1000	0.0970	0.0764	0.0750	0.133	0.0771
	(0.154)	(0.120)	(0.137)	(0.108)	(0.150)	(0.112)
Loan from Friends and Rel.	-0.220*	-0.179**	-0.202*	-0.159	-0.214**	-0.167*
	(0.118)	(0.0815)	(0.121)	(0.0976)	(0.105)	(0.0967)
Loan from Bank	-0.606	-0.348	-0.576	-0.325	-0.591	-0.371
	(4.041)	(4.653)	(3.934)	(5.245)	(2.452)	(5.097)
Loan from NGO	-0.327*	-0.231**	-0.308*	-0.211*	-0.305	-0.158
	(0.180)	(0.117)	(0.183)	(0.120)	(0.198)	(0.195)
Loan for Farming	0.0737	0.0161	0.0475	-0.00322	0.0580	0.00928
	(0.228)	(0.171)	(0.267)	(0.152)	(0.202)	(0.245)
Loan for Business	0.0816	-0.0747	0.0777	-0.0688	-0.0111	-0.0918
	(0.318)	(0.348)	(0.258)	(0.280)	(0.335)	(0.300)
Loan for Food	0.242***	0.247**	0.255***	0.263***	0.179**	0.207***
	(0.0862)	(0.114)	(0.0920)	(0.0758)	(0.0872)	(0.0584)
Loan for Travel	0.663**	0.593	0.669*	0.598*	0.664*	0.595**
	(0.320)	(0.373)	(0.368)	(0.327)	(0.365)	(0.301)
Logged Income	0.0919***	0.0921***	0.0916***	0.0936***	0.0731***	0.0900***

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Table A.7 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)
	(0.0218)	(0.0155)	(0.0232)	(0.0163)	(0.0217)	(0.0195)
Logged Nonfarm Income	-0.0415**	-0.0270	-0.0401**	-0.0258	-0.0338*	-0.0258
	(0.0192)	(0.0179)	(0.0175)	(0.0159)	(0.0194)	(0.0176)
Logged Business Income	-0.00224	-0.00267	0.000564	-0.00209	0.0141	0.00631
	(0.0165)	(0.0173)	(0.0137)	(0.0185)	(0.0136)	(0.0186)
Plot Area Per Person	0.304***	0.309**	0.292***	0.295**	0.294***	0.303
	(0.0869)	(0.142)	(0.0903)	(0.118)	(0.0722)	(0.239)
Household Size	0.000831	0.00604	0.00202	0.00667	0.00292	0.00787
	(0.0144)	(0.0100)	(0.0146)	(0.0129)	(0.0127)	(0.0136)
Time Trend		-0.0782*		-0.0760**		-0.0721
		(0.0458)		(0.0349)		(0.0665)
Fixed Effects	Dist.-Round	District	Village-Round	Village	Region-Round	Region
Clustered S.E.	District	District	Village	Village	Region	Region
Number of Groups	60	15	72	18	24	6
Time Trend	No	Yes	No	Yes	No	Yes
N	5,604	5,604	5,576	5,576	5,576	5,576

Notes: Bootstrapped standard errors are in parentheses. *: $p < 0.1$, **: $p < 0.0.05$, ***: $p < 0.0.01$.

Table A.8: Robustness Check (5): Conditional Logit Model without Fixed Effects

Dependent Variable: Migrate (0 or 1)					
	(1)	(2)	(3)	(4)	(5)
WTP	0.718***	0.714***	0.612***	0.625***	0.733***
	(0.190)	(0.219)	(0.154)	(0.214)	(0.190)
Round 2		-0.715***		-0.726***	
		(0.0834)		(0.0964)	
Round 3		-0.775***		-0.786***	
		(0.0974)		(0.121)	
Round 4		-0.173**		-0.165*	
		(0.0832)		(0.0980)	
Time Trend					-0.0782**
					(0.0380)
Controls	No	No	No	No	Yes
District Dummy	No	No	Yes	Yes	No
Round Dummy	No	Yes	No	Yes	No
Time Trend	No	No	No	No	Yes
N	5,613	5,613	5,613	5,613	5,604

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Control variables included: access to loan, loan from friends and relatives, loan from bank, loan from NGO, loan for farming, loan for business, loan for food, loan for travel, income, non-farm income, business income, plot size per person, household size

Bootstrapped standard errors are in parentheses. *: $p < 0.1$, **: $p < 0.0.05$, ***: $p < 0.0.01$.

Appendix B

1. Wheat production, cost, and profit when price of wheat is **$5/bushel**.

(1) Wheat Production (1,000 bushels)	(2) Price ($/bushel)	(3) Cost = 2 X (1)$^{1.4}$+15 ($ 1,000)	(4) Profit = (1)X(2)-(3) ($1,000)
0	5	15	-15.00
1	5	17	-12.00
2	5	20	-10.28
3	5	24	-9.31
4	5	29	-8.93
5	5	34	-9.04
6	5	40	-9.57
7	5	45	-10.49
8	5	52	-11.76
9	5	58	-13.35
10	5	65	-15.24
11	5	72	-17.41
12	5	80	-19.85
13	5	88	-22.54
14	5	95	-25.47
15	5	104	-28.63
16	5	112	-32.01
17	5	121	-35.60
18	5	129	-39.40
19	5	138	-43.39
20	5	148	-47.58

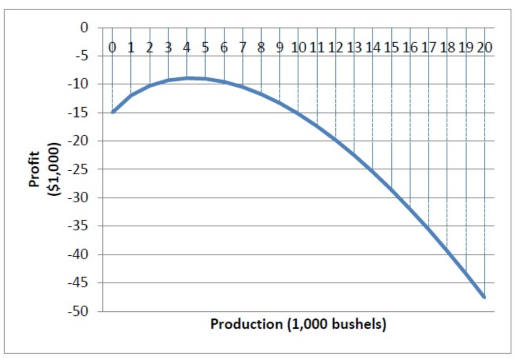


Figure B.1: Chart Showing Payoffs at Various Output Levels for $p = 5$.

2. Wheat production, cost, and profit when price of wheat is $6/bushel.

(1) Wheat Production (1,000 bushels)	(2) Price ($/bushel)	(3) Cost = 2 X $(1)^{1.4}$+15 ($ 1,000)	(4) Profit = (1)X(2)-(3) ($1,000)
0	6	15	-15.00
1	6	17	-11.00
2	6	20	-8.28
3	6	24	-6.31
4	6	29	-4.93
5	6	34	-4.04
6	6	40	-3.57
7	6	45	-3.49
8	6	52	-3.76
9	6	58	-4.35
10	6	65	-5.24
11	6	72	-6.41
12	6	80	-7.85
13	6	88	-9.54
14	6	95	-11.47
15	6	104	-13.63
16	6	112	-16.01
17	6	121	-18.60
18	6	129	-21.40
19	6	138	-24.39
20	6	148	-27.58

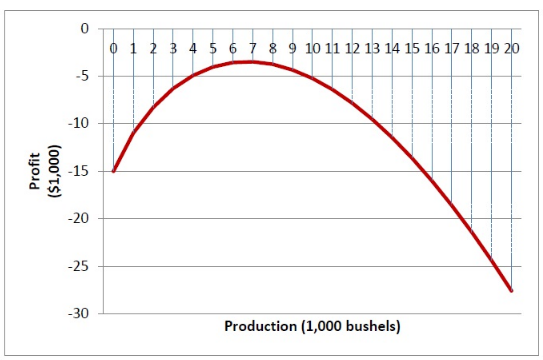


Figure B.2: Chart Showing Payoffs at Various Output Levels for $p = 6$.

3. Wheat production, cost, and profit when price of wheat is **$7/bushel**.

(1) Wheat Production (1,000 bushels)	(2) Price ($/bushel)	(3) Cost = 2 X (1)$^{1.4}$+15 ($ 1,000)	(4) Profit = (1)X(2)-(3) ($1,000)
0	7	15	-15.00
1	7	17	-10.00
2	7	20	-6.28
3	7	24	-3.31
4	7	29	-0.93
5	7	34	0.96
6	7	40	2.43
7	7	45	3.51
8	7	52	4.24
9	7	58	4.65
10	7	65	4.76
11	7	72	4.59
12	7	80	4.15
13	7	88	3.46
14	7	95	2.53
15	7	104	1.37
16	7	112	-0.01
17	7	121	-1.60
18	7	129	-3.40
19	7	138	-5.39
20	7	148	-7.58

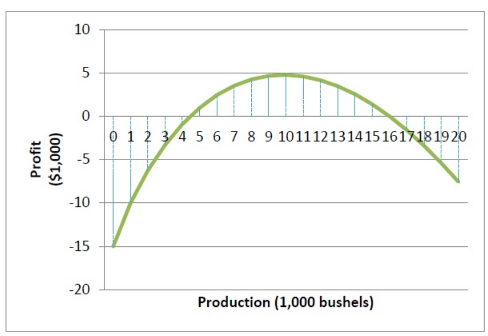


Figure B.3: Chart Showing Payoffs at Various Output Levels for $p = 7$.

4. Wheat production, cost, and profit when price of wheat is **$8/bushel**.

(1) Wheat Production (1,000 bushels)	(2) Price ($/bushel)	(3) Cost = 2 X (1)$^{1.4}$+15 ($ 1,000)	(4) Profit = (1)X(2)-(3) ($1,000)
0	8	15	-15.00
1	8	17	-9.00
2	8	20	-4.28
3	8	24	-0.31
4	8	29	3.07
5	8	34	5.96
6	8	40	8.43
7	8	45	10.51
8	8	52	12.24
9	8	58	13.65
10	8	65	14.76
11	8	72	15.59
12	8	80	16.15
13	8	88	16.46
14	8	95	16.53
15	8	104	16.37
16	8	112	15.99
17	8	121	15.40
18	8	129	14.60
19	8	138	13.61
20	8	148	12.42

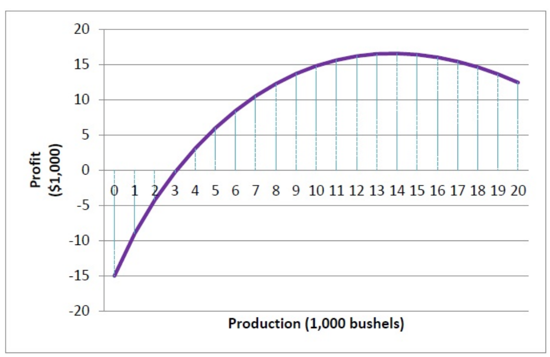


Figure B.4: Chart Showing Payoffs at Various Output Levels for $p = 8$.

5. Wheat production, cost, and profit when price of wheat is **$9/bushel**.

(1) Wheat Production (1,000 bushels)	(2) Price ($/bushel)	(3) Cost = 2 X (1)$^{1.4}$+15 ($ 1,000)	(4) Profit = (1)X(2)-(3) ($1,000)
0	9	15.00	-15.00
1	9	17.00	-8.00
2	9	20.28	-2.28
3	9	24.31	2.69
4	9	28.93	7.07
5	9	34.04	10.96
6	9	39.57	14.43
7	9	45.49	17.51
8	9	51.76	20.24
9	9	58.35	22.65
10	9	65.24	24.76
11	9	72.41	26.59
12	9	79.85	28.15
13	9	87.54	29.46
14	9	95.47	30.53
15	9	103.63	31.37
16	9	112.01	31.99
17	9	120.60	32.40
18	9	129.40	32.60
19	9	138.39	32.61
20	9	147.58	32.42

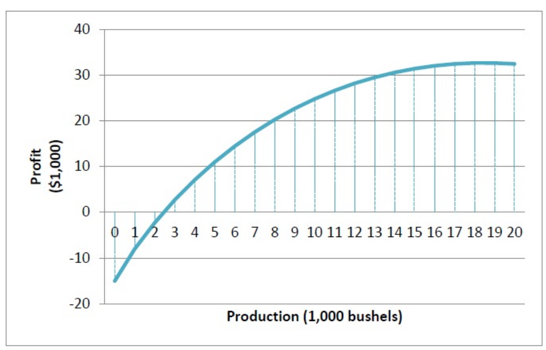


Figure B.5: Chart Showing Payoffs at Various Output Levels for $p = 9$.

6. Profits when price of wheat is **$5/bushel-$9/bushel**.

Wheat Production	Profit				
	P = $5	P = $6	P = $7	P = $8	P = $9
0	-15.00	-15.00	-15.00	-15.00	-15.00
1	-12.00	-11.00	-10.00	-9.00	-8.00
2	-10.28	-8.28	-6.28	-4.28	-2.28
3	-9.31	-6.31	-3.31	-0.31	2.69
4	-8.93	-4.93	-0.93	3.07	7.07
5	-9.04	-4.04	0.96	5.96	10.96
6	-9.57	-3.57	2.43	8.43	14.43
7	-10.49	-3.49	3.51	10.51	17.51
8	-11.76	-3.76	4.24	12.24	20.24
9	-13.35	-4.35	4.65	13.65	22.65
10	-15.24	-5.24	4.76	14.76	24.76
11	-17.41	-6.41	4.59	15.59	26.59
12	-19.85	-7.85	4.15	16.15	28.15
13	-22.54	-9.54	3.46	16.46	29.46
14	-25.47	-11.47	2.53	16.53	30.53
15	-28.63	-13.63	1.37	16.37	31.37
16	-32.01	-16.01	-0.01	15.99	31.99
17	-35.60	-18.60	-1.60	15.40	32.40
18	-39.40	-21.40	-3.40	14.60	32.60
19	-43.39	-24.39	-5.39	13.61	32.61
20	-47.58	-27.58	-7.58	12.42	32.42

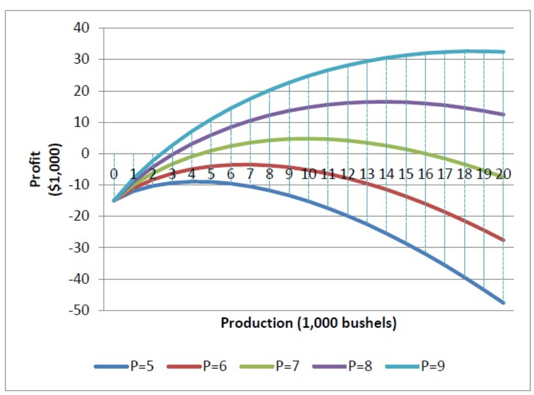
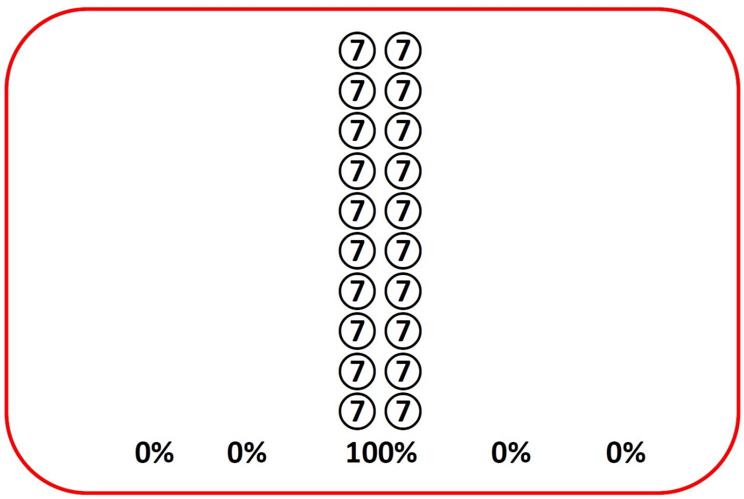


Figure B.6: Chart Summarizing Payoffs at Various Output and Price Levels.

Setting 1

- There are 20 balls in the bag marked with prices \$5, \$6, \$7, \$8, and \$9. The number of balls marked with each price are shown in the following picture.

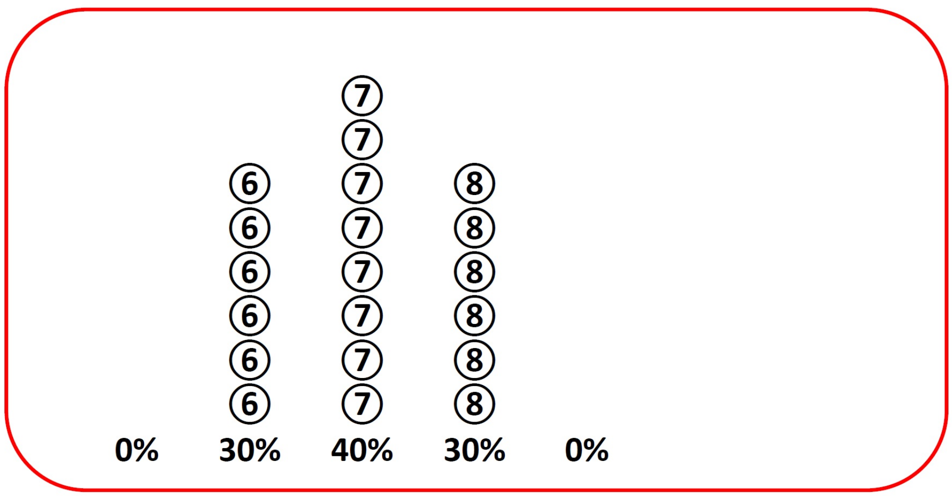


- Write down your choice of input (0-20) on the answer sheet.

Figure B.7: Setting 1, with $\mu = 7$ and $\sigma = 0$.

Setting 2

- There are 20 balls in the bag marked with prices \$5, \$6, \$7, \$8, and \$9. The number of balls marked with each price are shown in the following picture.

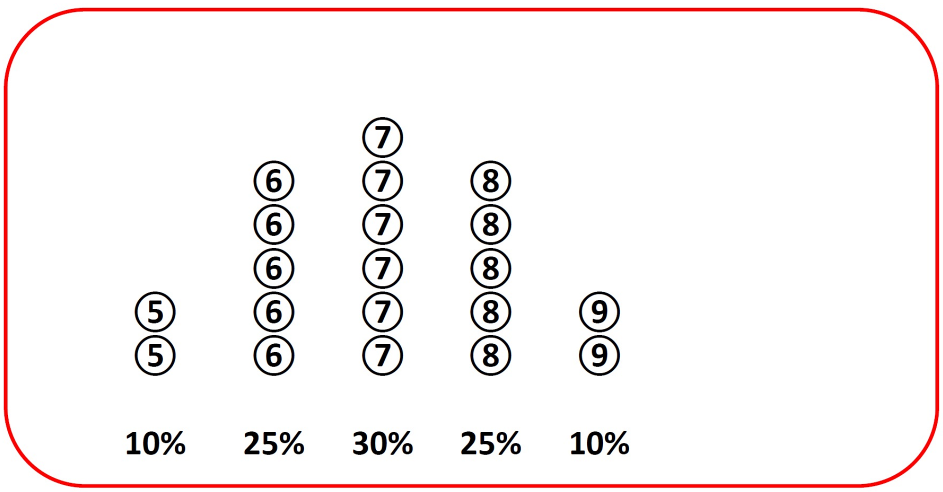


- Write down your choice of input (0-20) on the answer sheet.

Figure B.8: Setting 2, with $\mu = 7$ and $\sigma = 0.795$.

Setting 3

- There are 20 balls in the bag marked with prices \$5, \$6, \$7, \$8, and \$9. The number of balls marked with each price are shown in the following picture.



- Write down your choice of input (0-20) on the answer sheet.

Figure B.9: Setting 3, with $\mu = 7$ and $\sigma = 1.17$.

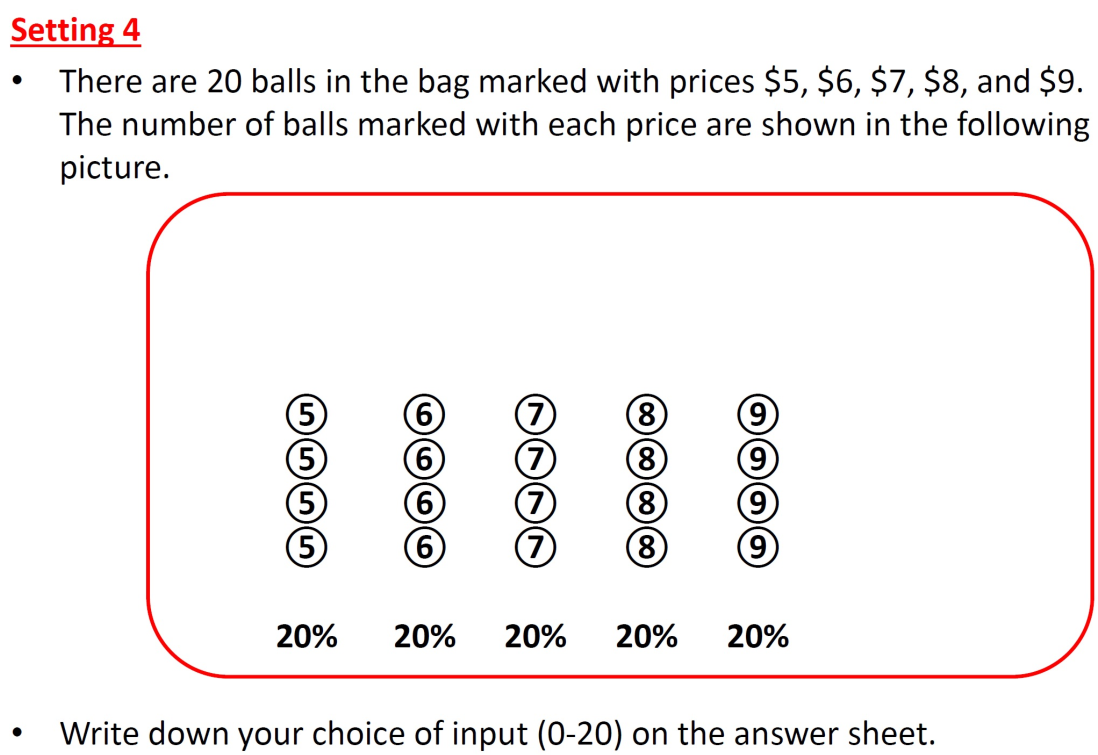
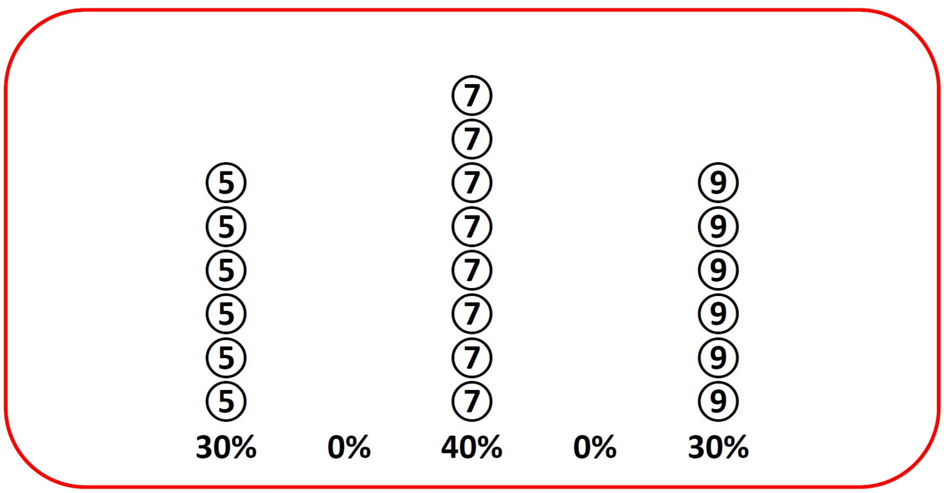


Figure B.10: Setting 4, with $\mu = 7$ and $\sigma = 1.451$.

Setting 5

- There are 20 balls in the bag marked with prices \$5, \$6, \$7, \$8, and \$9. The number of balls marked with each price are shown in the following picture.



- Write down your choice of input (0-20) on the answer sheet.

Figure B.11: Setting 5, with $\mu = 7$ and $\sigma = 1.58$.

	Option A	Option B	Your Choice (circle one)
1	1/10 of $2.00, 9/10 of $1.60	1/10 of $3.85, 9/10 of $0.10	A , B
2	2/10 of $2.00, 8/10 of $1.60	2/10 of $3.85, 8/10 of $0.10	A , B
3	3/10 of $2.00, 7/10 of $1.60	3/10 of $3.85, 7/10 of $0.10	A , B
4	4/10 of $2.00, 6/10 of $1.60	4/10 of $3.85, 6/10 of $0.10	A , B
5	5/10 of $2.00, 5/10 of $1.60	5/10 of $3.85, 5/10 of $0.10	A , B
6	6/10 of $2.00, 4/10 of $1.60	6/10 of $3.85, 4/10 of $0.10	A , B
7	7/10 of $2.00, 3/10 of $1.60	7/10 of $3.85, 3/10 of $0.10	A , B
8	8/10 of $2.00, 2/10 of $1.60	8/10 of $3.85, 2/10 of $0.10	A , B
9	9/10 of $2.00, 1/10 of $1.60	9/10 of $3.85, 1/10 of $0.10	A , B
10	10/10 of $2.00, 0/10 of $1.60	10/10 of $3.85, 0/10 of $0.10	A , B

Please stop once you have chosen the option B.

Figure B.12: Holt and Laury (2002) List Experiment to Elicit Risk Preferences.

Table B.1: OLS Estimation Results for Production with Subject-Specific Random Effects, Cornell Subjects Only

Variable	**Coefficient** (Std. Err.)
Uncertainty	2.041**
	(0.423)
Standard Deviation	-1.491**
	(0.352)
Arrow-Pratt Coefficient of RRA	-0.437
	(0.427)
Holt-Laury First	0.237
	(0.345)
Female	-0.084
	(0.335)
Round	-0.002
	(0.014)
Intercept	10.386**
	(0.588)
N	940
$\chi^2_{(6)}$	26.062

Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

Table B.2: OLS Estimation Results for Production with Subject-Specific Random Effects, Minnesota Subjects Only

Variable	**Coefficient** (Std. Err.)
Uncertainty	1.810**
	(0.551)
Standard Deviation	-1.184*
	(0.499)
Arrow-Pratt Coefficient of RRA	-0.618
	(0.886)
Female	-1.304*
	(0.647)
Round	0.006
	(0.019)
Intercept	10.889**
	(1.335)
N	459
$\chi^2_{(5)}$	13.821

Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

Table B.3: OLS Estimation Results for Production with Subject-Specific Random Effects, Peruvian Subjects Only

Variable	**Coefficient** (Std. Err.)
Uncertainty	-0.612
	(0.637)
Standard Deviation	0.878
	(0.561)
Arrow-Pratt Coefficient of RRA	0.045
	(0.270)
Holt-Laury First	0.767
	(0.516)
Female	-0.050
	(0.502)
Round	-0.053**
	(0.018)
Intercept	11.052**
	(0.525)
N	920
$\chi^2_{(6)}$	16.267

Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

Table B.4: OLS Estimation Results for Production with Subject-Specific Random Effects, Risk-Averse Subjects Only

Variable	**Coefficient** (Std. Err.)
Uncertainty	1.824**
	(0.340)
Standard Deviation	-1.212**
	(0.285)
Arrow-Pratt Coefficient of RRA	-0.286
	(0.388)
Holt-Laury First	0.450
	(0.285)
Female	-0.189
	(0.279)
Round	-0.019†
	(0.011)
Intercept	10.504**
	(0.432)
N	1739
$\chi^2_{(6)}$	35.383

Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

Table B.5: OLS Estimation Results for Whether Subjects Minimize the Probability of Loss with Subject-Specific Random Effects, Cornell Subjects Only

Variable	**Coefficient** (Std. Err.)
Uncertainty	0.051 (0.037)
Standard Deviation	-0.079* (0.034)
Arrow-Pratt Coefficient of RRA	0.006 (0.028)
Holt-Laury First	0.004 (0.026)
Female	0.054† (0.028)
Round	0.001 (0.001)
Intercept	0.950** (0.042)
N	940
$\chi^2_{(6)}$	10.06

Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

Table B.6: OLS Estimation Results for Whether Subjects Minimize the Probability of Loss with Subject-Specific Random Effects, Minnesota Subjects Only

Variable	**Coefficient** (Std. Err.)
Uncertainty	0.030
	(0.044)
Standard Deviation	-0.040
	(0.039)
Arrow-Pratt Coefficient of RRA	-0.004
	(0.025)
Female	-0.003
	(0.018)
Round	0.000
	(0.001)
Intercept	1.005**
	(0.048)
N	460
$\chi^2_{(5)}$	5.896

Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

Table B.7: OLS Estimation Results for Whether Subjects Minimize the Probability of Loss with Subject-Specific Random Effects, Peruvian Subjects Only

Variable	**Coefficient** (Std. Err.)
Uncertainty	0.019
	(0.074)
Standard Deviation	-0.131*
	(0.063)
Arrow-Pratt Coefficient of RRA	0.021
	(0.021)
Female	-0.024
	(0.036)
Round	0.001
	(0.002)
Intercept	0.971**
	(0.037)
N	920
$\chi^2_{(5)}$	29.998

Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

Table B.8: OLS Estimation Results for Expected Revenue with Subject-Specific Random Effects, Cornell Subjects Only

Variable	**Coefficient** (Std. Err.)
Uncertainty	0.368 (0.275)
Standard Deviation	-1.097** (0.265)
Arrow-Pratt Coefficient of RRA	-0.038 (0.268)
Holt-Laury First	0.068 (0.225)
Female	0.514* (0.231)
Round	0.001 (0.009)
Intercept	4.455** (0.345)
N	940
$\chi^2_{(6)}$	60.132

Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

Table B.9: OLS Estimation Results for Expected Revenue with Subject-Specific Random Effects, Minnesota Subjects Only

Variable	**Coefficient** (Std. Err.)
Uncertainty	0.191
	(0.402)
Standard Deviation	-0.789*
	(0.374)
Arrow-Pratt Coefficient of RRA	0.258
	(0.430)
Female	-0.158
	(0.214)
Round	0.001
	(0.012)
Intercept	4.498**
	(0.703)
N	459
$\chi^2_{(5)}$	57.321

Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

Table B.10: OLS Estimation Results for Expected Revenue with Subject-Specific Random Effects, Peruvian Subjects Only

Variable	**Coefficient** (Std. Err.)
Uncertainty	-0.192
	(0.527)
Standard Deviation	-1.280**
	(0.493)
Arrow-Pratt Coefficient of RRA	0.033
	(0.176)
Holt-Laury First	-0.321
	(0.307)
Female	0.041
	(0.297)
Round	0.022
	(0.015)
Intercept	4.025**
	(0.321)
N	920
$\chi^2_{(6)}$	63.415

Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

Table B.11: OLS Estimation Results for Production with Subject-Specific Random Effects, Cornell Subjects Only

Variable	**Coefficient** (Std. Err.)
$P(p = 5)$ or $P(p = 9)$	-21.257 (20.348)
$P(p = 6)$ or $P(p = 8)$	-15.076 (19.099)
$P(p = 7)$	-8.948 (9.701)
Expected Gain	0.107 (0.258)
Expected Loss	1.821** (0.262)
Arrow-Pratt Coefficient of RRA	-0.288 (0.423)
Holt-Laury First	0.088 (0.280)
Female	0.046 (0.281)
Round	0.001 (0.016)
Intercept	18.633† (9.611)
N	940
$\chi^2_{(9)}$	222.49

Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

Table B.12: OLS Estimation Results for Production with Subject-Specific Random Effects, Minnesota Subjects Only

Variable	Coefficient (Std. Err.)
$P(p=5)$ or $P(p=9)$	-76.275**
	(17.317)
$P(p=6)$ or $P(p=8)$	-67.254**
	(16.017)
$P(p=7)$	-35.114**
	(8.256)
Expected Gain	-0.191
	(0.458)
Expected Loss	1.424**
	(0.371)
Arrow-Pratt Coefficient of RRA	-0.639
	(0.790)
Female	-1.358*
	(0.619)
Round	-0.014
	(0.020)
Intercept	47.489**
	(7.664)
N	459
$\chi^2_{(8)}$	272.692

Significance levels: † : 10% $*$: 5% $**$: 1%

Table B.13: OLS Estimation Results for Production with Subject-Specific Random Effects, Peruvian Subjects Only

Variable	Coefficient (Std. Err.)
$P(p=5)$ or $P(p=9)$	-13.816
	(19.965)
$P(p=6)$ or $P(p=8)$	-13.755
	(18.235)
$P(p=7)$	-6.215
	(9.351)
Expected Gain	-0.419*
	(0.201)
Expected Loss	0.706**
	(0.269)
Arrow-Pratt Coefficient of RRA	0.051
	(0.217)
Holt-Laury First	0.579
	(0.414)
Female	-0.030
	(0.421)
Round	-0.040*
	(0.017)
Intercept	18.863*
	(9.330)
N	920
$\chi^2_{(9)}$	46.017

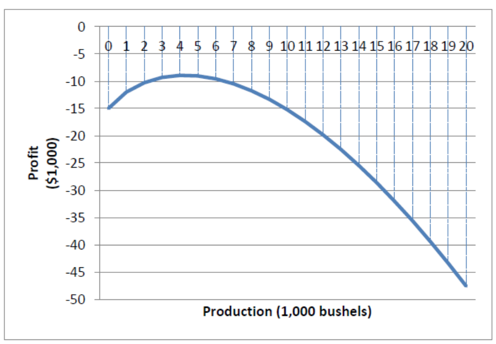
Significance levels: $\dagger$: 10% $*$: 5% $**$: 1%

Appendix C

C.1 Charts (English)

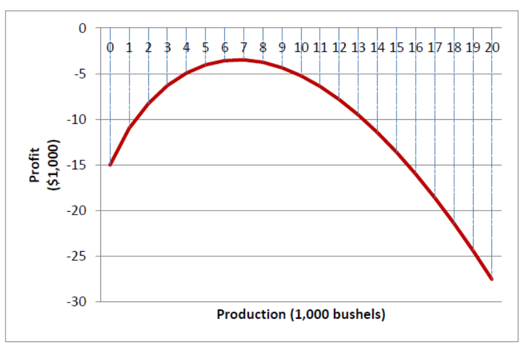
1. Wheat production, cost, and profit when price of wheat is **$5/bushel**.

(1) Wheat Production (1,000 bushels)	(2) Price ($/bushel)	(3) Cost $= 2 \times (1)^{1.4}+15$ ($ 1,000)	(4) Profit = (1)X(2)-(3) ($1,000)
0	5	15.00	-15.00
1	5	17.00	-12.00
2	5	20.28	-10.28
3	5	24.31	-9.31
4	5	28.93	-8.93
5	5	34.04	-9.04
6	5	39.57	-9.57
7	5	45.49	-10.49
8	5	51.76	-11.76
9	5	58.35	-13.35
10	5	65.24	-15.24
11	5	72.41	-17.41
12	5	79.85	-19.85
13	5	87.54	-22.54
14	5	95.47	-25.47
15	5	103.63	-28.63
16	5	112.01	-32.01
17	5	120.60	-35.60
18	5	129.40	-39.40
19	5	138.39	-43.39
20	5	147.58	-47.58



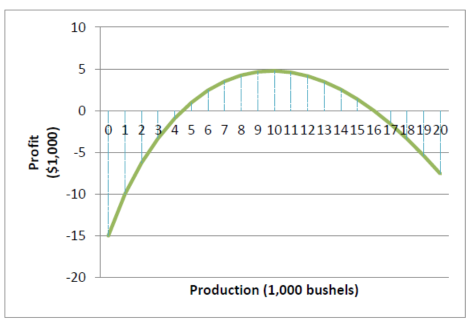
2. Wheat production, cost, and profit when price of wheat is <u>$6/bushel</u>.

(1) Wheat Production (1,000 bushels)	(2) Price ($/bushel)	(3) Cost $= 2 \times (1)^{1.4}+15$ ($ 1,000)	(4) Profit = (1)X(2)-(3) ($1,000)
0	6	15.00	-15.00
1	6	17.00	-11.00
2	6	20.28	-8.28
3	6	24.31	-6.31
4	6	28.93	-4.93
5	6	34.04	-4.04
6	6	39.57	-3.57
7	6	45.49	-3.49
8	6	51.76	-3.76
9	6	58.35	-4.35
10	6	65.24	-5.24
11	6	72.41	-6.41
12	6	79.85	-7.85
13	6	87.54	-9.54
14	6	95.47	-11.47
15	6	103.63	-13.63
16	6	112.01	-16.01
17	6	120.60	-18.60
18	6	129.40	-21.40
19	6	138.39	-24.39
20	6	147.58	-27.58



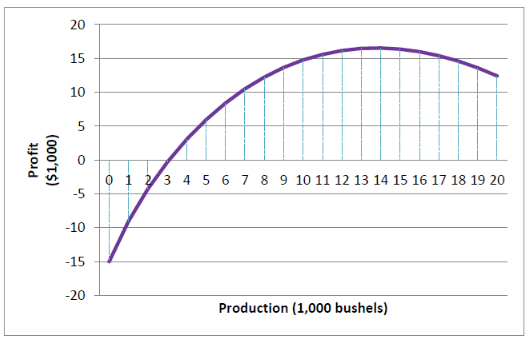
3. Wheat production, cost, and profit when price of wheat is **$7/bushel**.

(1) Wheat Production (1,000 bushels)	(2) Price ($/bushel)	(3) Cost $= 2 \times (1)^{1.4}+15$ ($ 1,000)	(4) Profit = (1)X(2)-(3) ($1,000)
0	7	15.00	-15.00
1	7	17.00	-10.00
2	7	20.28	-6.28
3	7	24.31	-3.31
4	7	28.93	-0.93
5	7	34.04	0.96
6	7	39.57	2.43
7	7	45.49	3.51
8	7	51.76	4.24
9	7	58.35	4.65
10	7	65.24	4.76
11	7	72.41	4.59
12	7	79.85	4.15
13	7	87.54	3.46
14	7	95.47	2.53
15	7	103.63	1.37
16	7	112.01	-0.01
17	7	120.60	-1.60
18	7	129.40	-3.40
19	7	138.39	-5.39
20	7	147.58	-7.58



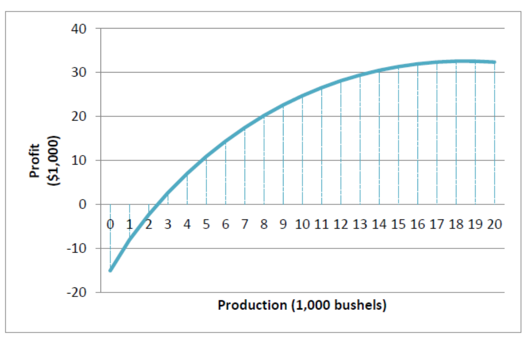
4. Wheat production, cost, and profit when price of wheat is **$8/bushel**.

(1) Wheat Production (1,000 bushels)	(2) Price ($/bushel)	(3) Cost = 2 X $(1)^{1.4}$+15 ($ 1,000)	(4) Profit = (1)X(2)-(3) ($1,000)
0	8	15.00	-15.00
1	8	17.00	-9.00
2	8	20.28	-4.28
3	8	24.31	-0.31
4	8	28.93	3.07
5	8	34.04	5.96
6	8	39.57	8.43
7	8	45.49	10.51
8	8	51.76	12.24
9	8	58.35	13.65
10	8	65.24	14.76
11	8	72.41	15.59
12	8	79.85	16.15
13	8	87.54	16.46
14	8	95.47	16.53
15	8	103.63	16.37
16	8	112.01	15.99
17	8	120.60	15.40
18	8	129.40	14.60
19	8	138.39	13.61
20	8	147.58	12.42



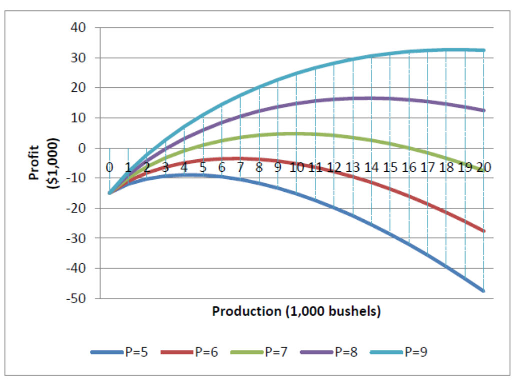
5. Wheat production, cost, and profit when price of wheat is **$9/bushel**.

(1) Wheat Production (1,000 bushels)	(2) Price ($/bushel)	(3) Cost $= 2 \times (1)^{1.4}+15$ ($ 1,000)	(4) Profit $= (1)\times(2)-(3)$ ($1,000)
0	9	15.00	-15.00
1	9	17.00	-8.00
2	9	20.28	-2.28
3	9	24.31	2.69
4	9	28.93	7.07
5	9	34.04	10.96
6	9	39.57	14.43
7	9	45.49	17.51
8	9	51.76	20.24
9	9	58.35	22.65
10	9	65.24	24.76
11	9	72.41	26.59
12	9	79.85	28.15
13	9	87.54	29.46
14	9	95.47	30.53
15	9	103.63	31.37
16	9	112.01	31.99
17	9	120.60	32.40
18	9	129.40	32.60
19	9	138.39	32.61
20	9	147.58	32.42



6. Profits when price of wheat is **$5/bushel-$9/bushel**.

Wheat Production	Profit				
	P = $5	P = $6	P = $7	P = $8	P = $9
0	-15.00	-15.00	-15.00	-15.00	-15.00
1	-12.00	-11.00	-10.00	-9.00	-8.00
2	-10.28	-8.28	-6.28	-4.28	-2.28
3	-9.31	-6.31	-3.31	-0.31	2.69
4	-8.93	-4.93	-0.93	3.07	7.07
5	-9.04	-4.04	0.96	5.96	10.96
6	-9.57	-3.57	2.43	8.43	14.43
7	-10.49	-3.49	3.51	10.51	17.51
8	-11.76	-3.76	4.24	12.24	20.24
9	-13.35	-4.35	4.65	13.65	22.65
10	-15.24	-5.24	4.76	14.76	24.76
11	-17.41	-6.41	4.59	15.59	26.59
12	-19.85	-7.85	4.15	16.15	28.15
13	-22.54	-9.54	3.46	16.46	29.46
14	-25.47	-11.47	2.53	16.53	30.53
15	-28.63	-13.63	1.37	16.37	31.37
16	-32.01	-16.01	-0.01	15.99	31.99
17	-35.60	-18.60	-1.60	15.40	32.40
18	-39.40	-21.40	-3.40	14.60	32.60
19	-43.39	-24.39	-5.39	13.61	32.61
20	-47.58	-27.58	-7.58	12.42	32.42



C.2 Instructions (English)

General Instructions

- This is an experiment in the economics of individual decision making. We are trying to understand how people make production decisions when they are unsure of the price they will receive. We have designed simple decision-making games in which we will ask you to make choices in a series of situations.
- There are two sets of games. In the first set of games, you will be making decisions assuming that you are a farmer producing a single commodity, wheat. In the second set of games, you will be given a series of lotteries to choose from. More detailed explanations will follow in each set.
- You will spend 60 to 90 minutes in this study playing economic games. You will spend about 30 minutes to receive your payment. You will receive $45 for participation and completion of the experiment and in addition may earn between $1.31 and $45.16 depending on your performance and also on the luck on the experiment.
- You should make your own decision and should not discuss your decisions or the decision scenarios with other participants. Also, please turn off your cell phones.
- You need to have a good understanding on how your decisions affect your payoff. Please raise your hand at any time during the session if you have any question.

Set I: Single-Commodity Production Game

- You are a farmer who produces and sells only one commodity, wheat.
- The selling price of wheat in dollars per bushel will be one of the five possible values: $5, $6, $7, $8, and $9, and it will be realized *after* you make your production decision to reflect the real-world output price uncertainty.
- You will be given charts 1 through 5 which document the amount of cost to be incurred according to production levels 0 through 20 (in 1,000 bushels), and the corresponding profit (in $1,000) that will occur *under the five different price scenarios*. These charts contain all the information about how your production decision, cost of production, and your profit relate to one another. Chart 6 is a summary of charts 1 through 5 and shows only the relationship between the production level and the profit.
- In each round, you will be given one of the two situations:

  (1) You know that your selling price will be exactly $7;

  (2) You know that the price will be one of the five values -- $5, $6, $7, $8, and $9.

  Under a given situation, you will be asked to determine how much wheat to produce by choosing any integer between 0 and 20 as your production level. You may refer to the charts 1-6 to facilitate your decision.
- Your goal is to maximize the profit (price times quantity produced minus cost of production), since maximizing profit is identical to maximizing your payoff.
- Note that there is no subsistence constraint, meaning that there is no minimum required level of production for your survival. Nor is there a requirement to make a positive profit in order for you to survive. Negative profits mean that you lose some of the money that you are endowed with.
- *After* you have chosen how much to produce, a ball will be drawn randomly from a bag, which will determine your selling price. You will sell your wheat at that price, which will determine your profit.
- You will first play 10 rounds of practice games. After the practice games, you will play 20 rounds of the real games. In the real games, your profits will affect your actual payoffs from the games.

- In this set of the game, you start from base payoff of $25. In a given round, your profit will be between -47.58 and 32.61. After the 20 actual rounds, we will randomly select a round. Your payoff from these games will be determined in the following way: $25 base payoff + a half of your profit in the randomly selected round. For example, if you have made a loss of 30 in the selected round, your final payoff will be $25 + (-$30 X 0.5) = $10. If you have made a profit of 28, your final payoff will be $25 + ($28 X 0.5) = $39.
- Your final payoff in this set of the games will range between $1.21 and $41.31.

Set II: Lottery Choice Game

- In this set of games, you will be presented a table of ten paired lotteries, A and B, from which you are asked to choose one that you prefer.
- Below is an example of the options that you will be given:

Option A	Option B
1/10 of $2.00, 9/10 of $1.60	1/10 of $3.85, 9/10 of $0.10

If you choose option A, there is a probability of 0.1 that you will be receiving $2.00, and a probability of 0.9 that you will be receiving $1.60. If you choose option B, there is a probability of 0.1 that you will be receiving $3.85 which is much bigger than $2.00 in option A. However, there is also a 0.9 probability that you will be receiving only $0.10.

- Stop once you have chosen the option B.
- Your payoff from this round of game will be determined in the following way: A random number will be drawn to determine the row number of one of your choices. Then, according to the probability that the row of the choice dictates, either option A or B will be drawn, which will determine your payoff.
- Your payoff from this round will range between $0.1 and $3.85.

C.3 Answer Sheet (English)

Answer Recording Sheet **ID#:**

<u>Set I: Single-Commodity Production Game</u>

- **Record your choices of output on the vouchers.**

<u>Set II: Lottery Choice Game</u>

	Option A	Option B	Your Choice (circle one)
1	1/10 of $2.00, 9/10 of $1.60	1/10 of $3.85, 9/10 of $0.10	A , B
2	2/10 of $2.00, 8/10 of $1.60	2/10 of $3.85, 8/10 of $0.10	A , B
3	3/10 of $2.00, 7/10 of $1.60	3/10 of $3.85, 7/10 of $0.10	A , B
4	4/10 of $2.00, 6/10 of $1.60	4/10 of $3.85, 6/10 of $0.10	A , B
5	5/10 of $2.00, 5/10 of $1.60	5/10 of $3.85, 5/10 of $0.10	A , B
6	6/10 of $2.00, 4/10 of $1.60	6/10 of $3.85, 4/10 of $0.10	A , B
7	7/10 of $2.00, 3/10 of $1.60	7/10 of $3.85, 3/10 of $0.10	A , B
8	8/10 of $2.00, 2/10 of $1.60	8/10 of $3.85, 2/10 of $0.10	A , B
9	9/10 of $2.00, 1/10 of $1.60	9/10 of $3.85, 1/10 of $0.10	A , B
10	10/10 of $2.00, 0/10 of $1.60	10/10 of $3.85, 0/10 of $0.10	A , B

Stop once you have chosen the option B.

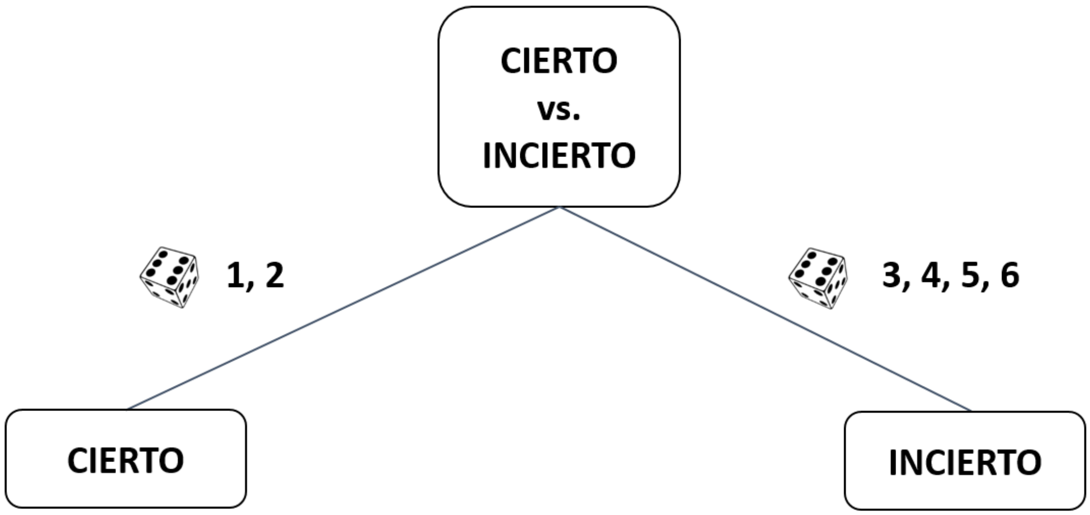
1

Demographics

- Age:_________
- Sex: M / F
- Ethnicity/Race:
  (1) Hispanic or Latino
  (2) American Indian or Alaska Native
  (3) Asian
  (4) Black or African American
  (5) Native Hawaiian or Other Pacific Islander
  (6) White
- Nationality: ___________

Thank you for your participation! ☺

C.4 Randomization Chart (Spanish)



C.5 Graphical Holt-Laury List (Spanish)