RISK, SHOCKS, AND MARKETS

THEORY AND EVIDENCE FROM AGRICULTURAL SYSTEMS IN LOW AND MIDDLE INCOME COUNTRIES

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Risk, Shocks, and Markets: Theory and Evidence from Agricultural Systems in Low and Middle Income Countries

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Dedicated to my parents

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Chapter 1

General Introduction

1.1 Overview

Markets are the bedrock of economic theory. The idea that prosperity is formed through the exchange of goods and services is as old as the study of economics itself (Smith 2008). Yet for agrarian societies, market-driven prosperity is far from certain. Economic actors in agricultural food systems continuously face uncertainty and risk – market price risk, climate risk, and political risk to name a few sources. Even if actors account for these risks *ex ante*, unexpected events (shocks) lie in wait to derail progress towards prosperity. This thesis investigates economic actors' adaptation to risk, responses to shocks, and markets' role in actors' decision-making under risk.

The thesis presents economic theory and empirical evidence from three countries in the Global South – Tanzania, Peru, and Ethiopia – across different levels of economic actors. First, the thesis starts with understanding how households use production diversification to manage risks *ex ante* and what the implications of diversification strategies and market access are for household nutrition. Next, the thesis aims to understand intra-household decision-making in agricultural investment under production and market risk and what the implications of gendered decision-making are for family labor requirements and productivity. The thesis then moves to the analysis of *ex post* responses to risk. It explores how coffee-farming households affected by negative production shocks change their marketing strategies as a coping mechanism. Finally, the thesis zooms out to the market-level to show how market price fluctuations in food markets can be a source of uncertainty and drive regional and national instability and conflict through price effects on producers and consumers.

Each chapter presents a stand-alone contribution to distinct strands of economic literature, but together the chapters underscore economic actors' heterogeneity in risk management and responses to shocks. Economic actors are diverse and operate in a myriad of contexts with distinct opportunities and constraints. Diverse contexts and actors necessitate diverse behavior. Despite this feature of the real-world, 'It is odd that heterogeneity does not play a greater role in economic models' (Kirman, 2006). Much of economic theory has been built on the notion of representative actors (Hartley, 1996; Marshall, 1920), and empirical work is often implicitly or explicitly concerned with mean impacts (Carneiro et al., 2002). In recent years, theoretical considerations have been evolving to consider actors' heterogeneity, especially when aggregating microeconomic actors into macroeconomic models (Cristelli, Pietronero, and

Zaccaria 2012; Gallegati and Kirman 2012; Chen 2012; Just et al. 1999). Similarly, empirical work is transitioning to place a greater emphasis on heterogeneity (Heckman & Vytlacil, 2001; Vivalt, 2015). Based on the logic of expanding generalizability of results in Vivalt (2015), often the issue in microeconomic literature lies in the questions asked, not the theory or methodology applied. For example, rather than asking, 'does X cause Y?' the more insightful question is often 'Under what circumstances and for which actors, does X cause Y?' In this thesis, each chapter presents research in a manner related to the latter form of questioning. The results in each chapter point towards a nuanced understanding of actors' decision-making. In Chapters 2 and 5, such nuance is a key topical contribution to the respective literatures. In all chapters, the exploration of heterogeneity helps translate the research findings into more effective and holistic policy contributions.

1.2 Expected Utility and Ex Ante Risk Management

'We abide in a perpetual state of risk. To escape from one peril is only to encounter another. There is, then, a certain minimum amount of risk which a person must bear' (Haynes, 1895). In his statement, Haynes makes a case for risk being central to economic inquiry, and this is especially true in agricultural economics. Agriculture is risky – variable rainfall, pests, and market price fluctuations ensure that there is no certainty for small farmers. These risks are only becoming more important in the backdrop of climate change and increasing global instability (Kerr, 2020; Raza et al., 2019).

Economists have long been interested in how actors make decisions under risk. In a letter from 1738, Bernoulli (1954) was the first to propose the expected utility framework, which has been the mainstream economic theory for understanding decision-making under risk and was later placed in formal axioms in Von Neumann and Morgenstern (1944). Expected utility theory proposes that rational decision-makers facing a choice of risky prospects make choices based on the probability and payoff of outcomes as well as their risk preferences. Whether decision-makers are rational, whether they are fully informed of probability distributions, and whether risk preferences can be treated as given have resulted in intense debate within economic circles over the past few centuries (Becker, 1976; Bentham, 1789; Friedman, 1953; Kahneman & Tversky, 1979; Voors et al., 2012). Despite the criticisms, expected utility theory remains a cornerstone of economic thought because of its mathematical tractability, its suitability as a normative economic theory, and its ability to describe behavior in at least some situations (Just and Peterson 2010).

Since Von Neumann and Morgenstern (1944), there have been numerous extensions, re-interpretations, and discussions surrounding expected utility theory (Fishburn, 1989; Savage, 1954), but the applicability of these models to smallholder farming households remains a challenge because expected utility does not address portfolio effects and assumes perfect markets (Schoemaker, 1993). Standard expected utility models generally address decisions individually, rather than collectively. Markowitz (1952) addresses this concern by developing portfolio theory, whereby prospects' risks are correlated with each other. Decision-makers value each prospect at its expected value, but certainty equivalents account for the inter-relationships between risks across all prospects. Small farmers engage in various activities and can cultivate numerous crops. The nature of farming requires a model taking into account multiple sources of income, and a portfolio approach to the farm has been applied in several studies (Collins, 1988; Coyle, 1992; Watts et al., 1984).

Another issue is that standard expected utility models assume that actors can participate in markets seamlessly. In the case of agricultural households, who participate as both suppliers and consumers of food, this means that households can maximize their income and consumption independently of each other (Singh et al., 1986). However, most smallholder farming households are semi-subsistence and often operate in imperfect markets – markets with high transaction costs (Barrett, 2008; Chamberlin & Jayne, 2013). In the presence of imperfect markets, households cannot seamlessly convert output into cash and cash into consumption goods. As a result, the household can consume its own output, but this consumption is valued at a shadow price, which differs from the market price. The value of the shadow price is based on the utility of consuming a good, so the household must maximize production and consumption simultaneously, creating a non-separable class of models used in several previous studies (de Janvry et al., 1991; Finkelshtain & Chalfant, 1990; Omamo, 1998).

While models of the agricultural household have addressed portfolio effects and market access separately, no attempt has been made to simultaneously address these issues within the same framework. Chapter 2 proposes an expected utility framework that allows for the production and consumption of *N* goods under imperfect markets. Simultaneously including diversification strategies and imperfect markets not only solves for weaknesses in expected utility approaches, but also has practical implications. Combining these features allows for an analysis of production levels and market access on the consumption of individual goods, rather than aggregate consumption levels. This enables a theoretical analysis of consumption diversity, which extends an exclusively empirical literature linking production diversity and market access with dietary diversity (Jones, 2017; Nandi et al., 2021; Sibhatu & Qaim, 2018).

Standard expected utility models are based on unitary households (Michael & Becker, 1973). However, households are comprised of several individuals with shared and competing preferences, and they do not always cooperate (Bergstrom, 1996, 1997; Lundberg & Pollak, 1996). As a result, household production and consumption decisions depend on which household member makes decisions (Doss 2013). Men and women have different risk preferences (Vieider et al., 2015) and perceived labor costs (Doss 2018), making gender a crucial component to understanding how intra-household decision-making can deviate from unitary models' predictions of production decisions. Chapter 3 looks at how households' labor-intensive investment decision-making differs when male spouses alone, female spouses alone, and both spouses together make decisions and how men and women's labor responses differ based on such decision-making. The chapter highlights how gendered decision-making can change households' *ex ante* exposure to production and market price risks and participation in high-value markets.

1.3 Ex Post Risk Responses: Production Shocks and Market Price Fluctuations

Ex ante risk management does not guarantee that downside risk will not be realized. Negative production shocks (e.g. droughts, flooding, and pests) lower household agricultural production and hence income and available food stores. With lower incomes, household liquidity demand increases to meet household's short-term needs. Households have several strategies to obtain liquidity in the event of a shock – for example, engaging in off-farm labor, changing marketing strategies, and selling household assets (Kahan, 2013).

Which coping strategies households choose and to what extent households engage in their chosen strategies have repercussions beyond the farm, especially if households engage in producer organizations. Producer organizations aggregate the production of their members, allowing them to negotiate more favorable prices downstream than individual members could (Wollni & Zeller, 2007). When members sell their produce outside of the producer organization, the ability of the organization to obtain scale economies and offer members price premiums is jeopardized (Bhuyan, 2007). There is an extensive literature exploring the determinants of side-selling in producer organizations (Alemu et al., 2021; Arana-Coronado et al., 2019; Bacon, 2005; Fischer & Qaim, 2011; Gadzikwa et al., 2007; Mujawamariya et al., 2013; Woldie, 2010; Wollni & Fischer, 2015; Wollni & Zeller, 2007), but the literature has yet to explore how shocks may influence such marketing behavior and whether engagement in other risk coping strategies crowds out side-selling. Chapter 4 explores how production shocks influence Peruvian specialty coffee cooperative members' marketing decisions and whether non-coffee income crowds out side-selling in the event of a shock by relieving liquidity constraints.

Market price risk is one of the most ubiquitous sources of risk for both producers and consumers. In agrarian settings where large portions of the population rely on agricultural markets for income and where households spend a large portion of their income on food, food prices are central to livelihoods. In countries with weak institutions, actors are more likely to engage in conflict to settle grievances (Hegre & Nygård, 2015; Wig & Tollefsen, 2016). Economic theory gives four key mechanisms through which food prices can affect conflict and unrest: the relative deprivation, predation, opportunity costs, and state capacity mechanisms (McGuirk & Burke, 2020). The relative deprivation mechanism describes the case of consumer frustration over higher food prices boiling over into unrest and/or conflict as in the Arab Spring or the 2008 food riots (Berazneva & Lee, 2013; Dreze & Sen, 1990; Sternberg, 2012). For producers, higher prices are beneficial and their opportunity cost of engaging in conflict and unrest increases with food prices, leading to a decline in conflict (McGuirk & Burke, 2020). The reverse holds for declines in food prices. Higher prices also increase the value of land, which incentivizes armed groups (government or otherwise) to violently take domestic land – the predation mechanism (Grossman, 1999; Hirshleifer, 1991). Finally, higher food prices result in higher tax revenues for the government, improving state capacity to suppress conflict and unrest and leading to a decrease in conflict (Besley & Persson, 2010).

Identifying which of these mechanisms predominates has been the focus of a growing empirical literature. Most of the literature has focused on cross-country studies using international food prices as a source of exogenous variation with the assumption that international prices sufficiently pass through to local markets (Smith 2014; Fjelde 2015; McGuirk and Burke 2020; De Winne and Peersman 2019; Hendrix and Haggard 2015). Until recently, the literature has focused on identifying relative deprivation effects on unrest in urban areas (Smith 2014; Bellemare 2015) or overall effects on large-scale conflict (Fjelde, 2015). Recent attempts have been made in cross-country to study international price effects on both unrest and large-scale conflict, and these studies show that both relative deprivation and opportunity costs are at play in urban areas and food-producing areas, respectively (De Winne & Peersman, 2019; McGuirk & Burke, 2020). However, no attempts have been made to study domestic prices' effect on conflict and unrest on more granular types of conflict. To better understand how food prices affect conflict and unrest, it is important to understand who engages in conflict (state actors, ethnic militias, rebel groups, or other armed groups), the scope of their aims (national or local), and the scale of their violent activities (small acts of violence or large-scale battles). Further, with the exception of Dube and Vargas (2013) (which looks at non-food commodity prices), there is a lack of within country studies, which are able to take into account context-specific considerations and uncover dynamics which cross-country studies are unable to (Hendrix & Haggard, 2015). Chapter 5 of this thesis extends the existing literature by taking a within country meso-economic approach to study the effect of changes in domestic cereal prices on conflict involving different actors, scopes, and scale in Ethiopia.

1.4 Objectives

The objective of this thesis is to study economic actors' *ex ante* and *ex post* risk management strategies and the role of markets in such decisions to gain a deeper understanding of how economic actors behave under risk. The core chapters each address distinct research questions as follows:

Chapter 2: How do risk, production diversity, and market access relate to farming households' nutrition?

Chapter 3: Do intra-household decision-making and labor arrangements affect on-farm investment?

Chapter 4: Do farmer cooperative members change their marketing behavior when affected by negative production shocks?

Chapter 5: Do changes in cereal market prices affect domestic conflict and unrest?

The research questions are answered using a combination of neo-classical economic theory and empirical analysis and give attention to heterogeneous outcomes.

1.5 Neo-Classical Economic Theory

Chapters 2 and Chapter 4 present neoclassical household models using expected utility theory. The models present normative frameworks for understanding decision-making under *ex ante* and *ex post* risk. Chapter 2 develops a non-separable agricultural household model, whereby households can consume and produce up to N goods under risk and imperfect market access – a novel innovation within the literature. Chapter 4 extends Wollni and Fischer (2015) to understand how rational households choose between selling to cooperatives and private buyers when price risk, fixed costs to marketing, and economies of scale are present. The models are intended to be stylized and highlight relevant mechanisms in decision-making so the models are not simulated. Rather, predictions are tested using descriptive empirical studies. Chapters 3 and 5 are do not present stylized models, but are nevertheless based on behavioral and neoclassical price theory, respectively. While behavioral and neoclassical theory are often regarded as opposing forces, behavioral theory can complement neoclassical theory by helping understand actors' deviations from rational behavior (Mullainathan & Thaler, 2000).

1.6 Empirical Methodology

Economic inquiry relies on the complementary functions of theory and empirical evidence to create knowledge. In the greater part of the 20th century, economic research was largely based on generating theoretical models of economic actors' behavior (Hamermesh, 2013). In the past decades, empirical work has become the norm in contemporary economic studies, largely due to digital transformation, and intellectual shifts within the field (Hamermesh 2013; Angrist et al. 2017; Paldam 2021). Further, empirical work is shifting towards the identification of causal effects and use of experimental primary data, rather than descriptive studies using secondary data. Built on the logic of controlled laboratory experiments, randomized field experiments have become the gold standard in causal analysis in economics (Banerjee and Duflo 2014). Like the previous intellectual waves of expected utility theory and behavioral economics changed general opinions of economic theory, the 'randomista revolution' – a contemporary shift in empirical methodology advocating for the use of randomized field experiments – has come to dominate discussions of empirical methodology (Ravallion, 2018).

Upheaval in economic thinking breeds schools of thought formed around particular theories or methodologies (Facarello & Kurz, 2016). Especially in the case of methodological considerations, such adherence to schools of thought limits the creation of knowledge. Methodologies are tools. Like all tools, different methodologies are used to solve different types of problems – "The gold standard is the best method for the question at hand" (Ravallion, 2018). Further, many important research questions cannot be answered with field experiments (Rosenbaum, 2010).

This thesis takes a pragmatic approach to methodology, drawing on methods from across the spectrum of economic thought. Each method corresponds to a different level of economic actor and requires different types of data. The rest of this subsection presents each methodology, its corresponding data, and the methodological contributions to existing literature.

1.6.1 Descriptive Studies

Despite the hype of experimental studies, the proportion of "classical" empirical studies have grown substantially in economic journals in the past twenty years (Paldam, 2021). Classical studies follow the general framework of presenting a theory, deriving an econometric specification, describing a dataset used, and presenting econometric results (Paldam, 2021). This approach is flexible and is particularly useful in cases where experimental approaches are infeasible or immoral (Rosenbaum, 2010). However, this approach often relies on descriptive empirical analysis, rather than causal inference. Descriptive analyses present empirical relationships in an attempt to fit the data structure into a story (Paldam, 2021). These studies are important for the scientific process because they can shed light on real-world phenomena and develop new hypotheses that can be more rigorously tested with experimental approaches (Casadevall & Fang, 2008). Even leaders in the 'randomista' wave of economic research perform descriptive studies to highlight previously unrecognized real-world phenomena (Banerjee and Duflo 2007, 2008).

Chapter 2 and Chapter 4 rely on descriptive analysis to complement the proposed economic theory. The literature underpinning Chapter 2 and Chapter 4 is based on descriptive studies of the determinants of household-level dietary diversity and side-selling, respectively. However, in both chapters, the descriptive analysis provides methodological improvements over existing studies and uncovers new relationships. In Chapter 2, the World Bank's Living Standards and Measurement Survey (LSMS) in Tanzania is combined with nutrition tables (Lukmanji et al., 2008), to create household nutrition concentration indices used in a cross-sectional analysis. These indices provide richer information than counts of food groups consumed, which most studies in the literature use (Jones, 2017; Nandi et al., 2021; Sibhatu & Qaim, 2018). Further, Chapter 2 explores a previously untested relationship – whether market participation mediates production diversity's relationship with dietary diversity. Chapter 4 presents the first paper to use panel methods when estimating determinants of cooperative side-selling. The panel methods allow for the control of individual level heterogeneity, which eliminates a major source of omitted variable bias inherent to cross-sectional studies (Allison, 2009). The descriptive study is the first to explore whether production shocks are correlated with side-selling behavior.

1.6.2 Instrumental Variable Estimation

Causal inference can still be performed in non-experimental settings, and instrumental variable methods provide one method for doing so. In non-experimental settings the variable of interest is typically endogenous. For causal inference, an instrument can be used if it meets the relevance condition and exclusion restriction. The relevance condition is met if the instrument is sufficiently correlated with the endogenous variable of interest, while the exclusion restriction is met if the instrument is not correlated with the outcome variable through any other channels aside from the endogenous variable of interest (Angrist et al. 1996).

Chapter 5 uses monthly price data from Ethiopian retail markets and international cereals markets. Market-level domestic prices are instrumented by international prices, leading to causal identification of domestic prices on conflict and unrest. This methodology presents an important contribution because most previous studies in the literature do not have domestic price data and rely on international prices as an exogenous regressor, which only allows for the estimation of reduced form effects.

1.6.3 Lab-in-the-Field Experiments

Field experiments give researchers control over a variable's value for each participant by randomly assigning participants into control and treatment groups (Banerjee and Duflo 2014). This allows for the causal identification of a variable's effect, when that variable would otherwise be endogenous in an observational study. Lab-in-the-field experiments are controlled laboratory experiments conducted with the population of interest (Gneezy & Imas, 2017). Lab experiments offer incentives to participants to elicit real-world behavior. In the study of labor economics, lab-in-the-field experiments often apply 'real-effort' tasks – tedious mental or physical activities – to simulate labor costs (Lezzi et al., 2015). These types of studies apply the gold standard of causal inference – randomization, which relies on the assumption that the only difference between treatment and control groups is the treatment itself (Banerjee and Duflo 2014).

Since intra-household decision-making regimes are endogenous to household characteristics, Chapter 3 applies a lab-in-the-field experiment to exogenously determine intra-household decision-making regimes in a controlled environment. It applies a real-effort tasked loosely based on Bulte, List, and van Soest (2020). The experiment is designed to uncover the causal effect of decision-makers' and laborers' gender on investment decisions and labor outcomes. Data is drawn from the experiment itself and a short exit survey.

1.7 Outline

The rest of the thesis is organized as follows. Chapter 2 presents a theoretical model linking market access and production diversity to dietary diversity and empirically explores these relationships using nationally representative data from Tanzania. Chapter 3 analyzes a lab-in-the-field experiment from rural Tanzania to explore the effect of gender in household's labor-intensive investment decisions. Chapter 4 theoretically and empirically explores whether production shocks are related to specialty coffee cooperative members' marketing decisions in Peru. Chapter 5 shows how changes in cereal prices affect different types of conflict and unrest in Ethiopia. Chapter 6 concludes.

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Chapter 2

Smallholder Farming Households' Make-or-Buy Decisions: Linking Market Access, Production Risks, and Production Diversity to Dietary Diversity

On-farm production diversity and improved access to markets are correlated with more nutritious household diets. However, the efficacy these relationships remains unclear. This paper provides a theoretical framework for understanding the relationship between market access, on-farm production diversity, and household diets. We develop a non-separable agricultural household model with N agricultural goods for consumption and/or sale, production risk, and imperfect markets. Households jointly maximize production, consumption, and marketing decisions. Empirically, the model's results are tested with non-causal econometric analysis using nationally representative data from Tanzania. The paper contributes to a growing empirical literature concerning the relationships between production diversity, market access, and dietary diversity. We show that while on average a household needs to grow six additional food groups to consume just one more food group, households not participating in markets need to grow just four more food groups to consume one more. This interaction helps explain why the literature typically finds weak correlations between dietary diversity and production diversity on average. The paper also contributes to the theoretical literature surrounding non-separable household models by providing a framework for understanding the role of markets and risk for household dietary diversity. Our model provides economic theory consistent with existing empirical evidence, providing theoretical structure to a largely empirical literature.

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2.1 Introduction

Malnutrition is a significant challenge for the world. In low-income regions, 780 million people are undernourished (FAO, 2018). The majority of undernourished people are smallholder farmers in rural areas of Africa and Asia (Pinstrup-Andersen, 2007; Sibhatu and Qaim, 2017). Despite the commitment of the Sustainable Development Goals (SDGs) in 2015 to end hunger, the share of undernourished people in Sub-Saharan Africa (SSA) grew from 17.4% in 2017 to 19.1% in 2019 (FAO, IFAD, UNICEF, WFP, 2020). Studies show that improving dietary diversity may be a promising strategy to address undernourishment (Arimond et al., 2010; Kant et al., 1993; Popkin and Slining, 2013; Sibhatu et al., 2015). Smallholder farmers are particularly vulnerable to under-nutrition, as poverty rates among smallholders are typically much higher than national averages (Rapsomanikis, 2015). For this reason, many development initiatives introduce new crops and production methods to smallholder farmers to boost their production diversity and improve their dietary diversity. However, empirical evidence suggests that households need to grow nine more crops to increase the number of food groups they consume by one (Sibhatu and Qaim, 2018). Vast differences in smallholder market access and participation may be influencing the (in)effectiveness of production diversity as a means to improve dietary diversity (Sibhatu et al., 2015).

This study assesses the interaction of smallholders' production diversity, market access and participation, and dietary diversity. We develop a non-separable agricultural household model for multiple crops, involving simultaneous decision making on consumption, production under risk, and market participation. Traditional models of agricultural households assume that food and production choices are separable under perfect markets. However, production and food choices in the context of rural farming households, particularly in developing regions, are non-separable because of market imperfections. Smallholder farmers usually face implicit and explicit transaction costs because they can be far away from markets and often lack market information on prices, buyers, and sellers (Chamberlin and Jayne, 2013). These transaction costs can make consumption of on-farm produce for smallholder farmers cheaper than purchasing food products from the market. In addition, smallholder farmers are exposed to market and production risks with limited access to financial instruments (e.g. loans and insurance) to mitigate the effects of those risks. Instead, they diversify their agricultural production to reduce risk exposure and include both food and cash crops in their production mix (Makate et al., 2016).

Specifically, our model is a variant of the mean-variance portfolio optimization model, taking the non-separable production and consumption choices of smallholder farmers into account. In the full model, the farming household is endowed with a fixed amount of land and labor and can produce multiple crops. The household can consume its own food production, or as a price taker, it can sell and purchase food items at exogenous market prices. However, both purchasing and selling in the market involve transaction costs (e.g., transportation costs and costs of accessing market information). The household allocates its endowments to maximize jointly (i) the returns from the production while trying to minimize joint production risks, and (ii) household welfare from the consumption of food items. The household's consumption and production diversity are estimated endogenously by our model for given market transaction costs and prices, production risk, and food preferences. Three factors potentially drive production diversity: production risks, the love of consumption variety, and transaction costs (i.e. market acces).

Consistent with earlier theories (Finkelshtain and Chalfant 1990; Fafchamps 1992), the model predicts that risk increases production diversification and reduces specialization in the production of the crop with the highest financial return. This causes a fall in overall income. Moreover, the household prefers producing cash crops (or crops with high financial returns) to food crops when it is well integrated into markets (as in Omamo, 1998), but it prefers to produce food crops when transaction costs prohibit easy access to markets.

Our novel findings concern the interaction between market participation, production, and consumption diversity. We find that the influence of production risks and diversification on dietary diversity depends on the household's level of market access. The model shows that increasing market access (via reducing transaction costs) improves dietary diversity, allowing the household to specialize in producing (cash) crops with the highest monetary returns. With those returns, the household can purchase and consume a diversified basket of food products from the market. When the household's level of market access is above a certain threshold, production diversity hinders consumption diversity. Increases in production risks incentivize the household to diversify their production to mitigate risk, causing a reduction in the returns from agriculture and consequently, dietary diversity. In contrast, production diversification positively contributes to the dietary diversity of a household with limited access to markets (under a given threshold of market access). Because of the household's love of variety, the household diversifies their production and grows multiple crops, which will primarily be consumed at home. The household aims to satisfy their preference for a diverse diet through a diverse production mix. However, growing more crops does not necessarily increase dietary diversity of food groups because it matters which crops are being grown, not just how many.

Finally, we test the predictions of the model through regression analysis. For this purpose, we use the nationally representative Living Standards Measurement Study (LSMS) data for Tanzania in 2013. Rural Tanzania is a suitable and relevant context to test the predictions of the model, as nearly 68% of Tanzanian households work in the agricultural sector (FAO, 2018). Many of these smallholder farmers' diets are susceptible to climate shocks. Despite improvements over the last two decades, Global Hunger Index (GHI) reports that Tanzania has a serious hunger problem and ranks as one of the least food secure countries in the world, scoring 95th out of 117 countries in 2019 (Global Hunger Index, 2019).

In our regression analysis, we use the presence of village markets to measure market access, and we use past production shocks to proxy production risks. The results from the analysis show that increased production diversity is positively correlated with past production shocks and negatively correlated with the presence of markets, confirming the theoretical basis of production diversification as a risk reduction strategy. Further, we test whether market participation/access and production diversity are correlated with dietary diversity and anthropometric measures. Our findings give evidence to the theoretical model by showing that both market participation and production diversity are positively and significantly correlated with dietary diversity. Market participation plays a small mediating role in the correlation of production diversity with dietary diversity – production diversity is positively and significantly correlated with dietary diversity at low levels market participation, but has zero correlation at higher levels. The results do not hold for anthropometric outcomes, as in Chegere and Stage (2020).

Our study provides a consistent theoretical framework for the extensive empirical literature surrounding production diversity, market access, and household nutrition of smallholder farmers. The study also gives novel insights to the interaction between these factors. It provides a clear set of policy implications on rural development and nutrition. Our findings show that improvements in market access of smallholder farmers while reducing their production risks enhances household nutrition. These suggest that improvements in the market participation of smallholders must be supported while introducing agricultural methods reducing production risk (e.g., new varieties and production methods). Their contribution depends on the market access, food choice, and risk exposure of smallholders. To this end, before introducing improved varieties or new crops, development practitioners should follow a participatory approach that involves smallholder households to understand their risks, food choices, market access challenges. In this way, programs can be tailored to meet the needs of different groups of smallholders.

Related literature: Our study contributes to two strands of literature. First, we contribute to the agriculture household modeling literature. There is an extensive literature on agricultural household models that assess the responses of household supply and demand to changes in food prices (Taylor and Adelman, 2003). The majority of those models are so-called separable household models where households decide on production and consumption separately. The assumption of perfect markets, which allows for separable optimization, makes those models relatively easy to implement and find analytical results. However, large portions of agricultural households in rural areas of developing countries are both consumers and producers of food. For this reason, several non-separable models have been developed to analyze smallholder farmer behaviour. Like their separable predecessors, these models address a variety of issues, particularly market access's role in crop diversification. For instance, Omamo (1998) shows that in the absence of risk, transaction costs explain the low-levels of specialization in agricultural production as a rational outcome. The paper suggests that in the case of two goods - a food crop and a cash crop - farmers with high transaction costs tend to inter-crop food and cash crops more, while farmers with low transaction cost specialize in the cash crop. de Janvry et al. (1991) introduces market imperfections (via transaction costs) for food and labour markets to analyze non-separable production decisions. Fafchamps (1992) uses a two-crop non-separable model to analyze the relationship between market access, risk, and crop allocations. The paper shows that small farms are food-crop oriented and large farms are cash crop oriented - a common observation in developing countries. Goetz (1992) illustrates a model whereby the households participate in markets based on fixed transaction costs. Key et al. (2000) extends this work by looking at the differences between the introduction of per-unit and fixed transaction costs on household market participation and supply response and by simultaneously solving the production, consumption, and market participation decisions.

The non-separable household models that are mentioned above cannot analyze the cases of many production and consumption goods, instead opting for two-good models. This omission makes it difficult to study household dietary diversity - a key component of household nutrition. This paper fills that gap in agricultural households modeling by introducing a non-separable household model with multiple goods produced under risk. For this purpose, we use the mean-variance framework that was originally proposed by Markowitz (1952) in the context of investors' portfolio allocation decisions in financial markets. The mean-variance approach and variants of it have been applied to farm planning in numerous studies (Collins 1988; Tauer 1983; Watts et al. 1984; Coyle 1992; Coyle 1999). Tzouvelekas (2011) uses a mean-variance approach with non-separability in labor markets. It tests the results for British farmers, in light of EU pricing policy support. In this study, we use the mean-variance approach with non-separable agricultural households models with imperfections in food markets in low-income countries, for (to our knowledge) the first time. While our model is focused on the relationships between risk, market access, production and consumption diversification, it is also generalizable enough to potentially add other components.

Second, this paper relates to the empirical literature investigating the relationship between production diversity, market access, and household nutrition in developing countries. Several papers have found increases in consumption diversity associated with increases in production diversity. In Zimbabwe, crop diversification increased the dietary diversity of children and women during a nutrition education intervention (Murendo et al., 2018). Similar results are found in Malawi using nationally representative data, where crop and livestock diversification were associated with higher consumption diversity (Jones et al., 2014). While much of the research regarding the relationship between production diversity and nutrition is in Sub-Saharan Africa, these relationships also have been observed in other regions, such as Bolivia (Jones, 2015) and India (Kumar et al., 2016). Despite the evidence that production diversity can improve household nutrition, the efficiency of production diversity as a lever to improve nutritional outcomes has been brought into question. In a meta-analysis of 45 studies in 26 countries analyzing this relationship, Sibhatu and Qaim (2018) find that the mean marginal effect of production diversity on household dietary diversity is low. Other interventions, such as improving market integration, are being touted as more effective in improving nutrition (Gupta et al., 2020).

Several studies empirically analyse the relationship of market access and household diversity. Overall, the market access is generally found to be positively correlated with household nutrition, but most results are context specific (Nandi et al., 2021). For instance, in a panel study in northern Ethiopia, being located closer to markets is associated with higher overall dietary diversity for children (Abay and Hirvonen, 2017). In Kenya, access to selling produce to supermarkets is found to improve household nutrition (Chege et al., 2015). Evidence even points towards market access being a more critical factor in improving household nutrition than production diversity in Malawi (Koppmair et al., 2017). Finally, cash income from produce is associated with higher dietary diversity and micro-nutrient consumption than production diversity in Uganda, Indonesia, and Kenya (Sibhatu and Qaim, 2016). Our theoretical model contributes to this literature by explaining how market access mediates the effect of production diversification on household dietary diversity by emphasizing the importance of the interaction between market access and production. The concepts of non-separability in this literature have been discussed (but not mathematically developed) in the empirical literature (Nandi et al. 2021; Bellon et al. 2016). Our model operationalizes these conceptual frameworks into non-separable utility model.

The structure of the paper is as follows. Section 2.2 outlines the theoretical model and its implications. Section 2.3 introduces the econometric methods for testing the production outcomes of the model. Section 2.4 discusses the data used in the econometric approach, and Section 2.5 shows the results of the econometric analysis. We conclude the paper with a brief discussion on the findings. All proofs are shown in the appendices.

2.2 Theoretical Model

The proposed model is a non-separable household model (i.e. households maximize consumption, production, and market participation simultaneously) with N agricultural goods. The goods can either be produced and consumed at home or produced and sold on the market in exchange for other agricultural goods. Households simultaneously try to maximize utility from consumption and minimize risk from production via a mean-variance utility function. The multi-good approach allows for the extrapolation of dietary diversity scores and can show how dietary diversity is related to market access and production risk (e.g. climate variability).

To simplify the model and focus on the linkages of consumption diversity and production diversity with production risk and market access, several assumptions are made. Households are price-takers in both supply and demand of agricultural goods. As consumers, households have a love of variety of goods. Further, households are risk-averse, and their production carries risk. Households are assumed to have no livestock holdings, cannot engage in off-farm labor, do not have leisure, and do not participate in land, labor, and other input markets.

This section first introduces the model's hypotheses, followed by a presentation of the model framework on both the consumption and production sides. The model framework culminates in a derivation of the household's value function. Then, the case of perfect markets in a riskless setting is analyzed to understand the simplest case of the model. The next two sub-sections relax the assumption of a risk-free environment and of perfect markets, respectively. These specific cases of the model uncover the effects of production risk and market access on household production decisions and on household dietary diversity.

2.2.1 Hypotheses

The theoretical model is intended to explain the economic theory behind the empirical evidence linking production diversity, market access, and dietary diversity. Four main propositions are put forward in examining these relationships:

Proposition 1 *Market access leads to greater specialization in production.*

Proposition 2 *Production risk leads to higher production diversity.*

Proposition 3 *Higher production diversity leads to higher (lower) dietary diversity if market access is low (high).*

Proposition 4 *Higher market access leads to higher dietary diversity through increased income.*

We show that these four propositions hold using specific cases of a non-separable agricultural household model presented below.

2.2.2 Model Setup

Let there be a utility-maximizing agricultural household that both produces and consumes up to N agricultural during one period. Utility takes a mean-variance form, whereby utility is gained through the consumption of each crop via an additive log-utility framework.[1] There are decreasing marginal returns to each good consumed in the additive log utility framework and the household has decreasing absolute risk aversion and constant relative risk aversion with respect to each good consumed. The household is assumed to be risk averse in production decisions, and utility decreases as the household takes on more production risk. Equation 2.1 describes the utility function:

$$U = \sum_{i=1}^{N} w_i \ln(c_i + 1) - \frac{a}{2}\psi \tag{2.1}$$

[1] While many studies assessing the consumption of multiple goods use a constant elasticity of substitution (CES) utility function, the CES utility function is unsuitable for our analysis because CES implicitly assumes that the consumption of each good only comes from one source (i.e. the market). When applying CES with consumption from both home production and the market, the demand functions are not linear in income, and analytical solutions for the non-separable case cannot be found. Another option is the additive quadratic utility function, but this is not used because it assumes increasing absolute and relative risk aversion whereas log utility assumes decreasing absolute risk aversion and constant relative risk aversion. Such risk aversion applies only to consumption *within* goods (i.e. consumption between the home production and market consumption of any good i), while the variance term applies to production decisions *across* goods. These properties will become important if the model is extended to have different risk properties for home and market consumption, for example stemming from market price risk. A previous version of this work uses the quadratic utility function.

where w_i is a preference parameter for good i and c_i is the consumption quantity of good i. Adding the constant 1 to consumption allows for zero consumption and ensures only positive consumption values can lead to positive utility.[2] ψ is a measure of risk that is based on production decisions and is fully defined below. a is a non-negative constant determining the variance's contribution to utility. The utility function is defined for all values of total consumption such that $0 \leq w_i \ln(c_i + 1) < \frac{1}{a}\psi$ because only on this interval is the utility function monotonically increasing.

The household can consume any good i through two different channels – by producing and selling crops on the market and using the resulting income to purchase and consume crop i ('market consumption') or through producing crop i at home and consuming the resulting home-production ('home consumption'). Consumption for good i is defined as:

$$c_i = c_i^m + c_i^h \tag{2.2}$$

where c_i^m is market consumption and c_i^h is home consumption. We assume the household does not differentiate between consumption from the market and consumption from home production (i.e. both types of consumption yield equivalent amounts of utility). In both consumption channels, production of crops is required to either sell on the market for income in the case of market consumption or to consume at home in the case of home consumption. Households are endowed with a productive asset and can allocate a proportion, $0 \leq s_i \leq 1$, of that productive asset to any good i of the N goods that can possibly be produced. This productive asset can be thought of as land and/or labor, and it may be a combination inputs. In Appendix 2.A, we show that the formulation in Equation 2.3 is compatible with a Cobb-Douglas production function for each crop i if all crops have identical output elasticities for land and labor. Production carries risk and is assumed to be normally distributed. Production, q_i, for any good i is given by:

$$q_i = s_i \gamma_i \epsilon_i, \ \epsilon_i \sim \mathcal{N}(1, \sigma_i^2) \tag{2.3}$$

where q_i is the quantity of good i produced, γ_i is a productivity parameter, and ϵ_i is the risk term following a normal distribution with mean 1 and variance σ_i. The expected quantity and the variance for each good i are respectively given by $s_i\gamma_i$ and σ_i^2. The variance of all production (analogous to a portfolio variance in standard mean-variance approaches) is given by:

$$\psi = \sum_{i=1}^{N} (s_i^2 \sigma_i^2 + \sum_{j \neq i}^{N} s_i s_j \sigma_i \sigma_j \rho_{ij}) \tag{2.4}$$

where ρ_{ij} is the correlation between the variance of good i and good j. The first term represents the variance of the production of each good, weighted by the share of productive inputs allocated to the good's production. The second term is the covariance of the production of each good i with all other goods j, weighted by the share of productive inputs going to producing goods i and j.

[2] This can be seen through the basic properties of the natural log function. $\ln(x)$ is undefined when $x = 0$. Then, log utility is undefined for zero consumption. In contrast, $\ln(x + 1) = 0$ when $x = 0$, indicating that utility is zero at zero consumption. The later is better suited in scenarios when zero consumption of an individual good is common. Since, $\ln(x)$ is monotonically increasing and has global diminishing marginal returns, and $\ln(x + 1)$ is defined for every values of $x \in -(1, \infty)$, then $\ln(x)$ and $\ln(x + 1)$ have the same proprieties for the range $[0, \infty)$, the possible range of consumption values.

Households choose how to allocate their productive inputs to maximize their utility. For each crop i, they can allocate resources to production for sale on the market, s_i^m, or production for home consumption s_i^h. If the household produces crops for sale on the market, they receive an expected income of:

$$E[I] = \sum_{i=1}^{N}(p_i - t_i)E[q_i] \tag{2.5}$$

where p_i is the market unit price for good i and t_i is the transaction cost for selling a unit of good i on the market. Equation 2.5 serves as the budget constraints for market purchases as well, and combining Equation 2.3 and Equation 2.5, the full expected income constraint is:

$$\sum_{i=1}^{N}(p_i + t_i)c_i^m \leq \sum_{i=1}^{N}(p_i - t_i)(s_i^m \gamma_i) \tag{2.6}$$

where the purchase price for good i on the market is the market price, p_i, plus the per unit transaction cost t_i. Home consumption does not need to be purchased, but it is constrained by home production. The household cannot consume more of a crop from home production than it produces for home consumption. Assuming there are no post-harvest losses, the expected home consumption is constrained by:

$$E[c_i^h] = E[q_i^h] = s_i^h \gamma_i \; \forall \, i \; \in \; N \tag{2.7}$$

Putting the utility, income constraints, and home-consumption constraints together, the household's utility maximization problem is:

$$\begin{aligned} \max E[U] = \sum_{i=1}^{N} w_i \ln(c_i^m + c_i^h + 1) - \sum_{i=1}^{N}(s_i^2\sigma_i^2 + \sum_{j\neq i}^{N} s_i s_j \sigma_i \sigma_j \rho_{ij}) \\ \text{s.t.} \sum_{i=1}^{N}(p_i + t_i)c_i^m \leq \sum_{i=1}^{N}(p_i - t_i)(s_i \gamma_i) \\ c_i^h = s_i^h \gamma_i \\ \sum_{i=1}^{N} s_i^h + s_i^m = 1 \end{aligned} \tag{2.8}$$

The maximization problem in Equation 2.8 is specified in terms of both c terms and s terms. The problem states that households simultaneously maximize their utility from consuming N goods (from home and/or the market) and minimize their risk exposure from production. The optimization decision is constrained by market consumption being equal to income, home consumption of each good being equal to home production, and all production shares summing to 1. To simplify the problem and specify it only in terms of s terms, the utility function can be expressed as an indirect utility function (which shows the maximum attainable utility given prices and income) via the principle of duality in optimization problems. Appendix 2.B shows how each c_i^m term can be written in terms of prices and income and the utility maximization problem can be converted into the value function maximization problem in Equation 2.9 whereby the household only chooses s values to maximize utility, and optimal c values are obtained *ex post*. In the resulting value function maximization problem, home production is simply substituted for home consumption to get:

$$\max E[V] = \sum_{i=1}^{N} w_i \ln([\frac{w_i}{(p_i+t_i)\sum_{j=1}^{N} w_j}\sum_{j=1}^{N}(p_j-t_j)s_j^m\gamma_j] + [s_i^h\gamma_i] + 1) - \frac{a}{2}\sum_{i=1}^{N}(s_i^h+s_i^m)^2\sigma_i^2$$
$$\text{s.t.} \sum_{i=1}^{N} s_i^h + s_i^m \leq 1 \tag{2.9}$$

where the constraint ensures that the proportion of productive resources allocated to all crops (for home and market production) is equal to one.

Equation 2.9 describes the entire model. The household chooses production levels and marketing decisions of N goods to maximize their additive log utility of consumption of N goods either at home or from the market. The two terms in brackets are the contributions to utility of consumption from the market place and from home production, respectively, for each good i.

There are two components to total market consumption. The first is household income from producing and selling goods on the market: $\sum_{j=1}^{N}(p_j - t_j)(s_j^m\gamma_j)$. This follows directly from the income constraint in Equation 2.8. The second term is the relative preference of good i divided by the purchase price: $\frac{w_i}{(p_i+t_i)\sum_{j=1}^{N} w_j}$. Income and the relative preference/price parameter a multiplied together to give this total consumption of a good i from the market place. Intuitively, this shows that households choose their consumption behavior in markets by spending all of their income while consuming more of goods they prefer, consuming less of expensive goods, and balancing these two attributes. Further, the household operates under imperfect markets, whereby it pays a per-unit transaction cost of t_i to participate in both production and consumption markets.

The second term in brackets is the consumption from home production, which follows directly from the second constraint in Equation 2.8. The final term inside the natural log function is the constant, 1, which ensures that zero consumption of any good is possible and leads to zero utility. Using Equation 2.9, the next subsections focus on specific cases of this model which can show two motivations for production diversity and their differential effects on consumption diversity.

2.2.3 The Base Case: Perfect Market without Production Risk

In the 'base case' of the model, the household engages in perfect markets without risk. Understanding how the household behaves under these assumptions, sets the comparison for the model with imperfect markets and/or risk. These comparisons will show how risk affects household outcomes (Propositions 2 and 3), and how market access affects household outcomes (Propositions 1 and 4).

In the case of perfect output markets, there are no transaction costs ($t_i = 0 \ \forall \ i$), and as a result, households can seamlessly sell their production on the market and exchange it for consumption goods. Households do not engage in home production in this case since home production is equivalent to selling a unit of good i on the market and buying it back at the same price, p_i. The scenario leads to a separable model, whereby households can maximize their income and consumption separately. Since the value function represents the maximized utility for a given level of income and prices, at this stage, the household only needs to maximize its income to maximize the value function.

In the case, we also assume that there is no production risk ($\sigma_i = 0 \ \forall \ i$). Combining these assumptions, Equation 9 becomes:

$$\max E[V] = \sum_{i=1}^{N} w_i \ln\left(\frac{w_i \sum_{j=1}^{N} p_j (s_j^m \gamma_j)}{p_i \sum_{j=1}^{N} w_j}\right)$$
$$\text{s.t.} \sum_{i=1}^{N} s_i^m \leq 1 \tag{2.10}$$

Since ln(.) is monotonically increasing on the domain specified for the value function, the function is maximized by maximizing the argument of Equation 2.10. Without production risk, the household chooses to invest in the highest returning productive activity, determined by the term $p_j \gamma_j$, which maximizes utility.

Proposition 1: Market access leads to greater specialization in production.

$$\begin{cases} \arg\max E[V] = s_k^* = 1 \\ s_i^* = 0 \;\forall\, i \neq k \end{cases} \tag{2.11}$$

where good k is the good that has the highest return, $p_k \gamma_k$, and yields the highest utility. Consumption can be calculated *ex post* and takes on the optimal consumption values found in Appendix 2.B. From these optimal consumption values, it is easy to see how dietary diversity improves with income. Let dietary diversity be defined by the Herfindahl-Hershman Index (HHI):

$$\text{HHI} = \sum_{i=1}^{N} c_i^2 / C \tag{2.12}$$

where C is total consumption. The HHI measures the level of concentration in a diet. A lower HHI indicates a less concentrated diet (or a more diverse diet) while a higher HHI indicates a more concentrated (less diverse) diet. In Appendix 2.C, we show that the comparative static of HHI with respect to income is negative, indicating that dietary diversity improves with increases in income:

$$\frac{\partial \text{HHI}}{\partial I} < 0 \tag{2.13}$$

Therefore, increasing dietary diversity for the household with perfect market access and no risk requires only increasing household income. Production diversity away from the most profitable crop will reduce income and consequently, reduce dietary diversity.

2.2.4 Perfect Markets with Production Risk

To understand why risk increases production diversity (Proposition 2), the assumption of riskless production is dropped, but the assumption of perfect markets is maintained to highlight the risk mechanism. For simplicity in demonstration, we show the case in which the household is extremely risk averse and only minimize variance such that Equation 2.9 becomes:

$$\max E[V] = -\frac{a}{2} \sum_{i} (s_i^h + s_i^m)^2 \sigma_i^2$$
$$\text{s.t.} \sum_{i=1}^{N} s_i^h + s_i^m \leq 1 \tag{2.14}$$

Proposition 2: Production risk leads to higher production diversity.

This is a case of the standard mean-variance problem and it leads to the well-known optimal solution:

$$\mathbf{s}^{m*} = \mathbf{s}^{*}_{\text{extreme}} = \frac{\Sigma^{-1}\mathbf{1}}{\mathbf{1}'\Sigma^{-1}\mathbf{1}} \tag{2.15}$$

where $\mathbf{s}^{m*}$ is an N-length vector and the return vector (with respect to $\mathbf{s}^{m*}$), Σ, the covariance matrix, is given by:

$$\Sigma = \begin{pmatrix} \sigma_1^2 & \sigma_1\sigma_2\rho_{12} & \dots & \sigma_1\sigma_n\rho_{1n} \\ \sigma_2\sigma_1\rho_{21} & \sigma_2^2 & \dots & \sigma_2\sigma_n\rho_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_n\sigma_1\rho_{n1} & \sigma_n\sigma_2\rho_{n1} & \dots & \sigma_n^2 \end{pmatrix} \tag{2.16}$$

In the optimal solution, the household diversifies to reduce exposure to risk. While risk is reduced, the income is necessarily lower than in the risk-less case because the household has diversified away from producing only the most profitable good in exchange for producing less profitable crops (and higher return is associated with higher risk). As in the case of perfect markets and no risk, the optimal consumption parameters fall directly from the optimal solution. However, since income is lower in the case involving risk than no risk, and the comparative static of HHI with respect to income is negative (see Equation 2.13) then diversification caused by risk also has a negative effect on HHI.

Proposition 3 (Part 1): Higher production diversity leads to lower dietary diversity if the market access is high.

$$\text{HHI}_{\text{risk}} > \text{HHI}_{\text{no risk}} \tag{2.17}$$

Equation 2.17 shows part of Proposition 3. Agricultural households with high market access who diversify production to mitigate risk have lower dietary diversity. This means that production diversity is not necessarily associated with higher consumption diversity and can depend on the level of market access. The next sub-sections show the role of production diversity when market access is low.

2.2.5 Imperfect Markets without Production Risk

To show the other part of Proposition 3, imperfect markets are introduced (i.e. transaction costs are present). For simplicity of demonstration, let each transaction cost be $t_i = p_i$, such that the household cannot earn any income from selling crops. The budget constraint collapses to zero and the household can only consume its own production. Equation 2.9 becomes:

$$\begin{aligned} \max E[V] = \sum_{i=1}^{N} w_i \ln(s_i^h \gamma_i + 1) \\ \text{s.t.} \sum_{i=1}^{N} s_i^h \leq 1 \end{aligned} \tag{2.18}$$

The solution to Equation 2.9 is given by:

$$s_i^* = \frac{w_i\gamma_i N - \sum_{j=1,j\neq i}^{N} w_j\gamma_j}{\sum_{j=1}^{N} w_j\gamma_j}\ \forall\ i \in N \tag{2.19}$$

In the optimal solution, the household's production decisions depend only on their consumption preferences w and productivity parameters γ. Therefore, a second source of production diversification is market access – when a household loses market access, then they diversify their production mix in order to meet their demand for different types of food consumption, and they do it in a way that is aligned with their consumption preferences and productive capacity. This is in contrast to the case where the household has perfect market access and no risk, as this household specializes its production completely in the most profitable crop.

Proposition 3 (Part 2): Higher production diversity leads to higher dietary diversity if the market access is low.

It is trivial to show that a decrease in production HHI (also known as Simpson's Index, and denoted SI) is equivalent to a decrease in consumption HHI:

$$\text{SI} = \text{HHI if } t_i = p_i\ \forall\ i \tag{2.20}$$

The effects of autarky on dietary diversity are negative. This result can be logically extended to less extreme cases of imperfect markets, such that $0\ <\ t_i\ < p_i$. When transaction costs are 0, then the there are perfect markets, and when they are equal to p_i, then the household operates in autarky for a given good, i. In the 'in between' cases, $t_i \to p_i$ is equivalent to a decrease in price and results in a decrease in income (this trivially follows from the definition of income in Equation 2.5). Further, this relationship is linear by definition. Appendix 2.C shows that a loss in income is associated with a loss in dietary diversity. Therefore, an increase in transaction costs (or a decrease in market access) is also associated with a decrease in dietary diversity. This results in Proposition 4:

Proposition 4: Higher market access leads to higher dietary diversity despite being associated with lower production diversification

$$\begin{gathered}\text{HHI}_{\text{Market Access}} < \text{HHI}_{\text{No Market Access}} \text{ if } t < t^* \\ \text{where } t^* = \frac{p_k - \frac{1}{\gamma_k}(\sum_{i\neq 1}\frac{p_i}{w_i})(\sum_{j\neq 1} w_j\gamma_j)}{1 + \frac{1}{\gamma_k}(\sum_{i\neq 1}\frac{1}{w_i})(\sum_{j\neq 1} w_j\gamma_j)}\end{gathered} \tag{2.21}$$

Equation 2.21 shows that market access increases dietary diversity, so long as transaction costs are below the 'transaction cost of indifference', t^*, which is the transaction cost at which the household is indifferent between producing for the market and exchanging and producing for home consumption. t^* is derived in Appendix 2.F, and assumes that all transaction costs are equal (for simplicity). p_k and γ_k respectively refer to the price and production of the most profitable good, as above.[3]

The result in Equation 2.21 explains why the empirical literature has found that households with higher market access have higher dietary diversity. They have higher incomes and can purchase a diverse range of foods from the markets. However, these households have lower production diversity than households without market access. This shows that market access

[3] p_k and γ_k are expressed as p_1 and γ_1 in the appendix because the k subscript denotes other terms in the proof. The subscripts have been changed in the main text for consistency.

is a mediating factor for the effect of production diversity (resulting from production risk) on dietary diversity.[4]

2.3 Empirical Methodology

The empirical analysis tests whether the propositions put forth in Section 2.2.1 hold among smallholder farmers in rural Tanzania. To better understand how the empirical analysis links with the model's propositions, the propositions can be re-stated using empirical terminology. However, the theoretical model outlines causal relationships, while the empirical methodology can only make non-causal claims. The terminology in the propositions below draws on the variables used in the analysis (Section 2.4). The propositions to be tested empirically are:

Proposition 1 *Market participation and/or living in a village with market is negatively correlated with production diversity.*

Proposition 2 *Households experiencing negative production shocks in the past ten years have higher production diversity than households not experiencing production shocks.*

Proposition 3 *Production diversity is positively correlated with dietary diversity for households with low market participation and negatively correlated with dietary diversity for households with higher market participation (or with regular village markets).*

Corollary to Proposition 3 *Overall, production diversity is positively correlated with dietary diversity in rural Tanzanian households because market participation is low.*[5]

Proposition 4 *Market participation and/or living in a village with a regular market is positively correlated with higher dietary diversity.*

2.3.1 The Production Side: Testing Propositions 1 and 2

Section 2.2 shows that production diversity can be driven by market access and risk exposure. To test Propositions 1 and 2, we follow an empirical strategy similar to Asante et al. (2018). The following regression model is estimated:

$$\text{pd}_i = \beta_0 + \beta_1 \text{shock}_i + \beta_2 \text{market}_i + \beta X_i + \alpha_j + \epsilon_i \tag{2.22}$$

where pd_i is a production diversity outcome (discussed in Section 2.4), shock_i is an indicator of whether the household experienced a negative production shock in the past ten years (a proxy for perceived risk), market_i is the market participation or access variable, X_i is a vector of household-level controls, α_j is a district fixed effects term, β_0 is a constant, and ϵ_i is the error term.

[4] Additionally, the difference between the range of goods offered on the market may also mean that the household operating in autarky has lower dietary diversity than the household operating in perfect markets. Let there by N crops that are able to be produced: $\gamma_i > 0 \ \forall \ i \in N$ and let there by $N + M$ foods that can be purchased on the market. The difference in the goods able to be produced and able to be purchased can occur for a myriad of reasons, e.g. on-farm limitations to the range of crops that can be produced and imports of foods grown in different climates from other areas. By default, the household operating in autarky will have a less diverse diet than if it operated under perfect market access.

[5] This corollary is added because we test for the overall correlation of production diversity with dietary diversity in addition to correlations based on market participation, in line with previous studies

Standard errors in the models which use count variables (e.g. Agricultural Diversity Score) as dependent variables are estimated assuming a Poisson distribution. The models with HHI (i.e. Simpson's Index) are estimated with a GLM model using a logistic functional link and binomial distribution of the outcome variable, as all values of Simpson's Index fall between 0 and 1. Marginal effects are calculated and reported in each model.

The main independent variables of interest are shock_i and market_i, whose coefficients, β_2 and β_3 respectively, indicate whether Propositions 1 and 2 hold.

2.3.2 The Consumption-Side: Testing Propositions 3 and 4

To test Proposition 4 and the Corollary to Proposition 3, we use models that are commonly run in the empirical literature surrounding production diversity, market access, and dietary diversity (Sibhatu and Qaim 2016; Jones 2017a; Jones 2017b; Koppmair et al. 2017). The model is given by:

$$\text{dd}_i = \beta_0 + \beta_1 \text{pd}_i + \beta_2 \text{market}_i + \beta X_i + \alpha_j + \text{month}_i + \epsilon_i \tag{2.23}$$

where dd_i is a household measure of dietary diversity (either HDDS or HHI), pd_i is a measure of crop diversity (Agricultural Diversity Score or Simpson's Index), market_i is a measure for market participation or market access, X_i is a vector of control variables, α_j is the district fixed effects, and month_i is a fixed effects variable for the month the survey was conducted (included because of seasonal variation in dietary diversity), and ϵ_i is the error term.

As in the production diversity models, standard errors with models using HDDS as an outcome variable are estimated using an assumed Poisson distribution (as HDDS is a count variable). Standard errors in models with Consumption HHI as an outcome are estimated with GLM with a logistic link and binomial distribution. Marginal effects are reported in each of the specifications.

To test Proposition 3, an interaction term between production diversity and market access/participation is added to Equation . The model becomes:

$$\text{dd}_i = \beta_0 + \beta_1 \text{pd}_i + \beta_2 \text{market}_i + \beta_3 \text{pd}_i \times \text{market}_i + \beta X_i + \alpha_j + \text{month}_i + \epsilon_i \tag{2.24}$$

The coefficient β_3 of the interaction term, $\text{pd}_i \times \text{market}_i$ indicates whether market participation has a moderating or exacerbating influence on the relationship between production diversity and dietary diversity. A negative β_3 indicates that crop diversity is less important for households with high access/participation in markets, while a positive β_3 indicates that crop diversity is more important for households with high market access/participation.

Due to well-known issues issues with the interpretation of coefficients for interaction terms in non-linear models (Shang et al., 2018), we calculate the marginal effects of crop diversity for different levels of market-participation and create margins plots to graphically understand and interpret the interaction effects.

2.4 Data, Variables, and Summary Statistics

2.4.1 Data Sources

The empirical analysis uses data from the third wave of the Tanzanian National Panel Survey (NPS), which forms part of the World Bank's Living Standards and Measurement Studies

(LSMS). Tanzania's National Bureau of Statistics (NPS) implemented the survey from October 2012 to September 2013. We restrict the analysis to 1,050 rural households engaging in agriculture and having less than two hectares of land, which is a cutoff for small-scale farmers (Lowder et al., 2016).

The NPS survey contains instruments regarding household demographics, household characteristics (e.g. income, assets), household consumption on 59 food items for the seven days prior to the survey, household plot-level agricultural information, and community-level data. We link the household food consumption data with nutrition tables for Tanzania from the Harvard School of Public Health (Lukmanji et al., 2008). We test the propositions in Section 2.2.1 using the combination of the NPS household and community surveys and Harvard School of Public Health nutrition tables.

2.4.2 Variables

Outcome Variables

Production diversity is measured using two common measures of production diversity: the Agricultural Diversity Score (ADS) and Simpson's Index (SI). The ADS is a simple count of the number of food crops grown by the household, according to the same twelve food groups used in the Household Dietary Diversity Score (HDDS) (see below). The ADS is a useful measure, but is unable to assess the evennesss' of production across different crops. SI is the HHI applied to measure the concentration of crops on a farm. SI captures the evenness of crop production and for a household, i, and is calculated as $\text{SI}_i = \sum_{j=1}^{N} s_j^2$, where s_j is the area share of cultivation for crop j. SI corresponds directly to the diversification measures used in Section 2.2. It has a maximum value of 1 (indicating perfect specialization) and a minimum value of 0 (indicating perfect diversification).

On the consumption side, dietary diversity is the main outcome variable of interest. Dietary diversity is measured in two ways - the HDDS index (used in Koppmair et al. 2017; Jones 2017a; Sibhatu and Qaim 2016) and the HHI for food consumption (Akerele et al., 2017). These are analogous to the production outcomes. HDDS is a simple count of the twelve food groups consumed by the household in the past seven days. The consumption HHI is a concentration index of the different foods consumed by the household (as in Section 2.2). Using the Harvard School of Public Health nutrition tables, we calculate the total number of calories consumed by the household in the past seven days and the number of calories coming from each food item. We then calculate the percentage of calories coming from individual food items. The consumption HHI for household i is given by $HHI_i = \sum_{j=1}^{N} s_j^2$, where s_j is the percentage share of calories coming from food item j.[6]

As additional analysis presented in Appendix 2.I, we test whether these results translate to children's anthropometric outcomes. Measures of children's anthropometric outcomes can be used as an indicator of overall household nutrition (WFP, 2005). Three anthropometric outcomes for children under five are used to proxy household nutrition. Wasting is measured by a low weight-for-height z-score (WHZ); stunting is measured by a low height-for-age z-score (HAZ); being underweight is measured by a low-weight-for-age z-score (WAZ). As in Chegere and Stage (2020), we create indicator variables for each of these measures. If the z-scores fall below -2 for WHZ, HAZ, or WAZ for any child in the household then a household is considered to have a stunted, wasted, or underweight child, respectively.

[6]The HHI is constructed using food items, not food groups because individual food items within a food group can also have important micro-nutrients (Steyn et al., 2006).

Main Independent Variables

Depending on the econometric model, the main independent variables of interest are producer market participation and access indicators, the presence of production shocks in the past 10 years, and crop production diversity indicators (discussed in Section 2.3).

Market participation is measured by a weighted average of the percent of crops sold, where the weight is the proportion of the total farm area of a crop under cultivation.[7] This measure follows the logic of the maize and non-maize market participation variables used in Koppmair et al. (2017), but combines all crops into one and applies weights based on the area of production for each crop. Doing so relaxes the implicit assumption that Maize is the primary crop for all smallholders in the study.

The primary market access indicator is the presence of a daily or weekly market in a given household's village. This measure is chosen because we make the assumption that market access should be positively correlated with market participation. The presence of a daily or weekly market has the highest positive, unconditional correlation with market participation of all the considered market access indicators (see Appendix 2.G).

Production risk is proxied by whether a household experienced a negative production shock (either drought or pests) in the past ten year. This measure provides a subjective perception of the risk levels of a household's production environment.

Control Variables

Each specification includes a series of household and community-level control variables. Household-level demographic variables include the household head's age, sex, an indicator for whether the household head is literate or not, and household size. These variables are related to the labor endowment available to households in Section 2.2. In relation to households' land endowment, the number of acres devoted to agriculture is included as a control variable. To control for effects of livestock on dietary diversity the number of tropical livestock units is included as a control. Outside income and wealth effects are controlled for using log annual non-agricultural income, log value of loans received, log agricultural input value, an indicator for mobile phone ownership, and an indicator for use of mobile money. Finally, we include the survey-month fixed effects to capture seasonal variation in consumption and district fixed effects to capture geographic variation in both production and consumption.

2.4.3 Descriptive Statistics

Table 2.1 displays the descriptive statistics for the households considered in the analysis of the 2012/2013 wave of the NPS. In terms of production diversity, every household cultivates a crop from at least one food group (Agricultural Diversity Score), with the average household cultivating around three food groups and the maximum cultivating seven. The average production concentration, measured by Simpson's Index, is 0.51 meaning that most households have a somewhat diverse crop mix. The average household sells only 19% of their crop production, indicating that most households are primarily engaged in subsistence agriculture.

The typical household consumes seven food groups (out of twelve possible groups) in the seven days prior to the survey, but this measure is fairly variable with a standard deviation of almost two food groups. The dietary HHI also shows that households have fairly diverse diets (more diverse than their production), but there is considerable variation with some households

[7] Mathematically this is: $\sum_{i=1}^{N} \frac{\text{Kgs. Sold}_i}{\text{Kgs. Harvested}_i} \times \frac{\text{area}_i}{\text{total area}}$

having a diet concentrated in only one food group. In terms of anthropometric measures, 28% of households have at least one child under five who is stunted, 3% have at least one wasted child, and 10% have an underweight child. However, only about half of the households have any children under the age of five.

The average household has 5.66 members, and the average household head is 46 years old. 77% of household heads are men, and 68% of household heads are literate. In terms of household agriculture, the average household owns about two acres of land.[8]

Financially, the average household earned 606,649 TZS (≈ 382 USD using January, 2013 exchange rates) in the twelve months prior to the survey. The average household received 37,480 TZS (≈ 24 USD) in the preceding twelve months and had 30,406 (≈ 19 USD) in outstanding loans. Households use 97,225 (≈ 61 USD) in agricultural inputs on average. Finally, 63% of households have mobile phones, but only 27% have access to mobile money.

Table 2.1: Descriptive Statistics

	(1)				
	Mean	Standard Deviation	Median	Minimum	Maximum
ADS	3.01	1.39	3.00	1.00	7.00
Simpson's Index	0.51	0.32	0.50	0.00	1.00
HDDS	7.11	1.91	7.00	0.00	10.00
Dietary HHI	0.34	0.20	0.29	0.00	1.00
Stunting = 1	0.28	0.45	0.00	0.00	1.00
Wasting = 1	0.03	0.18	0.00	0.00	1.00
Underweight = 1	0.10	0.30	0.00	0.00	1.00
Presence of Village Market	0.38	0.48	0.00	0.00	1.00
% of Crops Sold	18.76	25.85	0.00	0.00	100.00
Production Shock = 1	0.43	0.50	0.00	0.00	1.00
HH Head Age	46.34	16.60	44.00	18.00	108.00
HH Head Literate = 1	0.68	0.47	1.00	0.00	1.00
Male HH Head	0.73	0.44	1.00	0.00	1.00
HH Size	4.66	2.34	4.00	1.00	16.00
Total HH Acres	1.98	1.24	2.00	0.10	4.90
Annual Outside Income	606649.58	7724138.65	0.00	0.00	2.40e+08
Agricultural Input Value (Past 12 Months)	97225.02	282138.74	16000.00	0.00	2422800.00
Outstanding Loan Quantity	30406.38	298730.14	0.00	0.00	6200000.00
Remittances Received (Past 12 Months)	37480.76	166852.91	0.00	0.00	3000000.00
HH Tropical Livestock Units	1.40	5.19	0.04	0.00	102.56
Own Mobile Phone	0.55	0.50	1.00	0.00	1.00
Access to Mobile Money	0.21	0.41	0.00	0.00	1.00
Observations	1050				

[8]Only households with fewer than 4.95 acres (two hectares) are considered.

2.5 Empirical Results

The results show evidence for each of the four propositions put forth in Section 2.2. First, the production-side propositions are tested (Propositions 1 and 2), and then the consumption-side results are shown (Propositions 3 and 4, and the Corollary to Proposition 3).

2.5.1 The Production-Side: Evidence for Propositions 1 and 2

To test Propositions 1 and 2, Equation 2.22 is estimated using the ADS and SI as outcomes variables. The results using perception of production shocks and market participation are presented in Table 2.2.

Proposition 1: Proposition 1 states that households with higher market access grow fewer food groups because of gains from specialization. The empirical results related to Proposition 2 are presented in Table 2.2 (using market participation) and Table 2.3 (using the presence of village markets).

Table 2.2 shows that more market-oriented households grow fewer crops – a 1 percentage point increase in the percentage of crops old on the market is correlated with a decrease in the number of food groups produced by 0.006. This suggests that a household moving from complete home production to complete market participation (a 100 percentage point increase in the percent of crops sold) would reduce the number of food groups they grow by 0.6 on average. The specification without fixed effects and controls gives evidence that Proposition 1 holds. However, the results are not robust to the inclusion of district and interview month fixed effects (Column 2) and controls (Column 3).

When using Simpson's Index as an outcome variable, market participation appears to play a statistically significant role in determining production diversity. The unconditional correlation presented in Table 2.2 Column 4 shows that a one percentage point increase in the percentage of crops sold is correlated with 0.0015 point increase in SI. A household moving from complete autarky to complete market participation (a 100 percentage point increase) would increase SI by 0.15 points, which is a reduction of production diversity of nearly 0.5 standard deviations. These results are robust to the inclusion of district and interview month fixed effects (Column 5) and household controls (Column 6). The outcomes is stronger when using Simpson's Index (which is used in Section 2.2) as an outcome variable.

Proposition 2: Proposition 2 states that households with higher production risk will diversify their production as a risk mitigation mechanism. The empirical results for this proposition are presented in Tables 2.2 and 2.3 which show the estimated coefficients from Equation 2.22. Production risk is proxied using the number of production shocks experienced in the past ten years. Column 1 of Table 2.2 shows that households experiencing a production shock in the past ten years grow 0.38 crops more on average than households not experiencing a shock, conditional only on market participation. This coefficient is attenuated to 0.13 (and statistically significant at the 90% level) when controlling for district fixed effects and interview month fixed affects (Column 2). The result is not robust to the inclusion of controls (Column 3).

The correlations between Simpson's Index and the main independent variables are stronger and more robust than for ADS. This could be because the ADS measurement is relatively less variable than SI (see Table 2.1). Column 4 in Table 2.2 shows that households that experienced production shocks in the past ten years have more diverse production mixes than households not experiencing production shocks (by 0.06 points in SI, or 0.2 standard deviations). This correlation is attenuated to -0.04 (or 0.12 standard deviations), but robust at the 90% significance level when including fixed effects, and the result is robust to the inclusion of household controls.

These results are also robust to using the presence of a market in the village as a control instead of the rate of market participation (see Table 2.3). The evidence shows that Proposition 2 generally holds, and is strongest evidence is found when considering Simpson's Index as an outcome variable (as the theoretical model does) rather than ADS.

Table 2.2: Correlates of Production Diversity (Market Participation)

	(1) ADS	(2) ADS	(3) ADS	(4) SI	(5) SI	(6) SI
Production Shock = 1	0.377***	0.126*	0.0952	-0.0573***	-0.0375*	-0.0373**
	(0.0986)	(0.0764)	(0.0722)	(0.0199)	(0.0196)	(0.0183)
% of Crops Sold	-0.00620***	-0.00248	-0.00287	0.00148***	0.00101**	0.00164***
	(0.00206)	(0.00175)	(0.00175)	(0.000413)	(0.000399)	(0.000392)
HH Head Age			0.0108***			-0.000753
			(0.00237)			(0.000611)
HH Head Literate = 1			0.129			0.0344
			(0.0879)			(0.0226)
Male HH Head			0.0113			0.00491
			(0.0844)			(0.0212)
HH Size			0.0479***			0.00155
			(0.0124)			(0.00414)
Total HH Acres			0.0879***			-0.101***
			(0.0277)			(0.00746)
Visited by Agr. Extension = 1			0.0949			-0.0398
			(0.137)			(0.0393)
Improved Crops = 1			0.120			-0.0186
			(0.0748)			(0.0211)
Log Non-Agr. Income Past 12 Months			-0.00145			-0.00178
			(0.00608)			(0.00166)
Log Agr. Input Value			0.0672***			-0.00574
			(0.0256)			(0.00667)
Log Loan Value			-0.00236			0.000375
			(0.0122)			(0.00333)
Log Remittances Value			0.00149			0.00384*
			(0.00784)			(0.00206)
HH Tropical Livestock Units			-0.00598			0.00342**
			(0.0109)			(0.00170)
Elevation			0.000450**			0.0000194
			(0.000209)			(0.0000447)
District Fixed Effects	No	Yes	Yes	No	Yes	Yes
Survey Month Fixed Effects	No	Yes	Yes	No	Yes	Yes
Observations	1050	1050	1050	1050	1050	1050

Marginal effects; Standard errors in parentheses
(d) for discrete change of dummy variable from 0 to 1
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Columns 1-3 are estimated using a Poisson model
Columns 4-6 are estimated using a GLM model using a logistic functional link and binomial distribution.

Table 2.3: Correlates of Production Diversity (Market Access)

	(1) ADS	(2) ADS	(3) ADS	(4) SI	(5) SI	(6) SI
Production Shock = 1	0.417***	0.135*	0.101	-0.0668***	-0.0417**	-0.0416**
	(0.0994)	(0.0759)	(0.0724)	(0.0196)	(0.0195)	(0.0183)
Village Market = 1	-0.360**	-0.137	-0.112	0.0792***	0.0290	0.0399*
	(0.148)	(0.0992)	(0.0989)	(0.0245)	(0.0235)	(0.0214)
HH Head Age			0.0112***			-0.00106*
			(0.00235)			(0.000608)
HH Head Literate = 1			0.128			0.0342
			(0.0884)			(0.0223)
Male HH Head = 1			0.00709			0.0102
			(0.0850)			(0.0214)
HH Size			0.0493***			0.000827
			(0.0125)			(0.00412)
Total HH Acres			0.0837***			-0.0975***
			(0.0278)			(0.00756)
Visited by Agr. Extension = 1			0.0987			-0.0402
			(0.138)			(0.0389)
Improved Crops = 1			0.113			-0.0140
			(0.0750)			(0.0213)
Log Non-Agr. Income Past 12 Months			0.000275			-0.00267
			(0.00603)			(0.00169)
Log Agr. Input Value			0.0612**			-0.00278
			(0.0258)			(0.00665)
Log Loan Value			-0.00346			0.00102
			(0.0124)			(0.00334)
Log Remittances Value			0.00233			0.00345*
			(0.00778)			(0.00202)
HH Tropical Livestock Units			-0.00580			0.00316*
			(0.0109)			(0.00177)
Elevation			0.000431**			0.0000214
			(0.000213)			(0.0000473)
District Fixed Effects	No	Yes	Yes	No	Yes	Yes
Survey Month Fixed Effects	No	Yes	Yes	No	Yes	Yes
Observations	1050	1050	1050	1050	1050	1050

Marginal effects; Standard errors in parentheses
(d) for discrete change of dummy variable from 0 to 1
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Columns 1-3 are estimated using a Poisson model
Columns 4-6 are estimated using a GLM model using a logistic functional link and binomial distribution.

2.5.2 The Consumption-Side: Evidence for Propositions 3 and 4

Proposition 3: Proposition 3 states that production diversity is negatively correlated with dietary diversity in households with high market access and positively correlated with dietary diversity in households with low market access. Figure 2.1 to Figure 2.4 display the results of the estimation of Equation 2.24, which tests whether there is a significant interaction between market participation/access and production diversity. The results suggest that there is an interaction term, but there is only weak evidence for this.

Figure 2.1 plots the coefficient of ADS at different levels of market participation. At zero market participation, an increase in the number of food groups produced is correlated with a 0.25 increase in the number of food groups consumed (Panel 1). This suggests that a household would need to grow only four more food groups to consume one more food group.[9] This coefficient steadily decreases as market participation increases. Households selling 80-100% of their crops do not realize any statistically significant benefits to dietary from growing one more food group. These results are robust at the 90% confidence level to the inclusion of district and interview month fixed effects (Panel 2) and household controls (Panel 3). However, the coefficients are attenuated when including controls and fixed effects. The full specification suggests that households with no market participation still need to grow nine more food groups to consume just one more food group (a correlation of 0.11, conditional on the inclusions of controls and district and month indicators), and households selling over 40% of their crops do not gain any dietary diversity by growing more crops.

The results in Figure 2.2 show weaker evidence of an interaction effect. The results in Panel 1 suggest that increases in Simpson's Index are negatively correlated with HDDS for households with low market participation (0-40%). However, the results are only robust at the 90% level to the inclusion of district and interview month fixed effects for households with 20% and 40% market participation (Panels 2 and 3). These dynamics provide weak support for the results in Figure 2.1.

When using consumption HHI as an outcome, the results are similar. Figure 2.3 shows that an increase in ADS is correlated with a reduction in consumption HHI for households selling 40% or less of their crops. For households who sell low levels of their production (20%-40%), the results are robust at the 90% level to the inclusion of district and interview month fixed effects (Panels 2 and 3). The full specification in Panel 3 suggests that a one unit increase in the number of food groups produced, decreases dietary concentration by around 0.01 point (or 0.05 standard deviations) for with relatively low levels of market participation (i.e. selling 20% to 40% of their crops).

Figure 2.4 shows the results using Simpson's Index as an independent variable and consumption HHI as the dependent variable. The results in Panel 1, which does not include fixed effects or controls, shows that a one unit increase in Simpson's Index (a decrease production diversity) is associated with 0.05 increase in consumption HHI (a decrease in consumption diversity) for households operating in autarky. For households selling more than 0% of their crops, production diversity does not have a statistically significant relationship with consumption diversity. When including district and interview month fixed effects (Panel 2) and controls (Panel 3), there are no statistically significant relationships, although the curve of the margins plot slopes in the direction that Proposition 3 predicts. The findings are much weaker when using market access (Appendix 2.H), but this is likely because market access and market participation are only weakly correlated (Appendix 2.G). one explanation for this weak correlation may be the presence of small traders, who often pick up produce at the farm-gate. For example,

[9] The overall sample needs to produce about six food groups to consume one more. See Table 2.4, Column 1.

only 1/3 of the farmers in the sample who sold their crops transported them to the sale point, suggesting that traditional measures of market access (often based on distance or the presence of markets) are inadequate because farmers are often selling to traders at farm gate.

The results do not hold when using Anthropometric measures (results shown in Appendix 2.I). As with dietary diversity outcomes, the results even appear to be in contrast to the expected outcomes. However, this can be due to relatively low incidences of malnutrition and half of the households not having children under five (and therefore, by default, having values of zero for malnutrition). Another explanation is that the anthropometric outcomes are a stock variable taking into account dietary history of children, while dietary diversity is a flow variable, reflecting dietary diversity at one point in time. Therefore, production diversity and market access (which are also flow variables) will have less correlation with stock measures of nutrition than with flow measures.

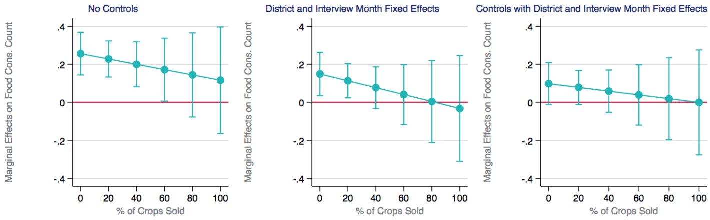

Figure 2.1: Correlates of HDDS: Interaction between ADS and Producer Market Participation (95% Confidence Intervals)
Note: Each panel is estimated via the general model: $\text{HDDS}_i = \beta_0 + \beta_1\text{ADS}_i + \beta_2\%\text{ crops sold}_i + \beta_3\text{ADS}_i \times \%\text{ crops sold}_i + \beta X_i + \alpha_j + \text{month}_i + \epsilon_i$, based on Equation 2.24 above. The first panel corresponds to the case where there are no controls nor fixed effects, the second includes fixed effects, and the third includes both controls and fixed effects.

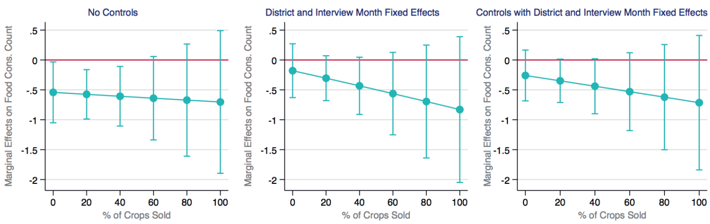

Figure 2.2: Correlates of HDDS: Interaction between SI and Producer Market Participation (95% Confidence Intervals)
Note: Each panel is estimated via the general model: $\text{HDDS}_i = \beta_0 + \beta_1\text{SI}_i + \beta_2\%\text{ crops sold}_i + \beta_3\text{SI}_i \times \%\text{ crops sold}_i + \beta X_i + \alpha_j + \text{month}_i + \epsilon_i$, based on Equation 2.24 above. The first panel corresponds to the case where there are no controls nor fixed effects, the second includes fixed effects, and the third includes both controls and fixed effects.

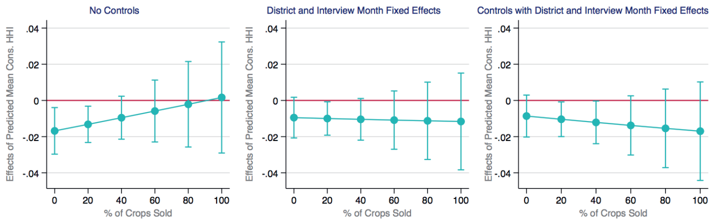

Figure 2.3: Correlates of HHI: Interaction between ADS and Producer Market Participation (95% Confidence Intervals)
Note: Each panel is estimated via the general model: $\text{HHI}_i = \beta_0 + \beta_1 \text{ADS}_i + \beta_2 \%\,\text{crops sold}_i + \beta_3 \text{ADS}_i \times \%\,\text{crops sold}_i + \beta X_i + \alpha_j + \text{month}_i + \epsilon_i$, based on Equation 2.24 above. The first panel corresponds to the case where there are no controls nor fixed effects, the second includes fixed effects, and the third includes both controls and fixed effects.

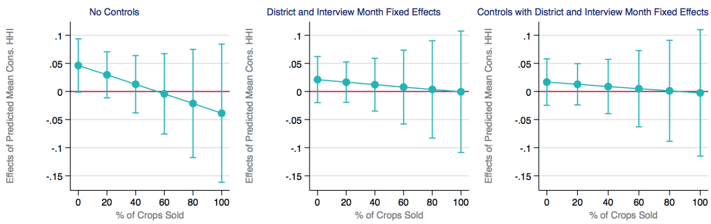

Figure 2.4: Correlates of HHI: Interaction between SI and Producer Market Participation (95% Confidence Intervals)
Note: Each panel is estimated via the general model: $\text{HHI}_i = \beta_0 + \beta_1 \text{SI}_i + \beta_2 \%\,\text{crops sold}_i + \beta_3 \text{SI}_i \times \%\,\text{crops sold}_i + \beta X_i + \alpha_j + \text{month}_i + \epsilon_i$, based on Equation 2.24 above. The first panel corresponds to the case where there are no controls nor fixed effects, the second includes fixed effects, and the third includes both controls and fixed effects.

The Corollary to Proposition 3: The Corollary to Proposition 3 states that production diversity should be positively correlated with consumption diversity in the overall sample because the overall sample has low market orientation (an average of 19% of crops sold on the market). This proposition is tested using Equation 2.3.2, and the results are presented in Table 2.4 and Table 2.5. Table 2.4 shows that there is robust evidence that the corollary to Proposition 3 holds when using HDDS as an outcome variable. Column 1 suggests that if a household cultivates an additional food group, then they will consume 0.16 additional food groups. This correlation is weaker (but still statistically significant) when including district and interview month fixed effects in Column 2. Column 3 shows that, conditional on household controls and district and interview month fixed effects, an increase in the production of one food group is correlated with the consumption of an additional 0.08 food groups.

Higher concentration of production is associated with lower HDDS, as seen in Columns 4-6 of Table 2.4. A one point increase in Simpson's Index is correlated with a reduction of 0.006 in the number of food groups consumed. Conditional on district and interview month fixed effects, this correlation is only 0.003 (and statistically significant at the 90% level). While these results are statistically significant and indicative that the corollary to Proposition 3 holds, they are not practically significant. If a household has perfect production concentration (an SI of 1), and changes their production system to perfect diversification (an SI of 0), they will consume 0.33

food groups more on average. In practical terms, gaining an extra food group of consumption from increasing production diversity can be an extremely inefficient solution.

Table 2.5 corroborates these results by showing that increases in the number of food groups grown are significantly correlated with higher dietary diversity. However, the results are small in absolute terms. Column 1 of 2.5 shows that an increase of production diversity by one food group is correlated with a reduction in consumption HHI of 0.014 (or 0.07 standard deviations). The result is robust to the inclusion of district and interview month fixed effects (Column 2) and household controls (Column 3). The full specification in Column 3 suggests that an increase in production of one food group reduces consumption concentration by 0.01 points (or 0.05 standard deviations). Columns 4-6 suggest that when using Simpson's Index as the explanatory variable related to production diversity, there are no statistically significant relationships between production diversity and dietary diversity. Table 2.5 supports the results in Table 2.4 indicating that there are statistically significant relationships between production and dietary diversity, but these correlations are extremely small in practical terms.

In terms of anthropometric outcomes, the correlations are much weaker. Food production does not appear to have a statistically significant correlation with the probability of malnutrition in Table 2.A.4, although the coefficient of food production is negative in seven of the nine specifications. Similarly, the coefficient of Simpson's Index is not statistically significant for the probability of being underweight and wasting, but it is significantly and negatively correlated the probability of stunting.This suggests that less production diversity leads to a lower probability of stunting (contrary to proposition 4a). However, there are only 35 observations with recorded stunting, so these results should be interpreted with caution. As with the correlation of market participation and anthropometric measures, this result does not disprove the proposition, but rather shows that the same factors driving household dietary diversity are not necessarily driving anthropometric malnutrition outcomes, perhaps because anthropometric outcomes are stock variables.

Proposition 4: Proposition 4 states that households with higher market access, have higher dietary diversity. Table 2.4 shows the estimates of Equation 2.3.2 using HDDS as the outcome variable. Across all specifications, there is no evidence in Table 2.4 that the percentage of crops sold has a statistically significant correlation with HDDS. However, when using the consumption HHI as an outcome variable, the percentage of crops sold is significantly and negatively correlated with consumption HHI (Table 2.5). These relationships are only observed when including district and interview month fixed effects (Columns 2, 3, 5, and 6). The results in Columns 2 and 5 of Table 2.5 suggest that a shift from autarky to complete market participation (a 100 percentage point increase in the percent of crops sold) is correlated with a 0.057 decrease in consumption HHI. This is equivalent to a 0.29 standard deviation increase in consumption diversity. The observed relationship is lower when controlling for household characteristics (Columns 3 and 6), where the results suggest that a shift from autarky to complete market orientation is correlated with 0.038 decrease in the consumption HHI. This is equivalent to a 0.19 standard deviation increase in dietary diversity.

The results for Proposition 4 are weak, but there is ample evidence for Proposition 4 in the existing literature, as is highlighted in comprehensive reviews of the literature on this topic (Sibhatu and Qaim 2018; Nandi et al. 2021). The weak evidence could be a result of the low levels of marketing in Tanzania (the weighted average of crops sold is only 19%). The results are also in-line with other studies from Tanzania – Chegere and Stage (2020) finds no statistically significant correlation between market orientation and dietary diversity outcomes, but does not use a dietary concentration index. This could highlight the importance of looking beyond count variables in dietary diversity outcomes and also analyzing concentration indices.

Further, the results do not hold when using anthropometric measures as outcome variables (presented in Table 2.A.4 and Table 2.A.5). This is consistent with Chegere and Stage (2020). The results even suggest that an increase in market participation is associated in an increase probability of a child under five being underweight. However, this result does not hold for wasting or stunting, and the coefficients are small – a 100 percentage point increase in the percentage of crops sold is correlated with an 8% increase in the probability of stunting. This result is contrary to the results presented above, but does not disprove the the theoretical model's propositions because the theoretical model focuses on dietary diversity – a flow measure. However, this result may open a discussion of whether dietary diversity is the best measure of household nutrition or whether anthropometric outcomes represent a better measure for household nutrition.

Table 2.4: Correlates of Household Dietary Diversity Score (Market Participation)

	(1) HDDS	(2) HDDS	(3) HDDS	(4) HDDS	(5) HDDS	(6) HDDS
ADS	0.162***	0.114**	0.0790*			
	(0.0505)	(0.0461)	(0.0458)			
SI				-0.568***	-0.279	-0.328*
				(0.213)	(0.192)	(0.185)
% of Crops Sold	-0.00206	0.00226	0.000529	-0.00225	0.00227	0.000775
	(0.00257)	(0.00250)	(0.00249)	(0.00260)	(0.00249)	(0.00249)
HH Head Literate = 1			0.609***			0.626***
			(0.139)			(0.139)
Male HH Head			0.0315			0.0306
			(0.137)			(0.137)
HH Size			0.0322			0.0372
			(0.0249)			(0.0250)
Total HH Acres			-0.111			-0.171
			(0.171)			(0.174)
Total HH Acres Squared			0.0367			0.0443
			(0.0338)			(0.0342)
HH Tropical Livestock Units			0.0139			0.0150*
			(0.00879)			(0.00886)
Log Non-Agr. Income Past 12 Months			0.0132			0.0122
			(0.00808)			(0.00807)
Log Non-Farm Enterprise Asset Val.			0.0373***			0.0374***
			(0.00963)			(0.00952)
Access to Mobile Money			0.564***			0.571***
			(0.144)			(0.143)
Own Mobile Phone			0.477***			0.479***
			(0.140)			(0.141)
District Fixed Effects	No	Yes	Yes	No	Yes	Yes
Survey Month Fixed Effects	No	Yes	Yes	No	Yes	Yes
Observations	1050	1050	1050	1050	1050	1050

Marginal effects; Standard errors in parentheses
(d) for discrete change of dummy variable from 0 to 1
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Columns 1-6 are estimated using a Poisson model

Table 2.5: Correlates of Consumption HHI (Market Participation)

	(1) HHI	(2) HHI	(3) HHI	(4) HHI	(5) HHI	(6) HHI
ADS	-0.0139***	-0.00999**	-0.0103**			
	(0.00524)	(0.00472)	(0.00491)			
SI				0.0322	0.0174	0.0136
				(0.0209)	(0.0181)	(0.0184)
% of Crops Sold	0.0000551	-0.000570**	-0.000387*	0.0000957	-0.000566**	-0.000382*
	(0.000267)	(0.000238)	(0.000231)	(0.000266)	(0.000238)	(0.000231)
HH Head Literate = 1			-0.0330***			-0.0343***
			(0.0123)			(0.0122)
Male HH Head			-0.0165			-0.0164
			(0.0136)			(0.0136)
HH Size			0.0111***			0.0105***
			(0.00252)			(0.00248)
Total HH Acres			0.00348			0.00481
			(0.0167)			(0.0170)
Total HH Acres Squared			-0.00286			-0.00312
			(0.00350)			(0.00353)
HH Tropical Livestock Units			-0.00122			-0.00125
			(0.000788)			(0.000773)
Log Non-Agr. Income Past 12 Months			-0.00121			-0.00115
			(0.000955)			(0.000947)
Log Non-Farm Enterprise Asset Val.			-0.00156			-0.00158
			(0.00111)			(0.00111)
Access to Mobile Money			-0.0367**			-0.0367**
			(0.0163)			(0.0165)
Own Mobile Phone			-0.0400***			-0.0400***
			(0.0135)			(0.0135)
District Fixed Effects	No	Yes	Yes	No	Yes	Yes
Survey Month Fixed Effects	No	Yes	Yes	No	Yes	Yes
Observations	1050	1050	1050	1050	1050	1050

Marginal effects; Standard errors in parentheses
(d) for discrete change of dummy variable from 0 to 1
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Columns 1-6 are estimated using a GLM model using a logistic functional link and binomial distribution.

2.6 Discussion and Conclusion

Nutrition-sensitive agriculture has become a center-piece of many government programs and agricultural interventions in recent decades as the international community aims to meet the SGDs. A central component of many of these programs is the link between production diversity and dietary diversity. As governments, NGOs, and international organizations become more focused on climate change, production diversity among smallholders is taking an even more central role because of its potential to build resilience to climate change and mitigate smallholder effects on climate change. Despite production diversity's assumed linkage with dietary diversity, the empirical evidence is not promising. Sibhatu and Qaim (2018) finds in a review of empirical studies that a smallholder farmer would need to grow nine more crops to consume one more food group. These results indicate that practitioners and researchers alike should rethink the link between dietary diversity and production diversity.

Our paper provides the first theoretical economic model to demonstrate the link between production diversity and dietary diversity, and we provide empirical evidence validating the predicted outcomes from our model. Much of the empirical literature has treated smallholder production diversity as exogenous, but smallholders choose which crops to grow and at what levels. When taking into account *why* farmers may diversify, the linkage between production diversity and dietary diversity becomes clearer, and we can better see which farmers benefit from production diversity (in terms of dietary diversity) and which ones do not. Our empirical estimates show that in order to increase consumption by one food group, the average household needs to produce six more food groups (unconditional on other factors). However, the households that do not participate in markets only need to grow four more food groups to consume an additional food group.

From a policy perspective, two major themes come from this research. First, there is not a 'one size fits all' approach to nutrition-sensitive agriculture. Households with and without access to output markets have very different requirements to improve their nutrition and respond to different incentives. In order to be effective, agricultural programs must take this into account or there will continue to be weak linkages between interventions and nutrition outcomes. In particular, programs seeking to promote new crops or climate smart agriculture (e.g. improved seeds or improved practices that build resilience to climate change), must carefully think about which crops and practices to promote for different households in different market access regimes. In other words, programs must be targeted based on market access to be effective. Second, both the links between production diversity and consumption diversity and market participation and consumption diversity are empirically weak, despite being theoretically strong. This suggests that policymakers should explore other avenues to improve household nutrition, such as improving mobile infrastructure, road infrastructure, reducing gender gaps in agriculture production, and increasing overall farm production.

Since the proliferation of non-separable agricultural household models in the 1990s, development in theoretical models of the agricultural household has been relatively slow. The literature has become increasingly empirical for a myriad of reasons. However, non-separable agricultural household models can provide many insights that the empirical literature may overlook. Further research should continue building on non-separable household models to explore other issues. Our model does not explore reasons for diversification beyond market access and risk mitigation. For example, these could be joint production or differences in output elasticities. Models looking at these motivations for diversification could also lead to important insights on household nutritional outcomes. Non-separable models should also be expanded to look at climate change mitigation efforts, adoption of technology, access to finance, access to labor markets, and various other topics.

Empirically, future research should explore the mediation effect of market access on production and dietary diversity. RCTs introducing new crops should also include survey modules on dietary diversity in order to explore the causal effects of increasing production diversity on dietary diversity. More broadly, future research should focus on the mechanisms of production diversity and their links to dietary diversity, as production diversity is driven by a number of factors that may have differential effects on dietary diversity.

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Appendix 2

2.A Combining Cobb-Douglas and Mean-Variance

In the two good case, we will show that at each efficient allocation of land and labour to crops 1 and 2, $\frac{a_i^*}{A_T} = \frac{l_i^*}{L_T}$, where a_i^* and l_i^* are efficient allocations and L_T and A_T are the total amounts of labour and land endowed. We note that since there are no *monetary* costs associated with land and labor, maximizing revenue and profit are the same. Land and labor can only be allocated to farm activities.

The revenue function is given by:

$$R = p_1 q_1 + p_2 q_2 = p_1 \phi_1 l_1^{\alpha} a_1^{1-\alpha} \epsilon_1 + p_2 \phi_2 l_2^{\alpha} a_2^{1-\alpha} \epsilon_2 \tag{2.A.1}$$

We can see that we have an additive Cobb-Douglas framework, whereby each crop takes the same functional form (i.e. has the same α terms). This assumption is key to the proof.

The household faces the problem:

$$\begin{aligned} \max E[R] = p_1 \phi_1 l_1^{\alpha} a_1^{1-\alpha} + p_2 \phi_2 l_2^{\alpha} a_2^{1-\alpha} & \\ \text{s.t } l_1 + l_2 = L_T & \\ a_1 + a_2 = A_T & \end{aligned} \tag{2.A.2}$$

The error terms go away in the case of maximizing the expectation. The constraints indicate that all labour and must be allocated.

The Lagrangian becomes:

$$\mathcal{L} = p_1 \phi_1 l_1^{\alpha} a_1^{1-\alpha} + p_2 \phi_2 l_2^{\alpha} a_2^{1-\alpha} + \lambda_l (L_T - l_1 - l_2) + \lambda_A (A_T - a_1 - a_2) \tag{2.A.3}$$

The first order conditions are:

$$\begin{aligned} \frac{\partial \mathcal{L}}{\partial l_1} &= \alpha p_1 \phi_1 l_1^{\alpha-1} a_1^{1-\alpha} - \lambda_L = 0 \\ \frac{\partial \mathcal{L}}{\partial l_2} &= \alpha p_2 \phi_2 l_2^{\alpha-1} a_2^{1-\alpha} - \lambda_L = 0 \\ \frac{\partial \mathcal{L}}{\partial a_1} &= (1-\alpha) p_1 \phi_1 l_1^{\alpha} a_1^{-\alpha} - \lambda_A = 0 \\ \frac{\partial \mathcal{L}}{\partial a_2} &= (1-\alpha) p_2 \phi_2 l_2^{\alpha} a_2^{-\alpha} - \lambda_A = 0 \\ \frac{\partial \mathcal{L}}{\partial \lambda_L} &= L_T - l_1 - l_2 = 0 \\ \frac{\partial \mathcal{L}}{\partial \lambda_A} &= A_T - a_1 - a_2 = 0 \end{aligned} \tag{2.A.4}$$

We cannot explicitly solve for our choice variables, but we can demonstrate key relationships between them: we will show that $\frac{a_i^*}{A_T} = \frac{l_i^*}{L_T}$.

We note that in the optimal case, from standard microeconomic theory, the marginal revenue from labour allocations to crops 1 and 2 must equal, and the marginal revenue from land allocations to crops 1 and 2 must equal.

As a result, we set FOC 1 equal to FOC 2, and we set FOC 3 equal to FOC 4. This is equivalent to setting the marginal revenues equal to each other (because FOCs 1-4 are marginal revenues excepting the λ term which drops out of the analysis in any case when we set FOCs 1 and 2 equal to each other FOCs 3 and 4 equal to each other).

We start with setting FOC 1 = FOC 2:

$$\alpha p_1\phi_1 l_1^{\alpha-1} a_1^{1-\alpha} - \lambda_L = \alpha p_2\phi_2 l_2^{\alpha-1} a_2^{1-\alpha} - \lambda_L \tag{2.A.5}$$

Simplifying:

$$p_1\phi_1 l_1^{\alpha-1} a_1^{1-\alpha} = p_2\phi_2 l_2^{\alpha-1} a_2^{1-\alpha} \tag{2.A.6}$$

Rearranging:

$$\frac{p_1\phi_1 a_1^{1-\alpha}}{p_2\phi_2 a_2^{1-\alpha}} = \frac{l_2^{\alpha-1}}{l_1^{\alpha-1}} \tag{2.A.7}$$

Simplifying:

$$\frac{p_1\phi_1 a_1^{1-\alpha}}{p_2\phi_2 a_2^{1-\alpha}} = \frac{l_2}{l_1} \tag{2.A.8}$$

Rearranging:

$$\frac{l_1}{l_2}\frac{p_1\phi_1 a_1^{1-\alpha}}{p_2\phi_2 a_2^{1-\alpha}} = 1 \tag{2.A.9}$$

Now we perform the same analysis on FOCs 3 and 4 (the FOCs for the a terms):

We start with setting FOC 3 = FOC 4:

$$(1-\alpha) p_1\phi_1 l_1^{\alpha} a_1^{-\alpha} - \lambda_A = (1-\alpha) p_2\phi_2 l_2^{\alpha} a_2^{-\alpha} - \lambda_A \tag{2.A.10}$$

Simplifying:

$$p_1\phi_1 l_1^{\alpha} a_1^{-\alpha} = p_2\phi_2 l_2^{\alpha} a_2^{-\alpha} \tag{2.A.11}$$

Rearranging:

$$\frac{p_1\phi_1 l_1^{\alpha}}{p_2\phi_2 l_2^{\alpha}} = \frac{a_2^{-\alpha}}{a_1^{-\alpha}} \tag{2.A.12}$$

Simplifying:

$$\frac{p_1\phi_1 l_1^{\alpha}}{p_2\phi_2 l_2^{\alpha}} = \frac{a_2}{a_1} \tag{2.A.13}$$

Rearranging:

$$\frac{a_1}{a_2}\frac{p_1\phi_1 l_1^{\alpha}}{p_2\phi_2 l_2^{\alpha}} = 1 \tag{2.A.14}$$

Now, we can see that we have two equations that are both equal to 1. So, we can set these equations equal to each other:

$$(\frac{l_1}{l_2})\frac{p_1\phi_1 a_1^{1-\alpha}}{p_2\phi_2 a_2^{1-\alpha}} = (\frac{a_1}{a_2})\frac{p_1\phi_1 l_1^{\alpha}}{p_2\phi_2 l_2^{\alpha}} \tag{2.A.15}$$

Cross-multiplying to get a terms and l terms on same side, and we get:

$$\frac{a_2}{a_1}\frac{p_1\phi_1 a_1^{1-\alpha}}{p_2\phi_2 a_2^{1-\alpha}} = \frac{l_2}{l_1}\frac{p_1\phi_1 l_1^{\alpha}}{p_2\phi_2 l_2^{\alpha}} \tag{2.A.16}$$

Cross multiply to cancel out constants:

$$\frac{a_2}{a_1}\frac{a_1^{1-\alpha}}{a_2^{1-\alpha}} = \frac{l_2}{l_1}\frac{l_1^{\alpha}}{l_2^{\alpha}} \tag{2.A.17}$$

Rearrange by cross multiplying:

$$\frac{l_1 a_1^{1-\alpha}}{l_2 a_2^{1-\alpha}} = \frac{a_1 l_1^{\alpha}}{a_2 l_2^{\alpha}} \tag{2.A.18}$$

Cross multiply the l terms and simplify:

$$\frac{l_2^{\alpha} a_1^{1-\alpha}}{l_2 a_2^{1-\alpha}} = \frac{a_1 l_1^{\alpha}}{a_2 l_1} \tag{2.A.19}$$

$$\frac{l_2^{\alpha-1} a_1^{1-\alpha}}{a_2^{1-\alpha}} = \frac{a_1 l_1^{\alpha-1}}{a_2} \tag{2.A.20}$$

Cross-multiply by a terms and simplify:

$$\frac{l_2^{\alpha-1} a_2}{a_2^{1-\alpha}} = \frac{a_1 l_1^{\alpha-1}}{a_1^{1-\alpha}} \tag{2.A.21}$$

$$l_2^{\alpha-1} a_2^{-\alpha} = l_2^{\alpha-1} a_1^{-\alpha} \tag{2.A.22}$$

Rearrange:

$$(\frac{l_2}{a_2})^{\frac{\alpha-1}{\alpha}} = (\frac{l_1}{a_2})^{\frac{\alpha-1}{\alpha}} \tag{2.A.23}$$

Simplify:

$$\frac{l_2}{a_2} = \frac{l_1}{a_1} \tag{2.A.24}$$

Rearrange:

$$\frac{a_1}{a_2} = \frac{l_1}{l_2} \tag{2.A.25}$$

So, we have shown that the ratios of allocations must equal, but we need to show that proportion of total allocations equal each other. So we use the definitions of total allocations: $l_1 + l_2 = L_2$ and $a_1 + a_2 = A_T$. The proof from here is quite trivial.

Let us substitute for a_2 and l_2:

$$\frac{a_1}{A_T - a_1} = \frac{l_1}{L_T - l_1} \tag{2.A.26}$$

Cross multiplying:

$$a_1(L_t - l_1) = l_1(A_T - a_1) \tag{2.A.27}$$

Expanding:

$$a_1 L_T - a_1 l_1 = l_1 A_T - a_1 l_1 \tag{2.A.28}$$

Adding $a_1 l_1$ to both sides:

$$a_1 L_T = l_1 A_T \tag{2.A.29}$$

Rearranging:

$$\boxed{\frac{a_1^*}{A_T} = \frac{l_1^*}{L_T}} \tag{2.A.30}$$

We denote a_1 and l_1 as a_1^* and l_1^* because these are efficient solutions. Now, we have proved that under efficient allocations, the proportion of total land and labour allocated to a crop are equal.

Because this result holds, the term $s_i = \frac{l_i}{L} = \frac{a_i}{A}$. We can then write:

$$s_i \phi_i A^{\alpha} L^{1-\alpha} = \phi_i (\frac{a_i}{A})^{\alpha} (\frac{l_i}{L})^{1-\alpha} \tag{2.A.31}$$

This concludes the proof for why s_i can be used in the mean variance model while maintaining the Cobb-Douglas production function for each good.

2.B Derivation of Optimal Market Consumption

This appendix derives the optimal consumption levels for goods consumed on the market. To demonstrate this, we present the utility function using only market consumption and an exogonous income constraint for simplicity. At the end of the derivation, we can plug in the income constraint specified in Section 2.2.

$$\begin{gathered} \max U = \sum_{i=1}^{N} w_i \ln(c_i + 1) \\ \text{s.t.} \sum_{i=1}^{N} p_i c_i = I \end{gathered} \tag{2.A.32}$$

The Lagrangian becomes:

$$\mathcal{L} = \sum_{j=1}^{N} w_j \ln(c_j + 1) - \lambda(I - \sum_{j=1}^{N} p_j c_j) \tag{2.A.33}$$

The FOCs are given by:

$$\begin{gathered} \frac{\partial \mathcal{L}}{\partial c_i} = \frac{w_i}{c_i + 1} - \lambda p_i = 0 \; \forall \, i \in \; N \\ \frac{\partial \mathcal{L}}{\partial \lambda} = I - \sum_{j=1}^{N} p_j c_j = 0 \end{gathered} \tag{2.A.34}$$

Solve for c_i in terms of exogenous variables and λ:

$$c_i = \frac{w_i}{\lambda p_i} - 1 \; \forall \, i \in \; N \tag{2.A.35}$$

Plug solution of c_i into $\frac{\partial \mathcal{L}}{\partial \lambda}$ and solve for λ^*:

$$\lambda^* = \frac{\sum_{j=1}^{N} w_j}{I + \sum_{j=1}^{N} p_j} \tag{2.A.36}$$

Plug solution of λ^* into c_i to get c_i^*:

$$c_i^* = \frac{w_i(I + \sum_{j=1}^{N} p_j)}{p_i \sum_{j=1}^{N} w_j} - 1 \; \forall \, i \in \; N \tag{2.A.37}$$

c_i^* can be plugged into the utility function to obtain the value function in Equation 2.9.

2.C Proof that HHI Decreases with Income

The optimal consumption was derived in Appendix 2.B and is given by:

$$c_i^* = \frac{w_i(I + \sum_{j=1}^{N} p_j)}{p_i \sum_{j=1}^{N} w_j} - 1 \; \forall \, i \in \; N \tag{2.A.38}$$

The consumption share of good i is equal to the proportion of good i consumed over total consumption: c_i/C where C is total consumption. Written out, this is:

$$\frac{c_i}{C} = \frac{\frac{w_i(I+\sum_{j=1}^{N} p_j)}{p_i \sum_{j=1}^{N} w_j} - 1}{\sum_{k=1}^{N} \frac{w_k(I+\sum_{j=1}^{N} p_j)}{p_k \sum_{j=1}^{N} w_j} - 1} \tag{2.A.39}$$

Rearranging:

$$\frac{c_i}{C} = \frac{[w_i(I + \sum_{j=1}^{N} p_j) - p_i \sum_{j=1}^{N} w_j]}{[\sum_{k=1}^{N} w_k(I + \sum_{j=1}^{N} p_j) - p_k \sum_{j=1}^{N} w_j]} \frac{[\sum_{k=1}^{N} p_k \sum_{j=1}^{N} w_j]}{[p_i \sum_{j=1}^{N} w_j]} \tag{2.A.40}$$

Distributing w terms in the first term's numerator and denominator:

$$\frac{c_i}{C} = \frac{[w_i I + w_i \sum_{j=1}^{N} p_j - p_i \sum_{j=1}^{N} w_j]}{[\sum_{k=1}^{N} w_k I + w_k \sum_{j=1}^{N} p_j - p_k \sum_{j=1}^{N} w_j]} \frac{[\sum_{k=1}^{N} p_k \sum_{j=1}^{N} w_j]}{[p_i \sum_{j=1}^{N} w_j]} \tag{2.A.41}$$

Recall the definition of consumption diversity is:

$$\text{HHI} = \sum_{i=1}^{N} \frac{c_i}{C} \tag{2.A.42}$$

So, HHI becomes:

$$\text{HHI} = \left(\frac{[w_i I + w_i \sum_{j=1}^{N} p_j - p_i \sum_{j=1}^{N} w_j]}{[\sum_{k=1}^{N} w_k I + w_k \sum_{j=1}^{N} p_j - p_k \sum_{j=1}^{N} w_j]} \frac{[\sum_{k=1}^{N} p_k \sum_{j=1}^{N} w_j]}{[p_i \sum_{j=1}^{N} w_j]}\right)^2 \tag{2.A.43}$$

Rearranging:

$$\text{HHI} = \left(\frac{[w_i I + w_i \sum_{j=1}^{N} p_j - p_i \sum_{j=1}^{N} w_j]}{[\sum_{k=1}^{N} w_k I + w_k \sum_{j=1}^{N} p_j - p_k \sum_{j=1}^{N} w_j]}\right)^2 \left(\frac{[\sum_{k=1}^{N} p_k \sum_{j=1}^{N} w_j]}{[p_i \sum_{j=1}^{N} w_j]}\right)^2 \tag{2.A.44}$$

We want to know if $\frac{\partial \text{HHI}}{\partial I} \gtrless 0$. The second term is simply a positive constant and can be ignored because it is irrelevant for determining the sign of the comparative static of HHI with respect to I.

For simplicity in taking the derivative, we expand the first term:

$$\begin{aligned}&(\frac{[w_i I]}{[\sum_{k=1}^N w_k I + w_k \sum_{j=1}^N p_j - p_k \sum_{j=1}^N w_j]}\\&+\frac{[w_i \sum_{j=1}^N p_j]}{[\sum_{k=1}^N w_k I + w_k \sum_{j=1}^N p_j - p_k \sum_{j=1}^N w_j]}\\&-\frac{[p_i \sum_{j=1}^N w_j]}{[\sum_{k=1}^N w_k I + w_k \sum_{j=1}^N p_j - p_k \sum_{j=1}^N w_j]})^2\end{aligned} \tag{2.A.45}$$

We will apply the chain rule. We take the derivative of the ”inside” function first and obtain:

$$\begin{aligned}\frac{-w_i I \sum_{k=1}^N w_k}{(\sum_{k=1}^N w_k I + w_k \sum_{j=1}^N p_j - p_k \sum_{j=1}^N w_j)^2} &+ \frac{w_i}{\sum_{k=1}^N w_k I + w_k \sum_{j=1}^N p_j - p_k \sum_{j=1}^N w_j}\\&-\frac{w_i \sum_{j=1}^N p_j}{(\sum_{k=1}^N w_k I + w_k \sum_{j=1}^N p_j - p_k \sum_{j=1}^N w_j)^2}\\&+\frac{p_i \sum_{j=1}^N w_j}{(\sum_{k=1}^N w_k I + w_k \sum_{j=1}^N p_j - p_k \sum_{j=1}^N w_j)^2}\end{aligned} \tag{2.A.46}$$

Simplifying:

$$\frac{p_i \sum_{j=1}^N w_j - w_i \sum_{j=1}^N p_j - w_i I \sum_{k=1}^N w_k}{(\sum_{k=1}^N w_k I + w_k \sum_{j=1}^N p_j - p_k \sum_{j=1}^N w_j)^2} + \frac{w_i}{\sum_{k=1}^N w_k I + w_k \sum_{j=1}^N p_j - p_k \sum_{j=1}^N w_j} \tag{2.A.47}$$

Getting a common denominator:

$$\frac{(p_i \sum_{j=1}^N w_j - w_i \sum_{j=1}^N p_j - w_i I \sum_{k=1}^N w_k) + w_i(\sum_{k=1}^N w_k I + w_k \sum_{j=1}^N p_j - p_k \sum_{j=1}^N w_j)}{(\sum_{k=1}^N w_k I + w_k \sum_{j=1}^N p_j - p_k \sum_{j=1}^N w_j)^2} \tag{2.A.48}$$

Notice that the sign of the ”inside” portion of the derivative relies only on the numerator. The denominator is positive (as it is a square), and thus if the numerator is positive (negative), the ”inside” portion is positive (negative):

$$(p_i \sum_{j=1}^N w_j - w_i \sum_{j=1}^N p_j - w_i I \sum_{k=1}^N w_k) + w_i(\sum_{k=1}^N w_k I + w_k \sum_{j=1}^N p_j - p_k \sum_{j=1}^N w_j) \gtrless 0 \tag{2.A.49}$$

Rearranging:

$$(p_i \sum_{j=1}^{N} w_j - w_i \sum_{j=1}^{N} p_j - w_i I \sum_{k=1}^{N} w_k) \gtrless -(w_i(\sum_{k=1}^{N} w_k I + w_k \sum_{j=1}^{N} p_j - p_k \sum_{j=1}^{N} w_j)) \quad (2.A.50)$$

Simplifying:

$$(p_i \sum_{j=1}^{N} w_j - w_i \sum_{j=1}^{N} p_j) \gtrless -(w_i \sum_{k=1}^{N} w_k \sum_{j=1}^{N} p_j - p_k \sum_{j=1}^{N} w_j) \quad (2.A.51)$$

Rearranging:

$$(p_i \sum_{j=1}^{N} w_j - w_i \sum_{j=1}^{N} p_j) \gtrless w_i(\sum_{k=1}^{N} p_k \sum_{j=1}^{N} w_j - w_k \sum_{j=1}^{N} p_j) \quad (2.A.52)$$

$$\frac{(p_i \sum_{j=1}^{N} w_j - w_i \sum_{j=1}^{N} p_j)}{\sum_{k=1}^{N}(p_k \sum_{j=1}^{N} w_j - w_k \sum_{j=1}^{N} p_j)} \gtrless w_i \quad (2.A.53)$$

Assuming that prices and preferences differ across crops, the LHS takes must be less than one. If w_i values are normalized such that $w_i >= 1 \, \forall \, i$, then the LHS is always less than the RHS and the 'inside' of the chain rule derivative is negative.

To complete the derivation of the comparative static of HHI with respect to I, we note that the 'outside' part of the chain rule is:

$$2(\frac{[w_i I + w_i \sum_{j=1}^{N} p_j - p_i \sum_{j=1}^{N} w_j]}{[\sum_{k=1}^{N} w_k I + w_k \sum_{j=1}^{N} p_j - p_k \sum_{j=1}^{N} w_j]} \frac{[\sum_{k=1}^{N} p_k \sum_{j=1}^{N} w_j]}{[p_i \sum_{j=1}^{N} w_j]}) \quad (2.A.54)$$

Since the "outside" is positive and the "inside" portion is negative, then then:

$$\frac{\partial \text{HHI}}{\partial I} < 0 \quad (2.A.55)$$

This means that as income increases, the concentration of consumption decreases. In other words, dietary diversity increases.

2.D Derivation of Solution of Imperfect markets Without Risk

The maximization problem is given by:

$$\begin{aligned} \max E[V] &= \sum_{i=1}^{N} w_i \ln(s_i^h \gamma_i + 1) \\ \text{s.t.} \sum_{i=1}^{N} s_i^h &\leq 1 \end{aligned} \quad (2.A.56)$$

The Lagrangian becomes:

$$\mathcal{L} = \sum_{i=1}^{N} w_i \ln(s_i^h \gamma_i + 1) + \lambda(1 - \sum_{i=1}^{N} s_i^h) \tag{2.A.57}$$

The FOCs are given by:

$$\begin{gathered} \frac{\partial \mathcal{L}}{\partial s_i^h} = \frac{w_i}{s_i^h \gamma_i + 1} - \lambda = 0 \, \forall \, i \in N \\ \frac{\partial \mathcal{L}}{\partial \lambda} = 1 - \sum_{i=1}^{N} s_i^h) = 0 \end{gathered} \tag{2.A.58}$$

Put s_i^h in terms of λ:

$$s_i^h = \frac{w_i \gamma_i}{\lambda} - 1 \tag{2.A.59}$$

Plug s_i^h into $\frac{\partial \mathcal{L}}{\partial \lambda}$:

$$\sum_{i=1}^{N} \frac{w_i \gamma_i}{\lambda} - 1 = 1 \tag{2.A.60}$$

After some basic algebra, we get:

$$\lambda^* = \frac{\sum_{i=1}^{N} w_i \gamma_i}{N + 1} \tag{2.A.61}$$

Using λ^* to obtain s_i^*:

$$s_i^* = \frac{w_i \gamma_i}{\frac{\sum_j w_j \gamma_j}{N+1}} \tag{2.A.62}$$

This simplifies to:

$$s_i^* = \frac{w_i \gamma_i N - \sum_{j=1, j \neq i}^{N} w_j \gamma_j}{\sum_{j=1}^{N} w_j \gamma_j} \tag{2.A.63}$$

The comparative statics are consistent with economic theory – an increase in the preference parameter w_i or the production parameter γ_i leads to an increase in s_i, while an increase w_j or γ_j for another good $j \neq i$ leads to a decrease in the allocation to s_i.

2.E Derivation of Minimum Variance Solution

For simplicity in this derivation, we denote s_i^m as s_i for all values of i.

The maximization problem is given by:

$$\begin{gathered} \max -\frac{a}{2} \sum_{i=1}^{N} (s_i^2 \sigma_i^2 + \sum_{j \neq i}^{N} s_i s_j \sigma_i \sigma_j \rho_{ij}) \\ \text{s.t.} \sum_{i=1}^{N} s_i = 1 \end{gathered} \tag{2.A.64}$$

The Lagrangian is:

$$\mathcal{L} = -\frac{a}{2}\sum_{i=1}^{N}(s_i^2\sigma_i^2 + \sum_{j\neq i}^{N} s_i s_j \sigma_i \sigma_j \rho_{ij}) + \lambda(1 - \sum_{i=1}^{N} s_i) \tag{2.A.65}$$

The FOCs are given by:

$$\begin{aligned} \frac{\partial \mathcal{L}}{\partial s_i} &= -a(s_i\sigma_i^2 + \sum_{j=1, j\neq i} s_j \sigma_i \sigma_j \rho_{ij}) - \lambda = 0 \,\forall\, i \,\in\, N \\ \frac{\partial \mathcal{L}}{\partial \lambda} &= 1 - \sum_{i=1}^{N} s_i = 0 \end{aligned} \tag{2.A.66}$$

Rearranged, the FOCs become:

$$\begin{aligned} \frac{\partial \mathcal{L}}{\partial s_i} &= a(s_i\sigma_i^2 + \sum_{j=1, j\neq i} s_j \sigma_i \sigma_j \rho_{ij}) = -\lambda \,\forall\, i \,\in\, N \\ \frac{\partial \mathcal{L}}{\partial \lambda} &= 1 - \sum_{i=1}^{N} s_i = 0 \end{aligned} \tag{2.A.67}$$

Let **s** be the following N-length vector:

$$\mathbf{s} = \begin{pmatrix} s_1 \\ s_2 \\ \vdots \\ s_N \end{pmatrix} \tag{2.A.68}$$

Let Σ be the following $N \times N$ matrix:

$$\Sigma = \begin{pmatrix} \sigma_1^2 & \sigma_1\sigma_2\rho_{12} & \ldots & \sigma_1\sigma_n\rho_{1n} \\ \sigma_2\sigma_1\rho_{21} & \sigma_2^2 & \ldots & \sigma_2\sigma_n\rho_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_n\sigma_1\rho_{n1} & \sigma_n\sigma_2\rho_{n1} & \ldots & \sigma_n^2 \end{pmatrix} \tag{2.A.69}$$

The FOCs can then be written as the following system of equation:

$$\begin{aligned} \mathbf{s}\Sigma &= -\mathbf{1}'\lambda \\ \mathbf{s}'\mathbf{1} &= 1 \end{aligned} \tag{2.A.70}$$

Solving the first matrix equation:

$$\mathbf{s} = -\Sigma^{-1}\mathbf{1}'\lambda \tag{2.A.71}$$

where Σ^{-1} is the inverse of the covariance matrix, known as the precision matrix.
Using **s** to solve for λ, we can show that:

$$\lambda^* = \frac{-1}{\mathbf{1}'\Sigma^{-1}\mathbf{1}} \tag{2.A.72}$$

Plugging $\mathbf{1}\lambda$ into $\mathbf{s}$, the optimal production shares can be given by:

$$\mathbf{s}^* = \frac{\Sigma^{-1}\mathbf{1}}{\mathbf{1}'\Sigma^{-1}\mathbf{1}} \tag{2.A.73}$$

Note that the solutions ensure that each weight is equivalent to the marginal contribution of each good i to the inverse variance of the portfolio. Let precision$_i = \Sigma_i^{-1}$ where Σ_i^{-1} is the sum of row i of Σ^{-1} (i.e. good i's marginal contribution to portfolio precision), and $\mathbf{1}'\Sigma^{-1}\mathbf{1}$ be the overall portfolio precision. Then each weight s_i is the ratio of the marginal contribution of good i to overall portfolio precision to the marginal contribution of all goods to portfolio precision. Under the assumption that each good carries risk ($\sigma_i^2 \neq 0 \ \forall\ i$) and for any two goods i and j, there is at least some correlation in risk ($\rho_{ij} \neq 0 \ \forall\ i,\ j$), then each share in the minimum portfolio will be non-zero.

2.F Derivation of Transaction Cost of Indifference

The goal is to find the transaction cost for good i such that the household is indifferent between selling on the market and producing at home. Consider the value function without risk. Since there is no risk, then the there is only one good produced for market sale. Since the household does not sell the marketed good and re-buy it from the market, the i terms with respect to price can be considered not to include 1. We denote this in the value function, and then simplify the notation to only include i rather than $i \neq 1$ in the following notation. In other words, the market consumption of good i is equal to zero.

Intuitively, the process for finding this transaction cost of indifference is to find the marginal rate of substitution between all home production and market production, and set this marginal rate of substitution equal to one. Then, we solve for the transaction cost that solves this equality.

The value function can be described as:

$$\begin{aligned} \max E[V] = w_1 \ln(s_1^h\gamma_1 + 1) + \sum_{i\neq 1} w_i \ln([\frac{w_i(p_1 - t_1)s_1^m\gamma_1}{(p_i + t_i)\sum_{j=1}^N w_j}] + [s_i^h\gamma_i] + 1) \\ \text{s.t.} s_1^m + \sum_{i=1}^N s_i^h \leq 1 \end{aligned} \tag{2.A.74}$$

The Lagrangian becomes:

$$\mathcal{L} = w_1 \ln(s_1^h\gamma_1 + 1) + \sum_{i\neq 1} w_i \ln([\frac{w_i(p_1 - t_1)s_1^m\gamma_1}{(p_i + t_i)\sum_{j=1}^N w_j}] + [s_i^h\gamma_i] + 1) + \lambda(1 - s_1^m - \sum_{i=1}^N s_i^h) \tag{2.A.75}$$

The FOCs are given by:

$$\frac{\partial \mathcal{L}}{\partial s_1^m} = \frac{\sum_i \frac{w_i^2(p_1-t_1)\gamma_1}{(p_i+t_i)\sum_{j=1}^N w_j}}{\sum_i [\frac{w_i(p_1-t_1)s_1^m\gamma_1}{(p_i+t_i)\sum_{j=1}^N w_j}] + [s_i^h\gamma_i] + 1} - \lambda = 0 \tag{2.A.76}$$

$$\frac{\partial \mathcal{L}}{\partial s_1^h} = \frac{w_1\gamma_1}{s_1^h\gamma_1 + 1} - \lambda = 0 \tag{2.A.77}$$

$$\frac{\partial \mathcal{L}}{\partial s_k^h} = \frac{w_k\gamma_k}{[\frac{w_k(p_1-t_1)s_1^m\gamma_1}{(p_k+t_k)\sum_{j=1}^N w_j}] + [s_k^h\gamma_k] + 1} - \lambda = 0 \; \forall \; k \; \neq \; 1 \tag{2.A.78}$$

$$\frac{\partial \mathcal{L}}{\partial \lambda} = 1 - \sum_{i=1}^{N} s_i^h + s_i^m = 0 \tag{2.A.79}$$

FOC 3: Solve for $s_k^h \; \forall \; k \; \neq \; 1$:

$$\frac{\partial \mathcal{L}}{\partial s_k^h} = \frac{w_k\gamma_k}{[\frac{w_k(p_1-t_1)s_1^m\gamma_1}{(p_k+t_k)\sum_{j=1}^N w_j}] + [s_k^h\gamma_k] + 1} = \lambda \tag{2.A.80}$$

$$w_k\gamma_k = \lambda\left([\frac{w_k(p_1-t_1)s_1^m\gamma_1}{(p_k+t_k)\sum_{j=1}^N w_j}] + [s_k^h\gamma_k] + 1\right) \tag{2.A.81}$$

$$\frac{w_k\gamma_k}{\lambda} = [\frac{w_k(p_1-t_1)s_1^m\gamma_1}{(p_k+t_k)\sum_{j=1}^N w_j}] + [s_k^h\gamma_k] + 1 \tag{2.A.82}$$

$$\frac{w_k\gamma_k}{\lambda} - \frac{w_k(p_1-t_1)s_1^m\gamma_1}{(p_k+t_k)\sum_{j=1}^N w_j} - 1 = s_k^h\gamma_k \tag{2.A.83}$$

$$\frac{w_k}{\lambda} - \frac{w_k(p_1-t_1)s_1^m\gamma_1}{(p_k+t_k)\gamma_k\sum_{j=1}^N w_j} - \frac{1}{\gamma_k} = s_k^h \tag{2.A.84}$$

Use FOC 1 to solve for s_1^m:

$$\frac{\partial \mathcal{L}}{\partial s_1^m} = \frac{\sum_i \frac{w_i^2(p_1-t_1)\gamma_1}{(p_i+t_i)\sum_{j=1}^N w_j}}{\sum_i[\frac{w_i(p_1-t_1)s_1^m\gamma_1}{(p_i+t_i)\sum_{j=1}^N w_j}] + [s_i^h\gamma_i] + 1} = \lambda \tag{2.A.85}$$

$$\sum_i \frac{w_i^2(p_1-t_1)\gamma_1}{(p_i+t_i)\sum_{j=1}^N w_j} = \lambda[\sum_i[\frac{w_i(p_1-t_1)s_1^m\gamma_1}{(p_i+t_i)\sum_{j=1}^N w_j}] + [s_i^h\gamma_i] + 1] \tag{2.A.86}$$

$$\sum_i \frac{w_i^2(p_1-t_1)\gamma_1}{\lambda(p_i+t_i)\sum_{j=1}^N w_j} = \sum_i[\frac{w_i(p_1-t_1)s_1^m\gamma_1}{(p_i+t_i)\sum_{j=1}^N w_j}] + [s_i^h\gamma_i] + 1 \tag{2.A.87}$$

$$\sum_i \frac{w_i^2(p_1-t_1)\gamma_1}{\lambda(p_i+t_i)\sum_{j=1}^N w_j} - [s_i^h\gamma_i] - 1 = \sum_i[\frac{w_i(p_1-t_1)s_1^m\gamma_1}{(p_i+t_i)\sum_{j=1}^N w_j}] \tag{2.A.88}$$

$$s_1^{m*} = [\sum_i \frac{w_i^2(p_1-t_1)\gamma_1}{\lambda(p_i+t_i)\sum_{j=1}^N w_j} - [s_i^h\gamma_i] - 1][\frac{\sum_i(p_i+t_i)\sum_{j=1}^N w_j}{\sum_i w_i(p_1-t_1)\gamma_1}] \tag{2.A.89}$$

Rearranging:

$$s_1^{m*} = \sum_i \frac{w_i}{\lambda} - (\sum_i s_i^h\gamma_i - 1)(\frac{\sum_i(p_i+t_i)\sum_{j=1}^N w_j}{\sum_i w_i(p_1-t_1)\gamma_1}) \tag{2.A.90}$$

Plug in s_i^h:

$$s_1^{m*} = \sum_i \frac{w_i}{\lambda} - (\sum_i \left(\frac{w_i}{\lambda} - \frac{w_i(p_1-t_1)s_1^m\gamma_1}{(p_i+t_i)\gamma_i\sum_{j=1}^N w_j} - \frac{1}{\gamma_i}\right)\gamma_i - 1)(\frac{\sum_i(p_i+t_i)\sum_{j=1}^N w_j}{\sum_i w_i(p_1-t_1)\gamma_1}) \tag{2.A.91}$$

$$s_1^{m*} = \sum_i \frac{w_i}{\lambda} - (\sum_i \left(\frac{w_i\gamma_i}{\lambda} - \frac{w_i(p_1 - t_1)s_1^m\gamma_1}{(p_i + t_i)\sum_{j=1}^N w_j} - 1 \right) - 1)(\frac{\sum_i (p_i + t_i)\sum_{j=1}^N w_j}{\sum_i w_i(p_1 - t_1)\gamma_1}) \quad (2.A.92)$$

$$s_1^{m*} = \sum_i \frac{w_i}{\lambda} - (\sum_i \left(\frac{w_i\gamma_i}{\lambda} - \frac{w_i(p_1 - t_1)s_1^m\gamma_1}{(p_i + t_i)\sum_{j=1}^N w_j} \right))(\frac{\sum_i (p_i + t_i)\sum_{j=1}^N w_j}{\sum_i w_i(p_1 - t_1)\gamma_1}) \quad (2.A.93)$$

$$s_1^{m*} = \sum_i \frac{w_i}{\lambda} - \sum_i \frac{w_i\gamma_i(p_i + t_i)\sum_{j=1}^N w_j}{\lambda w_i(p_1 - t_1)\gamma_1} + s_1^m \quad (2.A.94)$$

Plugging s_k^h into the first FOC and solving for t_1:

$$\frac{\partial \mathcal{L}}{\partial s_1^m} = \frac{\sum_i \frac{w_i^2(p_1 - t_1)\gamma_1}{(p_i + t_i)\sum_{j=1}^N w_j}}{\sum_i [\frac{w_i(p_1 - t_1)s_1^m\gamma_1}{(p_i + t_i)\sum_{j=1}^N w_j}] + [(\frac{w_i}{\lambda} - \frac{w_i(p_1 - t_1)s_1^m\gamma_1}{(p_i + t_i)\gamma_i\sum_{j=1}^N w_j} - \frac{1}{\gamma_i})\gamma_i] + 1} = \lambda \quad (2.A.95)$$

$$\frac{\sum_i \frac{w_i^2(p_1 - t_1)\gamma_1}{(p_i + t_i)\sum_{j=1}^N w_j}}{\sum_i [\frac{w_i(p_1 - t_1)s_1^m\gamma_1}{(p_i + t_i)\sum_{j=1}^N w_j}] + [\frac{w_i\gamma_i}{\lambda} - \frac{w_i(p_1 - t_1)s_1^m\gamma_1}{(p_i + t_i)\sum_{j=1}^N w_j}]} = \lambda \quad (2.A.96)$$

$$\frac{\sum_i \frac{w_i^2(p_1 - t_1)\gamma_1}{(p_i + t_i)\sum_{j=1}^N w_j}}{\sum_i \frac{w_i\gamma_i}{\lambda}} = \lambda \quad (2.A.97)$$

$$[\sum_i \frac{w_i^2(p_1 - t_1)\gamma_1}{(p_i + t_i)\sum_{j=1}^N w_j}][\frac{\lambda}{\sum_i w_i\gamma_i}] = \lambda \quad (2.A.98)$$

Change notation of $\sum_i w_i\gamma_i$ to $\sum_j w_j\gamma_j$ to keep the subscripts distinct:

$$[(p_1 - t_1)\gamma_1 \sum_i \frac{w_i}{(p_i + t_i)}][\frac{1}{\sum_j w_j\gamma_j}] = 1 \quad (2.A.99)$$

$$(p_1 - t_1)\gamma_1 \sum_i \frac{w_i}{(p_i + t_i)} = \sum_j w_j\gamma_j \quad (2.A.100)$$

Note: Intuitively, the LHS of the equation above is the total amount of consumption of goods 2 to N that the household can have weighted by it's preference. The RHS is the total amount of home consumption goods, weighted by preference. When these two equations are equal, then the household is indifferent between home consumption and market consumption. Rearraning:

$$(p_1 - t_1) = \frac{1}{\gamma_1} \sum_i \frac{(p_i + t_i)}{w_i} (\sum_j w_j\gamma_j) \quad (2.A.101)$$

The sale price of good 1 is then equal to the ratio of home production (weighted by preference) and market consumption (weighted by preference). The transaction cost of indifference follows:

$$t_1^* = p_1 - \frac{1}{\gamma_1}\sum_i \frac{(p_i + t_i)}{w_i}(\sum_j w_j\gamma_j) \tag{2.A.102}$$

From observation, when buy-side transaction costs increase, the transaction cost of indifference decreases because the income needed to maintain indifference must now be higher. When home prediction γ_j increases, the transaction cost of indifference also decreases, because now home production is more attractive and more income is needed to have market consumption keep pace.

Assuming $t_i = t \; \forall \; i$

$$t = p_1 - \frac{1}{\gamma_1}\sum_i \frac{(p_i + t)}{w_i}(\sum_j w_j\gamma_j) \tag{2.A.103}$$

$$t + \frac{1}{\gamma_1}\sum_i \frac{(p_i + t)}{w_i}(\sum_j w_j\gamma_j) = p_1 \tag{2.A.104}$$

$$t + \frac{1}{\gamma_1}\sum_i \frac{p_i}{w_i}\sum_j w_j\gamma_j + \frac{1}{\gamma_1}\sum_i \frac{t}{w_i}\sum_j w_j\gamma_j = p_1 \tag{2.A.105}$$

$$t + \frac{1}{\gamma_1}\sum_i \frac{t}{w_i}\sum_j w_j\gamma_j = p_1 - \frac{1}{\gamma_1}\sum_i \frac{p_i}{w_i}\sum_j w_j\gamma_j \tag{2.A.106}$$

$$t + \frac{t}{\gamma_1}\sum_i \frac{1}{w_i}\sum_j w_j\gamma_j = p_1 - \frac{1}{\gamma_1}\sum_i \frac{p_i}{w_i}\sum_j w_j\gamma_j \tag{2.A.107}$$

$$t(1 + \frac{1}{\gamma_1}\sum_i \frac{1}{w_i}\sum_j w_j\gamma_j) = p_1 - \frac{1}{\gamma_1}\sum_i \frac{p_i}{w_i}\sum_j w_j\gamma_j \tag{2.A.108}$$

$$t^* = \frac{p_1 - \frac{1}{\gamma_1}(\sum_{i\neq 1}\frac{p_i}{w_i})(\sum_{j\neq 1} w_j\gamma_j)}{1 + \frac{1}{\gamma_1}(\sum_{i\neq 1}\frac{1}{w_i})(\sum_{j\neq 1} w_j\gamma_j)} \tag{2.A.109}$$

From observation, as p_1 (the sale price of the primary sales good) increases, the transaction cost of indifference also increases (to compensate for the increased attractiveness of the market). As γ_1 increases, the transaction cost of indifference increases (similar logic to p_1). As the purchase price of any good i increases, the transaction cost of indifference decreases (as the market becomes less attractive). As γ_i increases, the transaction cost of indifference also decreases (as the market becomes less attractive).

2.G Correlates of Market Participation: Choosing a Market Access Variable

In Table 2.A.1, the measure that is most positively correlated with market participation is the presence of a daily or weekly market in a village. While log distance to the market (from either household or plots) is significantly correlated with market participation, the direction of the correlation suggests that household further from markets, participate in markets more frequently. This relationship runs contrary to theory, and the market access variable should correlated theoretically and empirically with increased participation. As a result, the presence of any market in a village is chosen (despite not being robust to the inclusion of fixed effects). This exercise underscores the need for careful and better measurement of market access variables.

Table 2.A.1: Correlates of Market Participation

	(1) % of Crops Sold	(2) % of Crops Sold	(3) % of Crops Sold	(4) % of Crops Sold	(5) % of Crops Sold	(6) % of Crops Sold	(7) % of Crops Sold	(8) % of Crops Sold	(9) % of Crops Sold	(10) % of Crops Sold
Log Plot Distance to Market	0.0133					0.0156**				
	(0.00872)					(0.00775)				
Log House-hold Distance to Market		0.0250**					0.0122			
		(0.0115)					(0.0193)			
Presence of Weekly Village Market			0.0361					-0.0361*		
			(0.0244)					(0.0216)		
Presence of Daily Village Market				0.0187					0.0234	
				(0.0241)					(0.0257)	
Presence of Any Village Market					0.0364*					0.00777
					(0.0220)					(0.0213)
District Fixed Effects	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Observa-tions	1050	1050	1050	1050	1050	1050	1050	1050	1050	1050

Marginal effects; Standard errors in parentheses
(d) for discrete change of dummy variable from 0 to 1
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Columns 1-10 are estimated using a GLM model using a logistic functional link and binomial distribution.

2.H Consumption Diversity and Market Access

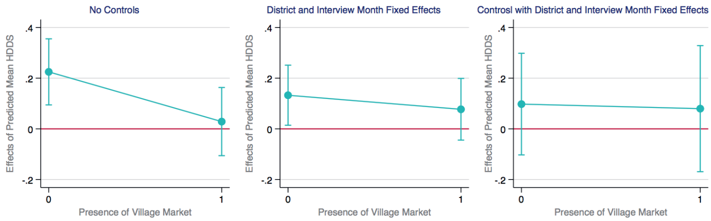

Figure 2.A.1: Correlates of HDDS: Interaction between ADS and Producer Market Participation (95% Confidence Intervals)

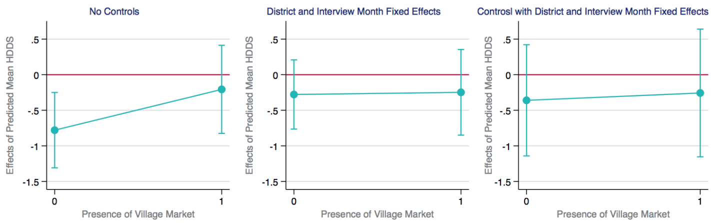

Figure 2.A.2: Correlates of HDDS: Interaction between SI and Producer Market Participation (95% Confidence Intervals)

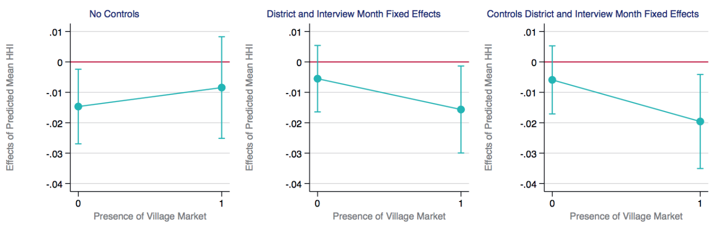

Figure 2.A.3: Correlates of HDDS: Interaction between ADS and Producer Market Participation (95% Confidence Intervals)

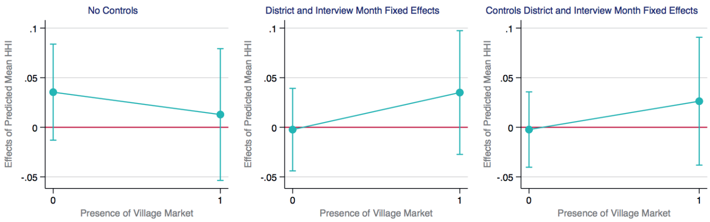

Figure 2.A.4: Correlates of HHI: Interaction between SI and Producer Market Participation (95% Confidence Intervals)

Table 2.A.2: Correlates of Household Dietary Diversity Score (Market Access)

	(1) HDDS	(2) HDDS	(3) HDDS	(4) HDDS	(5) HDDS	(6) HDDS
Food Crop Count	0.159***	0.112**	0.0777*			
	(0.0500)	(0.0466)	(0.0453)			
Crop HHI				-0.555***	-0.266	-0.318*
				(0.206)	(0.191)	(0.182)
Daily or Weekly Market = 1	-0.194	0.0722	-0.0393	-0.206	0.0646	-0.0399
	(0.156)	(0.174)	(0.152)	(0.155)	(0.173)	(0.151)
HH Head Literate = 1			0.611***			0.628***
			(0.139)			(0.139)
Male HH Head			0.0329			0.0332
			(0.138)			(0.137)
HH Size			0.0317			0.0365
			(0.0250)			(0.0251)
Total HH Acres			-0.108			-0.164
			(0.168)			(0.170)
Total HH Acres Squared			0.0363			0.0436
			(0.0336)			(0.0338)
HH Tropical Livestock Units			0.0139			0.0149*
			(0.00878)			(0.00884)
Log Non-Agr. Income Past 12 Months			0.0132*			0.0122
			(0.00800)			(0.00800)
Log Non-Farm Enterprise Asset Val.			0.0374***			0.0374***
			(0.00963)			(0.00952)
Access to Mobile Money			0.566***			0.574***
			(0.143)			(0.142)
Own Mobile Phone			0.477***			0.480***
			(0.141)			(0.141)
District Fixed Effects	No	Yes	Yes	No	Yes	Yes
Survey Month Fixed Effects	No	Yes	Yes	No	Yes	Yes
Observations	1050	1050	1050	1050	1050	1050

Marginal effects; Standard errors in parentheses
(d) for discrete change of dummy variable from 0 to 1
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Columns 1-6 are estimated using a GLM model using a logistic functional link and binomial distribution.

Table 2.A.3: Correlates of Consumption HHI (Market Access)

	(1) HHI	(2) HHI	(3) HHI	(4) HHI	(5) HHI	(6) HHI
Food Crop Count	-0.0126**	-0.00925*	-0.00973**			
	(0.00511)	(0.00472)	(0.00487)			
Crop HHI				0.0267	0.0130	0.00829
				(0.0200)	(0.0182)	(0.0185)
Daily or Weekly Market = 1	0.0351*	0.00990	0.0196	0.0373**	0.0103	0.0199
	(0.0184)	(0.0175)	(0.0167)	(0.0182)	(0.0175)	(0.0168)
HH Head Literate = 1			-0.0348***			-0.0358***
			(0.0121)			(0.0121)
Male HH Head			-0.0176			-0.0174
			(0.0139)			(0.0139)
HH Size			0.0114***			0.0108***
			(0.00253)			(0.00249)
Total HH Acres			0.00100			0.00138
			(0.0165)			(0.0168)
Total HH Acres Squared			-0.00257			-0.00272
			(0.00347)			(0.00349)
HH Tropical Livestock Units			-0.00115			-0.00117
			(0.000807)			(0.000793)
Log Non-Agr. Income Past 12 Months			-0.00120			-0.00116
			(0.000963)			(0.000953)
Log Non-Farm Enterprise Asset Val.			-0.00152			-0.00154
			(0.00109)			(0.00109)
Access to Mobile Money			-0.0373**			-0.0372**
			(0.0163)			(0.0165)
Own Mobile Phone			-0.0407***			-0.0407***
			(0.0134)			(0.0134)
District Fixed Effects	No	Yes	Yes	No	Yes	Yes
Survey Month Fixed Effects	No	Yes	Yes	No	Yes	Yes
Observations	1050	1050	1050	1050	1050	1050

Marginal effects; Standard errors in parentheses
(d) for discrete change of dummy variable from 0 to 1
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Columns 1-6 are estimated using a GLM model using a logistic functional link and binomial distribution.

2.I Anthropometric Measures

Table 2.A.4: Correlates of Anthropometric Measures (Market Paricipation)

	(1) Under-weight = 1	(2) Under-weight = 1	(3) Under-weight = 1	(4) Wasting = 1	(5) Wasting = 1	(6) Wasting = 1	(7) Stunting = 1	(8) Stunting = 1	(9) Stunting = 1
Food Crop Count	0.00483	0.00372	-0.00406	-0.00701	-0.0146	-0.0286***	-0.00108	-0.00452	-0.00856
	(0.00727)	(0.00983)	(0.00945)	(0.00967)	(0.0107)	(0.0101)	(0.00368)	(0.00703)	(0.00661)
% of Crops Sold	0.000737**	0.000866**	0.000851**	0.000445	0.000283	0.000364	0.000209	0.000207	0.000143
	(0.000367)	(0.000430)	(0.000409)	(0.000595)	(0.000607)	(0.000544)	(0.000175)	(0.000288)	(0.000264)
HH Head Literate = 1			-0.0278			0.0415			-0.0219
			(0.0226)			(0.0303)			(0.0170)
Male HH Head			0.0827***			0.0852**			0.109***
			(0.0275)			(0.0343)			(0.0306)
HH Size			0.0294***			0.0615***			0.0103***
			(0.00364)			(0.00575)			(0.00347)
Total HH Acres			-0.0406			-0.0545			0.0530*
			(0.0376)			(0.0409)			(0.0303)
Total HH Acres Squared			0.00868			0.0104			-0.0127**
			(0.00780)			(0.00858)			(0.00637)
HH Tropical Livestock Units			-0.00129			-0.00447			-0.000209
			(0.00186)			(0.00321)			(0.00103)
Log Non-Agr. Income Past 12 Months			-0.000661			0.00102			0.00115
			(0.00177)			(0.00236)			(0.00140)
Log Non-Farm Enterprise Asset Val.			-0.00172			-0.00113			-0.00232
			(0.00207)			(0.00253)			(0.00148)
Access to Mobile Money			-0.0914***			-0.147***			-0.0313
			(0.0335)			(0.0358)			(0.0222)
Own Mobile Phone			-0.0117			-0.0333			0.00973
			(0.0211)			(0.0286)			(0.0169)
District Fixed Effects	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Survey Month Fixed Effects	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Observa-tions	1050	875	875	1050	1050	1050	1050	672	672

Marginal effects; Standard errors in parentheses
(d) for discrete change of dummy variable from 0 to 1
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Columns 1-9 are estimated using a Probit model
The numbers of observations in Columns 2, 3, 8, and 9 are lower because the Probit model predicts some cases perfectly with fixed effects.

Table 2.A.5: Correlates of Anthropometric Measures (Market Paricipation)

	(1) Under-weight = 1	(2) Under-weight = 1	(3) Under-weight = 1	(4) Wasting = 1	(5) Wasting = 1	(6) Wasting = 1	(7) Stunting = 1	(8) Stunting = 1	(9) Stunting = 1
Crop HHI	-0.0213	-0.0260	-0.0128	-0.0506	-0.0497	-0.0564	-0.0299*	-0.0604**	-0.0685**
	(0.0301)	(0.0367)	(0.0380)	(0.0422)	(0.0423)	(0.0432)	(0.0175)	(0.0290)	(0.0321)
% of Crops Sold	0.000734**	0.000875**	0.000897**	0.000578	0.000412	0.000590	0.000262	0.000264	0.000262
	(0.000374)	(0.000430)	(0.000411)	(0.000598)	(0.000608)	(0.000563)	(0.000191)	(0.000293)	(0.000285)
HH Head Literate = 1			-0.0279			0.0417			-0.0209
			(0.0224)			(0.0299)			(0.0162)
Male HH Head			0.0826***			0.0860**			0.105***
			(0.0275)			(0.0344)			(0.0304)
HH Size			0.0292***			0.0602***			0.0103***
			(0.00361)			(0.00567)			(0.00354)
Total HH Acres			-0.0441			-0.0731*			0.0378
			(0.0388)			(0.0419)			(0.0302)
Total HH Acres Squared			0.00905			0.0125			-0.0110*
			(0.00788)			(0.00866)			(0.00620)
HH Tropical Livestock Units			-0.00123			-0.00429			0.0000955
			(0.00191)			(0.00335)			(0.00115)
Log Non-Agr. Income Past 12 Months			-0.000749			0.000775			0.000650
			(0.00176)			(0.00236)			(0.00134)
Log Non-Farm Enterprise Asset Val.			-0.00173			-0.00120			-0.00234
			(0.00208)			(0.00255)			(0.00148)
Access to Mobile Money			-0.0913***			-0.150***			-0.0312
			(0.0336)			(0.0356)			(0.0236)
Own Mobile Phone			-0.0112			-0.0313			0.0121
			(0.0209)			(0.0289)			(0.0168)
District Fixed Effects	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Survey Month Fixed Effects	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Observa-tions	1050	875	875	1050	1050	1050	1050	672	672

Marginal effects; Standard errors in parentheses
(d) for discrete change of dummy variable from 0 to 1
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Columns 1-9 are estimated using a Probit model
The numbers of observations in Columns 2, 3, 8, and 9 are lower because the
Probit model predicts some cases perfectly with fixed effects.

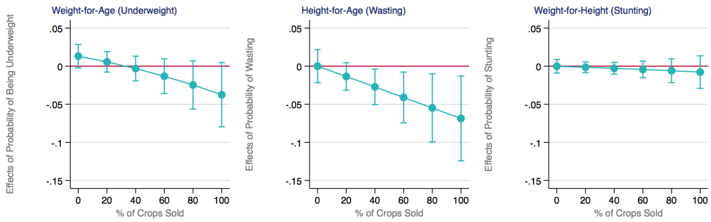

Figure 2.A.5: Correlates of Anthropometric Measures: Interaction between ADS and Producer Market Participation (95% Confidence Intervals)

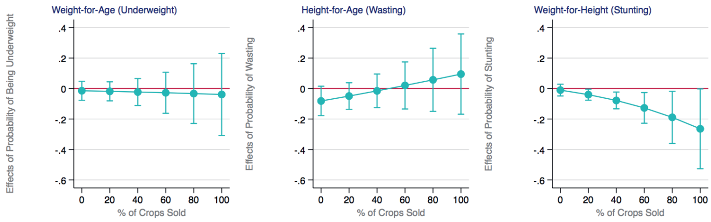

Figure 2.A.6: Correlates of Anthropometric Measures: Interaction between SI and Producer Market Participation (95% Confidence Intervals)

Chapter 3

Gender, Investment Decisions, and Labor Responses in Small-Scale Farming Households: A Lab-in-the-Field Experiment from Rural Tanzania

Agricultural investments on family farms are often labor-intensive, and spouses consider risk, returns, expected labor productivity, and labor costs to make investment decisions. In some households, individuals may make investment decisions alone, and in others, spouses negotiate to agree on investments. These decision-making regimes can affect not only the decisions themselves, but also the productivity of the laborers responsible for ensuring investment success. This paper aims to uncover how couples' joint decision-making affects labor-intensive investment decisions and laborers' corresponding productivity levels, when compared to male-only and female-only decision-making. To uncover these dynamics, we analyze how couples behave in a randomized lab-in-the-field experiment with a real-effort task. Couples are randomly assigned to decision-making regimes (male-only, female-only, and joint) and labor assignments (male-only and female-only). Decision-makers choose investment levels and choose between risky and riskless investment alternatives. Assigned laborers engage in a real-effort task to realize investments returns. Our findings show that joint and male-only decision-making results in higher investment levels compared to female-only decision-making. Further, couples making decisions together take into account the assigned laborer's relative productivity and, compared to individual decision-makers, have higher investment success rates when relatively less productive spouses perform labor. In terms of labor responses, men are less productive across all investment levels compared to women, but productivity is not dependent on who makes decisions. Our results suggest that agricultural development programs promoting new on-farm investments should target both spouses to increase investment levels and improve men's effort in labor. This paper contributes to the literature on gendered investment decision-making and effort in on-farm labor.

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3.1 Introduction

How do spouses in small-scale farming households make investment decisions when risk and labor costs are present? Specifically, are investment decisions and the productivity of household laborers affected by *who* is making decisions – women alone, men alone, or both spouses together?

Small-scale farming households in Sub-Saharan Africa (SSA) are generally characterized by a reliance on family labor, an increasing exposure to climate risks, and stagnating productivity over the past few decades (Salami et al., 2010). In the hopes of building resilience to climate change and boosting productivity to spur an African "Green Revolution", agricultural development programs are promoting new practices, inputs, technologies, and crops (Hassan 2010; Dawson, Martin, and Sikor 2016). Whether such programs are able to improve farming outcomes in a gender-equitable manner has been called into question (Negin et al., 2009). Due to a large gender gap in agricultural investment and consequently, productivity, such programs are increasingly targeting female farmers (Quisumbing and Pandolfelli, 2010; UNDP, 2015). Further, women tend to make decisions that benefit households collectively rather than themselves individually, making them more effective agents of positive change within households than men (Quisumbing, 2003; World Bank, 2001). However, most women in rural SSA live in male-headed households, and decisions are typically not made independently from their spouses. As a result, even programs that successfully improve investment in female-headed households do not necessarily improve investment on female-managed plots in male-headed households (Fisher and Kandiwa, 2014).

It remains unclear whether targeting female farmers is the most effective way to increase investment to boost agricultural productivity and resilience to climate change. The adoption of most new practices, inputs, technologies, and crops involves an assessment of risk versus return (i.e. an investment decision) and additional (family) labor allocations. To understand how to target household members to increase agricultural investment, a thorough understanding of household decision-making processes for investment and the corresponding labor responses to adoption is necessary. Obtaining causal evidence on decision-making processes and labor responses is difficult because decision-making regimes and labor allocations are endogenous to the household.

This paper provides causal evidence for the role of gender and joint decision-making in household investment decision-making processes and labor responses to adoption using a lab-in-the-field experiment with a real-effort task in Iringa, Tanzania.[1] From an investment decision-making standpoint, the study addresses whether investment decisions differ by the gender of the decision-maker and by the gender of the laborer. It also assesses whether investment decisions made by both spouses together differ from decisions made by men and women individually. From a labor standpoint, the study aims to understand whether labor productivity is dependent on laborers' gender and whether *who* makes investment decisions (men alone, women alone, or both spouses together) affects laborers' productivity.

The experiment is designed to mimic labor-intensive investment processes with 529 couples across 15 villages in Iringa. Participating couples are given an endowment that they

[1] Tanzania is a suitable location to study spousal investment decisions in rural SSA as 77% of working age adults work in the agricultural sector, making up 28% of GDP (USAID, 2021). Further, the labor share of

can use to buy cups of unsorted beans, sort the cups of beans for a fixed time period, and return the sorted cups for a monetary return. The monetary return depends on the type of cups they choose to sort – cups with low, but certain returns or cups with high, but uncertain returns. Cups remaining unsorted after the allocated time have no value (i.e. a 100% loss on the investment). Following a semi-factorial design, which spouse makes decisions (women alone, men alone, or both spouses together) and which spouse performs the labor[2] (women alone or men alone) are randomized to identify the causal effects of gender and joint decision-making on investment decision-making and labor responses.

The results of our study show that there are significant differences in investment decision-making and labor responses across men and women. Women making decisions alone invest nearly 10% less than men making decisions alone, and this difference is likely driven by men's overconfidence in their own abilities as laborers. Neither women nor men appear to free-ride by investing at higher levels when their spouse is sorting, but rather invest at similar rates regardless of who provides the labor. Further, participants making decisions alone fail to adjust their decision-making to the relative productivity[3] of the assigned laborer, which leads to a greater chance of failed investments – cups that are left unsorted and yield a complete loss of the investment.

Spouses making decisions together reveal bargaining power dynamics, but also can overcome some of the weaknesses of decisions made by sole decision-makers. Joint decision-makers choose investment levels in line with levels of men who decide alone, suggesting that men have more bargaining power in the investment decision. But, joint decision-makers' investment levels are adjusted to the relative productivity of laborers, which mediates the overconfidence displayed by men deciding alone. When a relatively less productive laborer is assigned, joint decision-makers have lower rates of failed investments than sole decision-makers.

In terms of labor responses, *who* makes decisions does not appear to matter for laborers' effort. Male laborers are less productive when compared to female laborers, regardless of who makes investment decisions. As laborers, men have a failure rate (the percentage of cups left unsorted) of about 17% across all decision-makers, while women have a failure rate less than 10%. Further, comparing men and women with similar workloads reveals that men consistently underperform in terms of both productivity (minutes per cup sorted) and failure rates.

These results underscore the complexity of household decision-making and labor responses to adoption and contribute to two strands of literature. First, this paper contributes to the literature on causal evidence of household bargaining mechanisms and decision-making by analyzing gendered decision-making in the context of labor-intensive investments. Second, our paper contributes to a growing literature surrounding labor inefficiencies within the household by exploring how such inefficiencies are linked to decision-making regimes, and providing causal evidence of how inefficiencies differ by gender. (Please see section 2 below for detailed discussion on the literature and our contribution.)

From a policy standpoint, the results suggest that agricultural programs should target both spouses to achieve the highest investment levels, reduce the risk of failed investments,

[2] Only one spouse is allowed to perform the labor.

[3] Relative to the other spouse.

and achieve balanced portfolios across gendered crops or technologies. Further agricultural programs should explicitly address men's labor inefficiencies that may arise from adoption. Such inefficiencies threaten investment success and may place greater labor burdens on women, who already provide the majority of labor on East African farms and are spend far more time on domestic duties (Doss 2014; Palacios-Lopez and Lopez 2014).

The paper is structured as follows. Section 3.2 discusses existing literature on spouses' decision-making and labor inefficiencies in small-scale farming households, outlines the research questions answered in this paper, and describes this paper's corresponding contributions. Section 3.3 describes the experiment design and implementation. Section 3.4 describes the data used in the analysis. Section 3.5 provides the empirical methodology, and Section 3.6 presents the results. Finally, Section 3.7 concludes with a discussion of the findings, policy recommendations, and areas for future research.

3.2 Related Literature, Research Questions, and Contributions

Investment levels in new technologies on female-managed plots are lower than investment levels on male-managed plots (Cairns et al., 2021). For example, women have been shown to be less likely to adopt improved varieties, mechanization, and high-value cash crops (Fisher and Kandiwa, 2014; Paudel et al., 2020; Vargas Hill and Vigneri, 2014). These differences help contribute to a gender gap in incomes and productivity, slowing progress towards poverty reduction and gender equality (UNDP, 2015).

While there are number of institutional factors driving differences in investment levels by gender, behavioral and economic differences in decision-making also can contribute to such differences. This section proposes this paper's research questions and discusses previous work in and our contributions to two strands of literature – intra-household investment decision-making and labor productivity and effort.

3.2.1 Intra-Household Investment Decision-making

Several behavioral and economic factors affect household investment decision-making. Risk preferences, overconfidence, expected labor productivity, perceived labor costs, and intra-household negotiation are some of the key elements identified in previous literature. The literature generally shows across different contexts and countries that men are more willing to take risks than women (Ahmad et al., 2019; Cullen et al., 2018; Jin et al., 2017; Liu, 2013; Nielsen et al., 2013; Vieider et al., 2013). In some instances women are shown to be less risk averse, but these cases are the exception rather than the norm (Ambali et al., 2021; Cardenas and Carpenter, 2013). Men's lower risk aversion may explain their higher investment levels in productivity-enhancing technologies and practices (Paudel et al., 2020). By the same token, risk aversion has been identified as a leading constraint to female investment in the adoption of technology (Achandi et al., 2018; Fletschner et al., 2010).[4]

[4] While risk aversion is a constraint in productivity-enhancing technologies and practices (the focus of our paper), risk aversion has been shown to increase investment in risk-reducing technologies and practices, resulting in higher female investment levels in such technologies and practices (Ward and Singh, 2014).

Overconfidence is closely linked to risk preferences, as decision-makers exhibiting overconfidence tend to perceive an investment's associated risk to be lower than it is in reality (Just, 2008). Consequently, overconfident investors tend to invest at higher levels and in riskier investments (Pikulina et al., 2017). Further, overconfidence has been shown to be more prevalent among men across different settings, which results in higher investment levels by male decision-makers (Barber and Odean 2001; Hassan, Khalid, and Habib 2014; Dittrich, Güth, and MacIejovsky 2005; Mishra and Metilda 2015).

The first research question addressed in this paper is: *Do labor-intensive investment decisions differ by the gender of the decision-maker?* Existing literature surrounding risk preferences and overconfidence assesses differences in decision-making by gender in the context of general investment decision-making, but this paper analyses these factors specifically in the context of labor-intensive decision-making, which is relevant to the adoption of many on-farm investments. We show that men have higher investment levels, but take on similar levels of market risk as women. Further, evidence from questionnaires suggests that men and women have similar risk preferences.

In the case of labor-intensive investments, expected productivity and labor costs are linked to investment levels. Overconfidence can influence expected productivity levels because it leads to a higher appraisal of one's own abilities and increases the perceived probability of success in investments (Nur Aini and Lutfi, 2019). Since men tend to be more overconfident than women, their perceived probability of success when they provide the labor is skewed. Thus, when men make decisions based on their own perceived labor productivity, they may invest at levels above the optimal.

From the labor cost perspective, opportunity costs of labor and leisure are not explicitly defined in small-scale farming households, and decision-makers' perceptions of these costs are important in determining investment levels. In East Africa, women provide the majority of on-farm labor and also contribute the lion's share of household duties (Palacios-Lopez, Christiaensen, and Kilic 2017; Doss 2014). Assuming men and women have similar opportunity costs of labor, a higher labor burden for women means that their marginal cost of any additional labor is higher. However, men have more opportunities to work in off-farm activities, which could mean their opportunity cost of working on their family farm is higher (Doss 2018). Additionally, patriarchal societal norms may dictate that women's time and effort on farms is undervalued (Rahman et al. 2020). If men underestimate costs of labor for women, then their labor-intensive investments are likely to be higher when women provide labor than when men provide labor.

The second research question addressed is: *Do investment decisions differ by the gender of the laborer?* The overconfidence mechanism suggests that individual decision-makers invest at higher rates when they provide labor themselves, while the labor cost mechanism suggests that individual decision-makers invest at higher rates when their spouse provides labor. We show that the overconfidence mechanism is present when men make decisions, but not when women make decisions. This finding extends existing literature by showing that overconfidence can not only skew risk perception, but also increase investment levels because of labor productivity perceptions in the case of labor-intensive investment decision-making. The paper also extends the literature surrounding labor costs and gendered decision-making by showing whether men and women value each other's labor costs differently. The results suggest that spouses do not undervalue each other's labor costs and free-riding behavior is not observed in the decision-making process (in contrast to Lecoutere and Jassogne (2019)).

The aforementioned mechanisms are all affected when spouses make decisions together. Spouses with different risk preferences and levels of confidence must negotiate with each other to reach a final decision. Spouses' preferences for investments are not necessarily in line with utility maximization of the household, but rather some combination of individual and household utility maximization (Chen and Woolley, 2001). Each spouse's relative bargaining power can be thought to determine the outcome of the negotiation, and bargaining power can be dependent on control over household assets and societal norms (Shibata et al., 2020). If both spouses have some bargaining power, then decisions made jointly are likely to take into account both spouses' preferences to varying degrees (Michalscheck et al., 2020).

Further, when spouses make decisions together, they are able to share information. In labor-intensive investments, this information can reflect external investment risks, perceived labor productivity, and perceived labor costs. Information sharing between spouses is not necessarily perfect, but can affect the decision-making process (Fletschner and Mesbah, 2011).[5] When information asymmetries are not present, then joint bargaining can lead to more cooperative decision-making, which can have higher returns to the household as a whole (Iversen et al., 2011). In non-agricultural contexts, the inclusion of spouses in decision-making has a mediating effect on overconfidence (related to perceptions of external risk) which moderates investment levels (Warmath, Piehlmaier, and Robb 2019; Mahalakshmi and Anuradha 2018).

The third research question addressed is: *How does joint decision-making influence investment decisions?* We contribute to the literature on joint decision-making by showing that spouses making decisions jointly take into account the laborer's relative productivity, while individual decision-makers do not. These results show that joint-decision making can lead to more efficient investment decision-making compared to individual decision-making. The likely mechanism behind this is the role of information sharing as a mediating factor on overconfidence.

3.2.2 Labor Responses

Actors on family farms not only make investment decisions, but also as laborers, they (implicitly or explicitly) decide their level of effort in completing the tasks necessary for successful investments. While there is a growing literature surrounding laborers' effort (Bulte et al., 2020; Masekesa and Munro, 2020), the effects of decision-making regimes on laborers' effort have yet to be explored. Kilic, Palacios-López, & Goldstein (2015) provides non-causal evidence that men provide less effort on female-managed plots than male-managed plots. Such shirking can lead to sub-optimal household outcomes and deepen the gender gap in agricultural productivity.

The fourth and fifth research questions are respectively: *Does labor productivity differ by gender? And, does who makes investment decisions influence labor productivity?* We provide exploratory analysis to test whether there are systematic differences in labor

[5] Other studies on information sharing between spouses focus on income and resource concealing (Ashraf, 2009; Castilla and Walker, 2013). While this is not the focus of our study, these studies do give further evidence that spouses do not always engage in cooperative behavior.

productivity between men and women. Even at the same investment levels, men are less productive than women. The results could reflect that the cost of effort is higher for men than women, corroborating evidence from Doss 2018 and Rahman et al. 2020.This paper then extends the existing literature by providing causal evidence for whether spouses change their effort levels depending on who makes decisions pertaining to labor. We show that there is only weak evidence to suggest that men change their effort levels based on the decision-maker, but there is no evidence that women do so. These results suggest that on-farm labor inefficiencies may not be related to plot managers and investment levels, but rather are inherent to men.

3.3 The Experiment

3.3.1 Experiment Design

To analyze the role of gender in labor-intensive investment decisions, we conduct a lab-in-the-field experiment involving a real-effort task. Real-effort tasks are non-trivial mental or physical tasks used in experimental settings to measure participants' labor response to a certain incentive structure (Lezzi et al., 2015). The real-effort task in our experiment involves sorting beans – a task employed in similar settings (Bulte et al., 2020). Green-colored beans were mixed with either grey-colored or red-colored beans[6] and placed in standard, disposable 65ml plastic cups, and couples were rewarded with cash for each cup of beans sorted in 40 minutes. To successfully sort a cup, they would need to place all green-colored beans in one cup and all of the grey/red-colored beans in another cup. Pre-testing showed that a fast bean-sorter could sort no more than 10 cups in 40 minutes.

Participants had to decide on how many cups of beans to sort before they began sorting. They were not allowed to change their decision after the sorting began. Couples were given an endowment of 3,000 Tsh (about 1.29 USD). They could purchase a cup of unsorted beans for 300 Tsh (so they could invest in a maximum of 10 cups).[7] Two types of cups were available to be purchased – cups of green-colored beans mixed with grey-colored beans (referred to as safe cups from here on) and cups of green-colored beans mixed with red-colored beans (referred to as risky cups from here on). If a participant successfully sorted a safe cup, they were paid 500 Tsh (a return of 67% over the buy-in price). If a participant successfully sorted a risky cup they would either be paid 900 Tsh (a 200% return) or 300 Tsh (a 0% return) with a 50% probability of each payment occurring. After sorting, the payment was determined by having participants draw a card from a full deck of playing cards. Drawing a red card resulted in participants receiving a 0% return for all sorted risky cups, and drawing a black card resulted in participants receiving a 200% return for all risky cups. Participants could also choose not to invest in cups to sort and keep their endowment. Therefore, participants could purchase any combination of safe and risky cups ranging from zero to ten cups in total. Unsorted cups were given a payment of 0 Tsh (a 100% loss) such that participants lost any endowment they put towards investing in cups they did not sort.

[6] All of the beans were the same size.

[7] Respondents could not use their own cash to buy cups.

To identify the role of gender in labor-intensive decision-making, we randomized the gender of the decision-maker (Treatment Arm 1) and the laborer (Treatment Arm 2) through a semi-factorial design. In the first treatment arm, couples were randomly assigned to have the woman, man, or both spouses (referred to as 'joint') decide how many and which cups to invest in. In the second treatment arm, couples were randomly assigned to have men or woman individually perform the bean sorting. Couples could also be assigned to the joint labor treatment, which allows couples to jointly decide whether men or women perform the bean sorting. This treatment provides a 'real-world' scenario, as labor assignment is not exogenously determined in households but rather endogenously decided upon by household members. The experiment's semi-factorial design is shown in Table 3.1.

Table 3.1: Experiment Design[8]

Treatment Arm 1: Decision making	Treatment Arm 2: Labor		
	Man	**Woman**	**Joint**
Man	Man, Man	Man, Woman	NA
Woman	Woman, Man	Woman, Woman	NA
Joint	Joint, Man	Joint, Woman	Joint, Joint

Treatment Arm 1 refers to whether the man alone, women alone, or both spouses together (joint) make investment decisions. Treatment Arm 2 refers to whether the man sorts beans, woman sorts beans, or the couple decides which spouse sorts beans (joint). Only one individual is allowed to sort. In each treatment group, the first item refers to the decision-maker and the second item refers to the laborer. For example 'Woman, Man' indicates that the woman decides and the man sorts, while 'Joint, Joint' indicates that both spouses decide on investment levels and they decide which spouse will sort.

The experiment design allows the research questions proposed in Section 3.2 to be answered by comparing the mean outcomes (which are presented in Section 3.4) of the treatment groups with one another. Research Question 1 asks whether investment decisions differ by gender of the decision maker. A comparison of the mean investment outcomes of the 'Man' and 'Woman' assignments in Treatment Arm 1 can answer this question. Similarly, Research Question 2, which asks whether investment decisions differ by the gender of the laborer, can be answered by comparing mean investment outcomes of the 'Man' and 'Woman' assignments in Treatment Arm 2. More nuanced comparisons are made to uncover whether overconfidence in one's own labor abilities or undervaluation of one's spouses are influencing differences in outcomes. Comparing 'Man, Man' investment outcomes with 'Man, Woman' investment outcomes and 'Woman, Woman' investment outcomes with 'Woman, Man' investment outcomes can uncover whether overconfidence or the undervaluing of spouse's labor costs predominates. Research Question 3 asks how joint decision-making influences investment outcomes, and this can be assessed by comparing mean outcomes of the 'Joint' assignment in Treatment Arm 1 with the 'Man' and 'Woman' assignments in Treatment Arm 1.

For Research Questions 4 and 5, which pertain to labor responses, similar comparisons can be made. Research Question 4 asks how labor productivity differs by the gender of the

[8] The experiment design also includes a treatment that tries to vary the costs of effort in each session. However, the treatment was too weak to have any effects and has been omitted from the main text. A discussion on this treatment and its effects is presented in the appendix.

laborer. This requires a comparison of mean labor productivity outcomes between the 'Man' and 'Woman' outcomes in Treatment Arm 2. Finally, the Research Question 5 asks whether *who* makes the investment decision affects labor productivity. To answer this for men, comparisons between 'Man, Man', 'Woman, Man', and 'Joint, Man' are made. Analogous comparisons are made to answer the question for women.

3.3.2 Sample

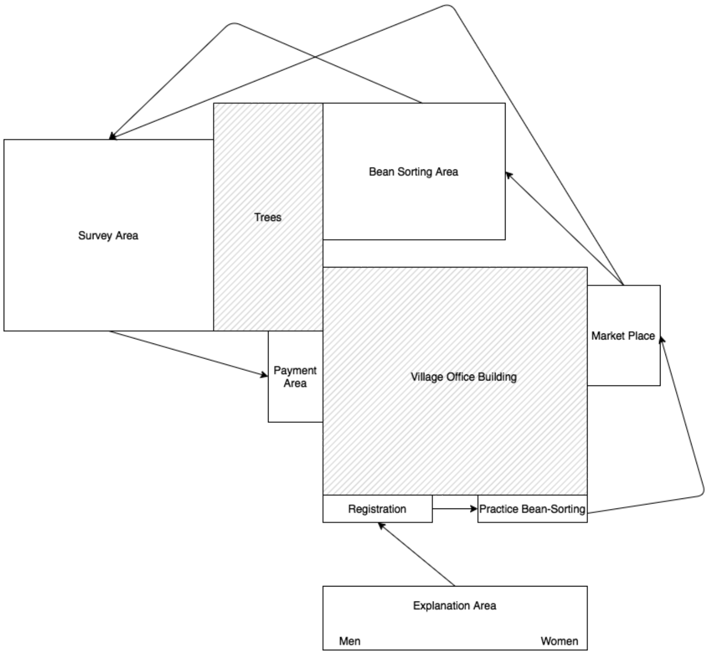
The experiment took place across fifteen villages in Iringa, Tanzania. In the villages, CARE-Tanzania implements the *Kukua ni Kujifunza* (KnK) project, which targets, but is not limited to, female farmers for the promotion of climate-smart agricultural (CSA) practices through farmer field schools (FFSs), integration into soybean value chains, gender sensitization training, and savings and investment in CSA practices through village savings and loans associations (VSLAs). The gender sensitization training involves discussions of wives' and husbands' roles in the household and agricultural activities. The experiment included 529 couples, some of which were involved in the CARE programs and some of which were not. Village and CARE officials recruited couples beforehand to come to village offices and participate in the experiment. There were two experiment sessions in each village: one in the morning and one in the afternoon. We aimed to have 18 couples participate in each session. If the quotas for a session were not met through recruitment (e.g. because of no-shows), then respondents were asked to contact additional couples to participate.

The 529 couples were required to be married and involved in small-scale agriculture. Both members of the couple were required to be between 18 and 65 years of age. Verification of the eligibility requirements was carried out by village officials and was verified by checks in the survey administered to each participant. Eight couples were dropped from the analysis because they did not understand the experiment or experimental conditions were violated (e.g. the couple was determined to be fake after participating in the experiment), leaving a final sample size of 521 couples.

3.3.3 Experiment process

The experiment took place outside of village offices in each village. While the setup slightly varied based on the location of the village office, a standard approach was taken to ensure that decisions were made in isolation and participants who had yet to begin the experiment could not see the bean-sorting area (i.e. they could not see what other couples had decided). This setup alleviated concerns over observability. Members of each couple were also separated at the beginning of each session so that they could not discuss the experiment before participating in it. A sample setup can be seen in Figure 3.1.

Figure 3.1: Example Experiment Setup



The arrows indicate the direction in which participants went through the experiment. From the marketplace (where participants decided their investments), one member went to the bean-sorting area and another to the survey area based on which treatment group to which the couple was assigned.

Each session lasted about four hours, but individual couples were compensated and able to leave once they completed the experiment. Once at least ten couples arrived at the beginning of a session, the experiment began with a detailed explanation of the experiment process to the entire group. Couples who arrived after the first explanation were given a subsequent explanation. Respondents were able to ask questions at any point during the explanation. During the explanation, men were asked to sit away from women so that couples could not discuss the experiment before making a decision. However, this did not prohibit men and women discussing the experiment amongst themselves.

After the explanation, couples were called one by one to register. At registration, they were required to give their names and ages and sign a consent form. Then, both members of the couple practiced sorting one cup of beans within a four-minute limit (one tenth of the time allotted for bean-sorting in the experiment). This allowed the participants to understand their own and their spouse's ability in sorting beans. Before and after the practice bean sorting, participants were asked questions about the experiment to test their understanding. If the participants did not have a firm understanding of the experiment, then the experimenters would explain the process again and then ask follow-up questions until the participants fully understood the process. An experimenter was assigned to usher and monitor participants through the experiment so that couples could not discuss the experiment before decisions were made.

Participants then passed to the decision-making area (the ‘marketplace’), where they were assigned to their treatment group by picking a slip with a treatment group written on it from a bowl. Each couple only picked one slip. Before drawing a slip, the participants were once again asked about the experiment and could bring up their (mis)understanding of the experiment, particularly regarding the randomization process and investment options. After drawing a slip, the relevant participant(s) decided how many and which cups to invest in. If a sole decision-maker was assigned, the decision was made in the absence of their spouse. To make the decision, the experimenter handed the decision-maker(s) ten vouchers worth 300 Tsh each (for a total endowment of 3,000 Tsh). The decision-maker(s) could then spend or keep their vouchers as they wished. Non-observability was ensured such that other participants could not view the decision-making area.

After the relevant participant(s) decided on how many and which cups to purchase, the cups were delivered to the bean-sorting area for the relevant participant to sort. The participant was given 40 minutes to sort the cups. Spouses who were not sorting beans were not allowed to help or observe their spouses sorting.

Finally, both members of each couple were required to complete a 10-minute exit survey before receiving payment. Once both members of each couple completed all of the tasks, then the couples could deliver their sorted and unsorted beans to the marketplace and receive payment based on what they sorted.

3.4 Data and Variables

3.4.1 Investment and Labor Outcomes

In the experiment design, there are seven main outcome variables: total number of cups invested in, the percentage of risky cups invested in, the number of cups left unsorted, the expected return of a decision, the standard deviation of a decision's returns, the final payment issued to participants, and the minutes spent on each sorted cup (a measure of laborer’s productivity).[9] The total number of cups invested in relates to endogenous production risk and overall investment level, while the number of risky and safe cups relates to exogenous market risk. The number of unsorted cups is an indicator of inefficiency (or realizations of production risk) in investment decision-making.

The outcome variables were recorded on paper forms when participants made their decisions (in the case of the variables related to cups purchased) and the bean-sorting and payment areas (for unsorted cups and time spent sorting). All recorded figures were crosschecked when payments were distributed to participants at the end of the experiment. Based on the number of cups and percentage of risk cups, we calculate the expected return and standard deviation of the decision. The minutes per cup measure was later derived from the total number of cups sorted and the time spent sorting.

[9] The cups per minute is an exploratory outcome and was not included in the pre-analysis plan.

3.4.2 Independent Variables

The main independent variables are categorical variables for assignment to treatment groups. The levels of the categorical variables correspond to the groups defined in

Table 3.1. When couples completed sorting beans in the experiment, we administered a short (ten minute) exit survey to both men and woman in each couple. In the exit survey, we asked some questions to be used as control variables in our econometric specifications for robustness checks.

Each participant was asked after the experiment which spouse is better at sorting. Respondents could report that the man is better, the woman is better, or both spouses sort beans equally well. We combine these answers to create a couple-level indicator variable for which spouse is better at sorting. If both spouses report the woman (man) as the better sorter, we indicate that the women (man) is better at sorting beans. If one spouse says the woman (man) is better and the other says they are equal, then woman (man) is indicated by the couple-level variable to be better at sorting beans. If both spouses say they are equal, then neither spouse is determined to better at sorting, and if both spouses report themselves as the best sorter, neither spouse is recorded to be better. Based on these calculations, we create an indicator variable, for whether the member of the couple who is relatively worse at sorting beans is assigned to be the laborer.[10] This variable is equal to zero if the better sorter is assigned or if the spouses have an equal ability to sort. The variable is not defined for the couples assigned to decide which spouse sorts beans because this is an endogenous decision.

In terms of control variables, we asked individuals about demographic, socio-economic, and behavioral variables. Individuals reported their ages and education levels. Household size may also be correlated with how spouses view labor costs, so we include this in the econometric specifications with controls. Respondents were also asked about their farm characteristics and participation in local organizations. Respondents reported their farm size in hectares and listed the two most important crops on their farms. They were also asked if they earn any income from activities outside of farming. We then inquired about knowledge and participation in local organizations/programs related to agriculture: FFSs, gender sensitization training, VSLAs, and CARE's marketing training.

The next set of questions focused on spousal bargaining power related to the two most important crops (self-reported). We asked who is mostly responsible for decision-making with regards to each of the following: crop choice decisions, input decisions, and selling decisions. The respondents could reply with man, woman, both spouses together, another man in the household, another women in the household, or others. We create an index of joint decision-making that simply adds the number of decisions that are made jointly between spouses. We then asked about income control concerning the two most important crops. We create a similar index equal to two if income from both crops is controlled jointly, one if only income from one crop is controlled jointly, and zero if no income is controlled jointly. Finally, we asked about labor divisions between men and woman in the household for the two main crops. We asked who is mainly responsible for land preparation, planting, weeding,

[10] This is an exploratory variable that was not included in the pre-analysis plan.

harvesting, and selling. Analogous to decision-making and income control, we create a simple index for the extent of joint labor tasks in the household.

To gauge individuals' risk preferences, we ask simple questions about individual's willingness to take risks using questions adapted from Vieider et al. (2015) to an agricultural setting. Individuals reported on a scale of zero to ten of how willing they are to take risks in general and in certain situations (where zero is completely unwilling and ten is completely willing). These situations refer to farming in general, input decisions, new crop adoption, new technology adoption, and marketing.

Finally, we asked questions about the experiment itself. To gauge preferences towards spousal cooperation, we asked spouses who were not assigned to bean sorting if they would rather be helping their spouse or resting. We then asked respondents whether they believe their spouse gets more easily distracted than them.[11]

3.4.3 Participant characteristics

Table 3.2 presents the participant characteristics by gender. Men reported larger farm areas than women by about 0.2 acres. The average household size has four members and 2.68 members work on the farm. However, the median number of farm laborers is two, highlighting the importance of spousal bargaining in farm outcomes. 39% of households receive income from wage work. Nearly all households reported one of their two main crops as maize. The majority of respondents also responded that beans were one of the most important crops. However, women were more likely to list beans than men. A small percentage of households reported a variety of other crops as being one of the most important.

In terms of participation in local organizations, nearly all participants are aware of both a VLSA in their village and a Farmer Field School (FFS). However, attendance differs among men and women. Women are more likely to attend gender training, marketing training, VSLAs, and FFSs.

In contrast to Vieider et al. (2015), we find no statistical difference between men and women with regards to risk aversion measures. Men and women do not report different levels of joint decision-making, joint labor, or income control. And with regards to the experiment, 71% of women say they sort better than their husband while only 61% of men say that their wife sorts better. But, when asked which member of the couple gets distracted more easily (i.e. is less able to concentrate in general), both women and men tend to think that they get more distracted than their spouse.

[11] This final question was included in the questionnaire to understand participants' reaction to the labor cost treatment, presented in the Appendix.

Table 3.2: Participant Characteristics by Gender

Variable	Man	Woman	Difference
Farm Area	3.11	2.89	-0.217*
	[0.07]	[0.08]	[0.111]
Household Size	5.1	5.16	0.052
	[0.09]	[0.08]	[0.125]
Household Farm Laborers	2.68	2.73	0.044
	[0.05]	[0.05]	[0.072]
Outside Income (Yes/No)	0.4	0.42	0.027
	[0.02]	[0.02]	[0.030]
Main Crop: Maize	0.99	0.98	-0.006
	[0.00]	[0.01]	[0.007]
Main Crop: Beans	0.55	0.61	0.060*
	[0.02]	[0.02]	[0.031]
Knowledge of VSLA	0.96	0.96	0
	[0.01]	[0.01]	[0.012]
Knowledge of FFS	0.9	0.92	0.017
	[0.01]	[0.01]	[0.018]
Attended Gender Trainings	0.64	0.75	0.111***
	[0.02]	[0.02]	[0.028]
Attended VSLA	0.42	0.69	0.267***
	[0.02]	[0.02]	[0.030]
Attended FFS	0.57	0.65	0.081***
	[0.02]	[0.02]	[0.030]
Attend Marketing Training	0.49	0.55	0.060*
	[0.02]	[0.02]	[0.031]
Risk Aversion: General	6.25	6.04	-0.205
	[0.12]	[0.13]	[0.176]
Risk Aversion: Farming in General	5.56	5.38	-0.18
	[0.13]	[0.13]	[0.180]
Risk Aversion: Inputs	4.72	4.72	-0.006
	[0.12]	[0.12]	[0.175]
Risk Aversion: Marketing	4.56	4.56	0.002
	[0.13]	[0.13]	[0.179]
Risk Aversion: Crop Adoption	4.65	4.68	0.023
	[0.13]	[0.13]	[0.184]
Risk Aversion: Tech. Adoption	5.04	4.98	-0.06
	[0.12]	[0.12]	[0.168]
Involved in Farm Management	0.98	0.98	0.006
	[0.01]	[0.01]	[0.009]
Joint Decision-Making Index	2.14	2.13	-0.012
	[0.06]	[0.06]	[0.079]
Joint Labor Index	0.93	0.93	0.001
	[0.01]	[0.01]	[0.012]
Income Control Index	0.49	0.48	-0.01
	[0.02]	[0.02]	[0.026]
Woman Sorts Better	0.59	0.7	0.111***
	[0.02]	[0.02]	[0.029]
Spouse More Distracted	0.28	0.26	-0.023
	[0.02]	[0.02]	[0.028]
N	521	521	1042
Desire to Help Spouse Sort	0.67	0.84	0.172***
	[0.03]	[0.02]	[0.038]
N	280	237	517

Significance levels: * < 10% ** < 5% *** < 1%. Standard errors in parentheses

Spouses come from the same households, but may differ in their responses to simple questions such as the number of household members. Differences in information from spouses has been found in other settings (Alwang et al., 2017).

3.5 Empirical Methodology

3.5.1 Preliminary Balance Checks

Before testing differences in outcomes during the experiment, we conduct several tests to ensure that the randomization was carried out properly and balance is observed across treatment groups. First, we check for balance across the seven treatment groups by performing iterative T-tests comparing each group across the covariates discussed in Section 3.4. The iterative T-tests first compare the mean covariate values of Treatment Group 1 to Treatment Groups 2 through 7, then Treatment Group 2 to Treatment Groups 3 through 7, and so on. 21 comparisons are made for each variable using this method. We count the number of statistically significant differences found in all comparisons for each variable with the idea that around five percent of the differences should be statistically significant if using a 95% confidence test. The results of these comparisons are presented in Table A.3.1 in the Appendix. Only farm area and the order in which the couple experimented within their session do not appear to be balanced across groups. Those assigned to joint decision-making for labor decisions appear to partake in the experiment later in each session. Since the research team did not know the area of any of the participant's farms and the assignment to each experimental group was completely random, these differences can only be explained as oddities arising from the randomization. Nevertheless, we control for all of the covariates in robustness checks to ensure that our analysis shows the true effect of the randomized assignment on experiment outcomes.

We then perform a similar check for balance across covariates for couples assigned to have the relatively less productive member sort beans and those not assigned to have this member sort. We perform student t-tests across both groups along the covariates discussed earlier. The results are displayed in Table A.3.2 in the Appendix and show that couples are successfully balanced across observables for these groups.

3.5.2 Comparisons Across Treatment Groups

The main analysis consists of comparing each individual treatment group's mean outcomes to every other treatment group's mean outcomes. For any outcome, Y_i (described in Section 3.4.1), for individual i, the comparisons are made using the following equation:

$$Y_i = \beta_0 + \sum_{j=1, j\neq k}^{7} \beta_{j,k} \mathrm{Group}_{\mathrm{i,j}} + \alpha X_i + \gamma_h + \zeta_s + \epsilon_i \ \forall\, k \in [1,7] \qquad (1)$$

where $\mathrm{Group}_{\mathrm{i,j}}$ refers to each treatment group j ('Male, Male', 'Female, Male', etc. from Table 3.1) and β_k is the coefficient representing the difference in mean outcomes between group j and the base (or comparison) group k. X_i is a vector of individual level controls described in Section 3.4.2, γ_h is a village fixed effect for one of the 15 villages, h, ζ_s is an indicator for the session (morning or afternoon), and ϵ_i is the error term. Each treatment group is used as a comparison group, k, such that Equation 1 is estimated for each $k \in [1,7]$. This ensures that differences for each combination of treatment groups are made. The main results reported in the text omit αX_i, γ_h, and ζ_s because the randomization ensures that ϵ_i is independently distributed unconditional on individual characteristics and session fixed effects. However, the full model is estimated for robustness, and the results are reported in Table A.3.3 in the Appendix. The results are generally robust to the inclusion of controls and fixed effects, unless otherwise specified in the text.

Analogous models are estimated to test differences across individual treatment arms, rather than each individual treatment group. For the decision-making treatment arm, Equation 1 is modified such that each group, j, refers only to male, female, and joint decision-makers. These groups also make up the three comparison groups, k, such that $k \in [1, 3]$. In this case, β_k refers to the difference in outcomes between decision-makers only. Similarly, the model can be adjusted to make comparisons between the labor treatment arms such that the three group means compared to each other are male laborers, female laborers, and the endogenous labor choice.

3.5.3 Decision-Making by Laborers' Relative Productivity

In exploratory analysis, we test whether decision-makers account for the relative productivity of the assigned laborer. In this set of analysis, couples assigned to make endogenous labor decisions are excluded. The comparisons for the main outcome variables Y_i (which are the same as in the Equation 1 above) are made using the model in Equation 2:

$$Y_i = \beta_0 + \beta_1 low_i + \beta_2 woman_i + \beta_3 joint_i + \beta_4 low_i \times woman_i + \beta_5 low \times joint_i + X_i + \alpha_h + \zeta_s + \epsilon_i \tag{2}$$

where low_i is an indicator equal to one if the exogenously assigned laborer is reported to be relatively less productive and zero otherwise. Male decision-makers are the comparison group, and $woman_i$ and $joint_i$ are indicators for whether the woman or both spouses together are assigned to make investment decisions, respectively. $low_i \times woman_i$ and $low \times joint_i$ are interaction terms, which respectively give the coefficients of interest β_4 and β_5. The coefficients of the interaction terms show whether decision-makers with relatively less productive laborers make different decisions than those without relatively less productive laborers. As in the main results, unconditional estimations are presented in the main text with results conditional on controls presented in Table A.3.4 in the Appendix.

3.5.4 Analysis of Labor Responses

We test whether productivity differs by the laborer's gender in exploratory analysis. Equation 3 shows the estimation strategy where the outcome variables, Y_i, are the number of unsorted cups (a measure of failure rates) and the minutes per cup sorted. We hypothesize that effort may have a non-linear relationship with workload. For example, individuals with a low workload may put in low effort because they are comfortable in their ability to complete the task without much strain. However, individuals with heavy workloads may also put forth low effort because they are discouraged by a difficult to complete task or they simply tire after working for some time. As a result, we include a quadratic term for the number of cups assigned to laborers in Equation 3:

$$Y_i = \beta_0 + \beta_1 cups_i + \beta_2 cups_i \times cups_i + \beta_3 woman_i + \beta_4 cups_i \times woman_i + \beta_5 cups_i \times cups_i \times woman_i + X_i + \alpha_h + \zeta_s + \epsilon_i \quad (3)$$

The β_1 and β_2 coefficients show how laborers' productivity is related to the number of cups they are tasked to sort. β_3 gives the difference between women's and men's productivity (as male laborers are the comparison group for the indicator, $woman_i$). The coefficients for the interaction terms $cups_i \times woman_i$ and $cups_i \times cups_i \times woman_i$ describe how the correlation between number of cups assigned and productivity differs for men and women. As in other estimations, the unconditional correlations are reported in the main text and the conditional correlations are reported in the appendix. Endogenous labor choices are excluded from the analysis, such that only the six treatment groups with exogenous labor assigned are included in the sample.

The number of cups assigned to a laborer is endogenous because decision-makers take into account the expected productivity of the laborer when deciding on investment levels. Further, men are reported to be less productive than women when sorting beans (Table 3.2), which makes the laborer's gender endogenous to the productivity outcomes – decision-makers may assign fewer cups to men because they are less productive. This means that we cannot interpret the coefficients as causal effects. However, two labors assigned the same number of cups have the same minimum upper bound of expected productivity.[12] Since, the gender of the assigned laborer is exogenous, this means that we can identify the effect of the laborer's gender on productivity when comparing laborers with the same assigned number of cups. This strategy eliminates endogeneity arising form expected productivity. To interpret these differences, we compare the predictive margins for men and women at each level of investment.

3.5.5 Estimation Models and Robustness Checks

To estimate the coefficients and standard errors of the models above, we use Poisson models for the number of cups invested in and the number of unsorted cups. For the percentage of risky cups, we use a fractional response model with a logit link (estimated by a generalized linear model). For expected portfolio return, portfolio standard deviation, final payment, and minutes per cup, OLS is used for the estimation of coefficients and standard errors. Since the treatment was assigned individually, and we do not attempt to make claims about the population as a whole, the standard errors are not clustered in the main analysis (Robinson, 2020). For robustness, we cluster the standard errors at the treatment-session level. These results are presented in Table A.3.3 and Table A.3.4 in the Appendix.

[12] We refer to the minimum upper bound of expected productivity because decision-makers expect laborers to be able to sort at least the number of cups assigned. Otherwise, they would choose lower investment levels.

3.6 Results

3.6.1 Joint Decision-Making with Endogenous Labor Choices

The 'Joint, Joint' group refers to the treatment group whereby spouses are assigned to make decisions jointly and to decide which spouse performs the real-effort task. This group is intended to provide a 'natural' case – the most similar scenario to the real world. Out of the 76 couples assigned to this group, only 20 (26%) choose the man to sort, while 56 (74%) choose the woman to sort. These choices can reflect two factors. First, women tend to be better at sorting, so often the optimal decision is to decide that women sort. 86% of the couples assigned to this group choose the partner who the spouses believe is better at sorting to sort. Second, the tendency to choose women to sort can reflect the fact that women tend to have higher labor burdens than men in agricultural and household duties (Palacios-Lopez et al., 2017). Therefore, assigning labor costs to women is consistent with real-life labor allocations in small-scale farming households.

Table 3.3 displays the experiment outcomes for the 'Joint, Joint' group. We test for differences between couples who choose men to sort and those who choose women to sort, but due to the low sample size (particularly for male laborers), these results should be interpreted with extreme caution. The average couple chooses to sort 5.86 cups with significant differences between the number of cups chosen for male and female laborers. When men sort, couples invest in 1.2 more cups compared to when women sort. However, the proportion of risky cups in both groups is statistically similar. Despite higher investment levels for male laborers, payment levels are not significantly different for male and female laborers because male laborers are less efficient, leaving 1.2 cups unsorted on average – an amount equivalent to the difference in investment levels between male and female laborers. This suggests that couples over-invest when choosing men to sort and are unable to realize the returns on the extra investment.

Table 3.3: Outcomes for Joint Decision Makers with Endogenous Labor Choice

Variable	Choose Man	Choose Woman	Difference (Woman – Man)	Total
Total Cups	6.75	5.54	-1.214*	5.86
	[0.74]	[0.41]	[0.812]	[0.36]
Proportion of Risky Cups	0.35	0.38	0.03	0.37
	[0.02]	[0.01]	[0.11]	[0.01]
Unsorted Cups	1.2	0.46	-0.736***	0.65
	[0.37]	[0.15]	[0.328]	[0.15]
Expected Return	4565	4319.64	-245.357	4384.21
	[166.11]	[105.82]	[203.078]	[89.70]
Investment Std. Dev.	0.15	0.15	0.00	0.15
	[0.04]	[0.02]	[0.046]	[0.02]
Payment	4295	4057.14	-237.857	4119.74
	[304.74]	[136.32]	[291.283]	[127.98]
N	20	56	76	

Significance levels: * < 10% ** < 5% *** < 1%. Standard errors in brackets.

For Total Cups and Unsorted Cups, standard errors are calculated using a Poisson Distribution. For Proportion of Red Cups, Investment Std. Deviation, Expected Return, and Payment, standard errors are calculated using a normal distribution, and significance levels are found using a student T-Test.

The number of observations for ‘Choose Man’, ‘Choose Woman’, and ‘Difference’ for the Proportion of Risky Cups are respectively, 20, 54, and 74 because two couples do not invest in any cups in the ‘Choose Woman’ group.

3.6.2 Investment Decision-Making

The first research question asks whether labor-intensive investment decisions differ by the gender of the decision-maker. Investment decisions can differ in terms of investment levels (number of cups) and portfolio mix (percentage of risky cups). Table 3.4 shows that within the experiment, men have higher investment levels than women by 0.53 cups (or nearly 10%). Monetarily, this translates to men’s expected returns being 165 Tsh higher than women’s. However, these returns are not realized because men’s decisions result in a higher number of failed investments (unsorted cups). As a result, final payments distributed to male and female decision-makers are statistically similar.

Overconfidence appears to be the key mechanism behind men’s higher investment levels because men’s higher investment levels are driven by the case when men are assigned to sort.[13] Table 3.6 shows that when men are assigned to sort, women only invest in 5.03 cups, while men invest in 5.74 cups (a statistically significant difference at the 90% confidence level). Further, despite the majority of men believing their spouse is the relatively more productive bean sorter (Table 3.2), men invest in a statistically similar number of cups when they are the assigned laborer (5.74) as when their spouse is the assigned laborer (5.87).

[13] If risk preferences were driving men’s higher investment levels, then the higher investment levels would be observed for men making decisions when both men and women are assigned to sort. If labor costs were the driving factor, the higher investment levels would be driven by men’s decisions when women are assigned to sort.

Evidence from the experiment supports the idea that men are less productive in the experiment than women (Section 3.6.3). Women do not display such overconfidence in the experiment.

In terms of portfolio mix, men and women take on similar levels of risk. Men and women's portfolios respectively are comprised of 48% and 42% risky cups, and this difference is not statistically different. Similarly, their investment standard deviations are not statistically different. The decision-making regarding portfolio composition reflects the similarity in men and women's responses to the survey questions on risk preferences reported in Table 3.2. While there is ample evidence that men and women have different risk preferences ((Ahmad et al., 2019; Cullen et al., 2018; Jin et al., 2017; Liu, 2013; Nielsen et al., 2013; Vieider et al., 2015), there is growing evidence that this is not always the case (Ambali et al., 2021; Cardenas and Carpenter, 2013). These results indicate that the women should not always be assumed to be more risk averse than men.

Table 3.4: Outcome Variables by Decision-Maker

Variable	Woman	Man	Joint	Diff (M-W)	Diff (M-J)	Diff (W-J)
Total Cups	5.28	5.80	5.73	0.525*	0.07	-0.456*
	[0.25]	[0.27]	[0.21]	[0.27]	[0.25]	[0.25]
Proportion Risky Cups	0.42	0.48	0.39	0.06	0.09	0.03
	[0.04]	[0.04]	[0.03]	[0.06]	[0.05]	[0.05]
Unsorted Cups	0.59	0.82	0.69	0.239**	0.134	-0.105
	[0.11]	[0.13]	[0.09]	[0.10]	[0.09]	[0.08]
Expected Return	4280.27	4445.27	4372.12	164.99*	73.14	-91.85
	[64.46]	[71.96]	[51.76]	[96.64]	[86.49]	[82.59]
Investment Std. Dev.	0.23	0.27	0.23	0.042	0.04	-0.001
	[0.02]	[0.02]	[0.02]	[0.03]	[0.03]	[0.03]
Payment	3980.27	4194.59	4085.40	214.32	109.19	-105.12
	[95.10]	[118.85]	[78.53]	[152.34]	[136.61]	[123.95]
N	147	148	226	295	374	373

Column 2-4 presents average outcomes listed in the first row for man-spouse, woman-spouse, and joint decisions. Column 5-7 show the differences between those three groups. Significance levels: * < 10% ** < 5% *** < 1%. Standard errors are in parentheses. Standard errors for total cups, grey cups, red cups, and unsorted cups differences are estimated from Poisson distribution using the delta method. Standard errors for expected return and Investment Std. Dev. Differences are estimated from a standard normal distribution (student T-test). For the mean proportion of risky cups, the sample sizes for woman, man, and joint are 141, 141, and 219, respectively. For the differences for M-W, M-J, and W-J, the sample sizes are 282, 360, and 360. These sample sizes are different from the other variables because some decision-makers choose to invest in zero cups.

Research Question 2 asks how investment decisions differ by the gender of the laborer. When men are the assigned laborers, investment levels are 0.42 cups lower than when women are assigned (a statistically significant difference at the 90% confidence level). This difference does not translate into a difference in expected returns. The difference in investment levels by laborers is driven by the fact that women invest less than men when men are assigned as laborers (likely because of men's overconfidence). There is no evidence to suggest that men and women are undervaluing each other's labor costs in the experiment – decision-makers do not invest less when they have to sort themselves compared to when the other spouse is assigned to sort (Table 3.6). Additionally, there is no difference in portfolio mix based on the gender of the assigned laborer, as decision-makers have portfolios with a similar percentage of risky cups when men and women are assigned as laborers. These results suggest that while men's overconfidence is driving gendered differences in labor-intensive investment, the other mechanisms (risk preferences and labor costs) are not at play.

Table 3.5: Outcomes Variables by Laborer

Variable	Woman	Man	Joint	Diff (M-W)	Diff (M-J)	Diff (W-J)
Total Cups	5.79	5.37	5.86	-0.418*	-0.481	-0.063
	[0.21]	[0.21]	[0.36]	[0.22]	[0.32]	[0.32]
Proportion Risky Cups	0.45	0.42	0.37	-0.03	0.05	0.08
	[0.03]	[0.03]	[0.05]	[0.05]	[0.07]	[0.07]
Unsorted Cups	0.5	0.92	0.66	0.418***	0.26**	-0.158
	[0.07]	[0.12]	[0.15]	[0.08]	[0.11]	[0.10]
Expected Return	4419.47	4306.85	4384.21	-112.62	-77.361	35.259
	[55.07]	[53.86]	[89.70]	[77.08]	[105.61]	[108.29]
Investment Std. Dev.	0.25	0.24	0.21	-0.018	0.023	0.041
	[0.02]	[0.02]	[0.03]	[0.024]	[0.03]	[0.03]
Payment	4286.73	3868.95	4119.74	-417.776***	-250.787	166.989
	[88.81]	[79.86]	[127.98]	[119.66]	[155.14]	[170.22]
N	226	219	76	445	295	302

Column 2-4 presents average outcomes listed in the first row for three groups: male-spouse, male-spouse assigned to work, the spouse jointly decide who works. Column 5-7 show the differences between those three groups. Significance levels: * < 10% ** < 5% *** < 1%.
Standard errors are in parentheses. Standard errors for total cups, grey cups, red cups, and unsorted cups differences are estimated from Poisson distribution using the delta method. Standard errors for expected return and Investment Std. Dev. differences are estimated from a standard normal distribution (student T-test).
For the mean proportion of risky cups, the sample sizes for woman, man, and joint are 214, 213, and 74, respectively. For the differences for M-W, M-J, and W-J, the sample sizes are 427, 287, and 288. These sample sizes are different from the other variables because some decision-makers choose to invest in zero cups.

Research Question 3 asks whether and how joint decision-making influences investment decision-making. Investment levels of couples deciding jointly (5.73 cups) are statistically similar to those of men deciding alone (5.80 cups), but significantly higher (at the 90% confidence level) than those of women deciding alone (5.28 cups). The differences in the investment levels do not translate into differences in expected returns, and there are no statistically significant differences in portfolio mixes between joint and individual decision-makers. These results suggest that men have higher bargaining power because decisions made jointly are more similar to those made by men alone, but the evidence is fairly weak.

Joint decision-making appears to reduce the prevalence of overconfidence. When men are assigned as laborers, joint decision-makers invest in 5.36 cups, compared to 5.74 cups when men decide alone (although this difference is not statistically significant). In exploratory analysis, we find that joint decision-makers choose investment levels based on the laborer's relative skill, while individual decision-makers do not make an adjustment.[14] Table 3.7 shows that individuals who are reported to be less productive leave nearly half an unsorted cup more and take a minute longer to sort each cup than individuals who are

[14] Spouses observed each other's results from the practice round, so they had the opportunity to observe their spouse's skill level.

reported to be as productive or more productive than their spouse. Despite the clear differences in productivity levels, individual decision-makers (both men and women) choose statistically similar investment levels regardless of the relative skill of the laborer. Failure rates and payments are lower when individuals make decisions and a relatively unproductive laborer is randomly assigned. However, when couples make decisions together, they account for relative productivity and assign fewer cups to relatively unproductive laborers. This results in lower failure rates by a factor of 0.56 (statistically significant at 99% level), but not higher payments. Higher payments may not be realized because joint decision-makers invest in fewer cups. The main result of adjusting investment levels is not robust to clustering standard errors at the treatment-session level in Table A.3.4(p-value of 0.13).

A possible explanation for this phenomenon is that spouses making decisions together have the opportunity to share information on expected productivity and perceived labor costs. If spouses share this information and use it in their decision-making process, then spouses can make decisions with reduced chances of failure. They could use the information to reduce inefficiencies in decision-making, such as overconfidence. The mediating effect of joint decision-making is in line with previous studies in other contexts (Warmath, Piehlmaier, and Robb 2019; Mahalakshmi and Anuradha 2018).

Table 3.6: Main Experiment Results – Mean Values of Outcome Variables by Treatment Group

	Total Cups	Proportion of Risky Cups	Unsorted Cups	Expected Return	Investment Std. Dev.	Payment	Observations
By Treatment Group (Decision-Maker, Laborer)							
Man-Man	5.74^{WM}	0.46	$1.00^{\mathit{MW}, \mathbf{WW}, \mathbf{JW}, \mathit{JJ}}$	4413.7	0.18	4046.58	73
	[.04]	[.01]	[.03]	[11.56]	[0]	[18.96]	
Man-Woman	5.87^{WM}	0.49	$0.65^{\mathit{MM}, \mathit{WW}, \mathrm{JM}}$	4476^{WM}	0.2^{JJ}	$4338.67^{\mathbf{WM}, \mathbf{JM}}$	75
	[.04]	[.01]	[.02]	[12.13]	[0]	[19.99]	
Woman-Man	$5.03^{\mathrm{MM}, \mathit{MW}, \mathit{JW}, \mathit{JJ}}$	0.43	$0.82^{\mathbf{WW}, \mathit{JW}}$	$4212.33^{\mathit{MW}, \mathrm{JW}}$	0.16	$3782.19^{\mathbf{MW}, \mathrm{WW}, \mathbf{JW}, \mathrm{JJ}}$	73
	[.04]	[.01]	[.02]	[10.14]	[0]	[12.68]	
Woman-Woman	5.53	0.42	$0.35^{\mathbf{MM}, \mathit{MW}, \mathbf{WM}, \mathbf{JM}, \mathbf{JJ}}$	4347.3	0.16	$4175.68^{\mathrm{WM}, \mathrm{JM}}$	74
	[.04]	[.01]	[.01]	[11.08]	[0]	[17.81]	
Joint-Man	5.36	0.37	$0.93^{\mathrm{MW}, \mathbf{WW}, \mathbf{JW}, \mathrm{JJ}}$	4294.52	0.16	$3778.08^{\mathbf{MW}, \mathrm{WW}, \mathbf{JW}, \mathrm{JJ}}$	73
	[.04]	[.01]	[.02]	[10.99]	[0]	[16.26]	
Joint-Woman	5.97^{WM}	0.44	$0.49^{\mathbf{MM}, \mathit{WM}, \mathbf{JM}}$	4433.77^{WM}	0.18	$4342.86^{\mathbf{WM}, \mathbf{JM}}$	77
	[.04]	[.01]	[.01]	[9.80]	[0]	[15.38]	
Joint-Joint	5.86^{WM}	0.37	$0.66^{\mathit{MM}, \mathbf{WW}, \mathrm{JM}}$	4384.21	0.15^{MW}	$4119.74^{\mathrm{WM}, \mathrm{JM}}$	76
	[.04]	[.04]	[.02]	[10.29]	[0]	[14.68]	

Superscripts denote which treatment group a given variable's value is significantly different from. For treatment group comparisons in the first panel, superscripts are abbreviated such that the first letter marks the decision-maker and the second letter marks the laborer. For example, FM denotes a female-decision maker and a male laborer, while JF denotes a joint decision-maker and a female laborer. In the second and third panels, comparisons are only made across the decision-making and labor treatment arms. Bolded superscripts denote a p-values <0.01, italicized superscripts denote p-values < 0.5, and superscripts that are neither bolded nor italicized denote p-values < 0.1.

Table 3.7: Incidence Rate Ratios of Decision-Making Responses to Relative Production Levels of Assigned Laborers

	(1) Total Cups	(2) Proportion of Risky Cups	(3) Unsorted Cups	(4) Expected Return	(5) Investment Std. Dev.	(6) Payment
Relatively Less Productive Laborer	1.026	0.760	2.073***	3.497	-0.0209	-454.8**
	(0.0762)	(0.282)	(0.376)	(146.0)	(0.0321)	(227.9)
Female Decision-Maker	0.927	0.776	0.823	-145.2	-0.0371	-339.5*
	(0.0548)	(0.221)	(0.152)	(112.8)	(0.0248)	(176.2)
Joint Decision-Maker	1.057	0.698	1.072	13.05	-0.0205	-86.12
	(0.0604)	(0.201)	(0.185)	(112.8)	(0.0248)	(176.2)
Relatively Less Productive Laborer x Female Decision-Maker	0.938	1.134	0.703	-66.16	0.0259	421.3
	(0.102)	(0.598)	(0.201)	(206.6)	(0.0455)	(322.5)
Relatively Less Productive Laborer x Joint Decision-Maker	0.763**	1.187	0.567**	-294.8	-0.00606	-105.9
	(0.0821)	(0.616)	(0.155)	(204.3)	(0.0450)	(318.9)
Constant	5.760***	0.994	0.625***	4444.2***	0.197***	4329.8***
	(0.235)	(0.200)	(0.0775)	(79.60)	(0.0175)	(124.3)
Order Controls	No	No	No	No	No	No
Survey Controls	No	No	No	No	No	No
Session Fixed Effects	No	No	No	No	No	No
N	445	427	445	445	445	445

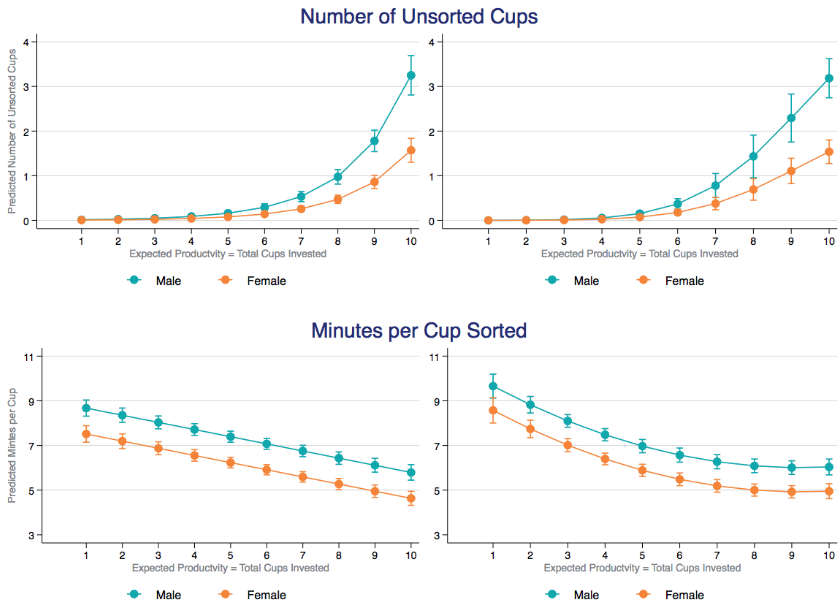
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.
Incidence rate ratios reported for Columns 1 and 3. Marginal effects reported in Column 2.
Relatively less productive laborer takes a value of one if the assigned laborer who is reported to be relatively worse at sorting beans than their spouse in the exit survey and takes a value of zero if the assigned laborer is reported to be

3.6.3 Labor Responses

Research Question 4 asks whether labor productivity and effort differ by gender. Table 3.5 shows that male laborers leave more unsorted cups than female laborers on average. In exploratory analysis, the bottom panel of Figure 3.2 shows that men are less productive than women across all investment levels, where productivity is measured by the time taken to sort each cup. This difference in productivity results in more unsorted cups at high levels of investment. At relatively low levels of investment (one to five cups), both men and women sort all the cups (a failure rate of 0%). However, men are still taking more time to sort their cups. For example, the bottom-right panel of Figure 3.2 shows that men and women are similarly productive at the lowest investment levels (one or two cups), but from investment levels of three to five cups, a productivity gap emerges with men falling behind. This widening productivity gap starts to affect failure rates at six cups – the failure rate for women is 0% for women at six cups invested, but about 8% for men. At the highest investment level (ten cups), men sort at a rate of six minutes per cup compared to five minutes per cup for women. This results in a failure rate of 30% for men and only about 17% for women at the highest investment levels. These general patterns (regardless of gender) in Figure 3.2 could come about for two reasons. First, the relationship is endogenous and decision-makers invest lower (higher) amounts when expected productivity is low (high). Second, laborers could expend little effort when they are sure that the task could be completed within 40 minutes and expend more effort when the completion of the task is more uncertain.

The endogeneity of investment levels is problematic when making comparisons across investment levels, but not within investment levels. Since the investment levels take into account expected productivity, the gender gaps at each investment level must be driven at least partly by effort. Observed investment levels are the minimum upper bound expected productivity level – decision-makers will not invest more than the expected production of the laborer (any higher investment would be irrational), but may invest less than expected productivity because of labor/effort costs. As a result, male and female laborers who are tasked to sort the same number of cups have the same minimum upper bound of expected productivity. Then, the only difference between male and female laborers who are tasked with sorting the same number of cups is their gender, which is randomly assigned. The results in Figure 3.2 are reflective of differences in perceived labor costs (or costs of effort) of laborers, with men having higher costs of effort, and therefore lower productivity levels. At all investment levels, the results suggest that men put forth less effort. These results are robust to the inclusion of controls in Figure A.3.1 in the appendix, which suggests that the differences are not driven by observable characteristics such as age.

Figure 3.2: Failure Rates and Productivity by Investment Level and Laborer Gender



Predictive margins are reported for each investment level. The error bars display the 95% confidence levels. Standard errors are not clustered.
The panels on the left and right display estimates from Equation 3 without the quadratic term and Equation 3 with the quadratic term, respectively. The estimations do not include control variables, or village fixed effects. Figure A.3.1 in the appendix displays the results conditional on control variables and village fixed effects with clustered standard errors.

Research Question 5 asks whether who makes the investment decision affects the productivity of laborers. Table 3.8 displays the effect of each treatment group on the incidence rates on productivity levels (measured by the length of time to sort each cup). The results show that who makes investment decisions may be important when men are laborers – men take significantly more time (by a full minute) to sort each cup when decisions are made jointly, compared to when decisions are made by men alone. However, there is no difference in male laborers' productivity when women make decisions compared to when men make decisions. These results are driven by outliers and are not robust to adjusting for outliers (Table A.3.5 in the Appendix). Women have similar productivity levels across all decision-makers. The evidence suggests that who makes decisions is not playing a significant role in laborers' productivity in the experiment.

Table 3.8: Female and Male Laborers' Productivity by Decision-Maker

	(1) Minutes per Cup Sorted	(2) Minutes per Cup Sorted	(3) Minutes per Cup Sorted	(4) Minutes per Cup Sorted
Female-Female Base				
Male-Female	-0.135	-0.136	-0.0657	-0.048
	(0.435)	(0.436)	(0.431)	(0.397)
Joint-Female	-0.210	-0.210	-0.0766	-0.174
	(0.430)	(0.430)	(0.426)	(0.343)
Male-Male Base				
Female-Male	0.322	0.322	0.213	0.280
	(0.437)	(0.437)	(0.432)	(0.488)
Joint-Male	0.926**	0.925**	0.796*	0.777*
	(0.433)	(0.433)	(0.427)	(0.426)
Total Cups	-1.893***	-1.892***	-1.647***	-1.443***
	(0.189)	(0.189)	(0.193)	(0.300)
Total Cups Squared	0.117***	0.117***	0.100***	0.087***
	(0.015)	(0.015)	(0.015)	(0.021)
Order Controls	No	Yes	Yes	Yes
Survey Controls	No	No	Yes	Yes
Village Fixed Effects	No	No	No	Yes
N	500	500	500	500

Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.
Coefficients are found via estimation Equation 3. The Joint-Joint treatment group is excluded from the sample because the labor decision is endogenous. The coefficients for the total number of cups do not change when the base for the treatment group variables is changed.

3.7 Conclusions

Development programs are increasingly targeting female farmers for agricultural investment in an effort to close the gender gap in agricultural productivity and reduce poverty. Yet, it remains unclear whether such targeting is welfare maximizing. One major constraint to women's investment is that most female farmers live in male-headed households, do not make decisions in isolation, and at least partially rely on family labor to ensure that labor-intensive investments are successful. This paper uses a lab-in-the-field experiment to uncover the gendered differences in investment decision-making and labor responses in the context of labor-intensive investments with risk.

Previous literature on intra-household investment decision-making has focused on individual risk preferences and overconfidence, and household bargaining processes. Another, more nascent, strand of literature seeks to identify individuals' effort levels when performing labor. This paper makes marginal contributions to each of these strands of literature by using exogenous variation in decision-making and labor assignment to uncover bargaining processes, observed risk tolerance by gender, and gendered productivity levels. The most important contribution of the paper comes from combining the two strands of literature to understand how laborers' expected productivity affects investment decision-making and how the gender of decision-makers and joint decision-making affect laborers' performance. We find weak evidence that spouses making decisions together take into account laborers' relative productivity, while individual decision-makers do not. Further, while male laborers consistently underperform relative to women, their productivity is not dependent on who makes decisions.

From a policy standpoint, the results are suggestive that targeting both spouses is optimal. In the experiment, when spouses make decisions together, investment levels are higher than when women make decisions alone. Further, decisions made jointly take into account the productivity of laborers so as to reduce investment failure rates. Gender sensitization training may also be helpful in improving investment outcomes. Male laborers consistently underperform, irrespective of investment levels. If men's effort does not meet expectations, then labor-intensive investments requiring their labor have higher chances of failure. Gender sensitization programs can address societal norms that enable men's shirking in order to increase on-farm productivity and the chances of investments' success.

This paper reveals the causal effects of gender on labor-intensive investment decisions and labor responses, but does not explicitly uncover the behavioral mechanisms underlying gendered differences in experiment outcomes. Future research should focus on identifying the possible mechanisms behind these differences: overconfidence, bargaining power, information sharing, risk preferences, and effort. In this study, we attempted to exogenously change costs of effort (Table A.3.6 and Table A.3.7 in the Appendix), but the treatment was too weak to have an effect. Doing so would uncover gendered differences in responses to cost of effort and allow for a more thorough understanding of why men underperform relative to women. Future research could also introduce differences in who receives payments to understand how this affects decision-making and labor responses.

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Appendix 3

3.8 Checks for Balance

The tables follow on the next page.

Table A.3.1: Balance along covariates across treatment groups

	Man-Man	Man-Woman	Woman-Man	Woman-Woman	Joint-Man	Joint-Woman	Joint-Joint	Proportion of Comparisons with Significant Differences
Male age	41.62	44.49	43.63	45.34	44.52	44.19	46.13	0.05
Female age	36.78	39.23	37.96	40.89	38.60	39.55	40.84	0.10
Household size	4.92	5.07	5.34	5.41	5.23	4.97	4.99	0.00
Man's number of spouses	1.04	1.11	1.07	1.11	1.04	1.03	1.04	0.10
Farm area	2.51	2.86	2.96	3.43	2.95	3.32	2.96	0.24
Wage income	0.68	0.64	0.52	0.54	0.63	0.62	0.64	0.05
Any spouse attended FFS	0.79	0.77	0.88	0.84	0.84	0.90	0.76	0.10
Any spouse attended gender training	0.88	0.89	0.89	0.92	0.89	0.92	0.87	0.00
Any spouse attended VSLA	0.77	0.85	0.79	0.78	0.71	0.79	0.80	0.05
Join decision-making index	2.18	1.88	2.04	2.09	2.32	2.19	2.22	0.10
Labor index	0.93	0.92	0.93	0.93	0.93	0.91	0.92	0.00
Income control index	0.44	0.47	0.51	0.52	0.50	0.46	0.47	0.00
Distraction treatment	0.44	0.48	0.45	0.50	0.47	0.49	0.42	0.00
Experiment order	9.22	10.87	9.41	10.18	9.88	10.44	13.34	0.29
Observations	73	75	73	74	73	77	76	

The table displays the means for each group. Iterative student t-tests are run for each of the variables. These t-test ensure comparisons are made between every combination of treatment groups. T-Tests that yield p-values less than 0.1 are considered statistically significant. For each variable, the proportion of group comparisons yielding statistically significant results is reported in the last column. Since 21 tests are run for each variable, at the 10% confidence level, about 2 comparisons (10%) should ordinarily return statistically significant differences.

Table A.3.2: Balance across covariates by assignment of optimal or sub-optimal laborer

	Relatively More (or Same) Productive Laborer	Relatively Less Productive Laborer	Difference
Male age	43.82	44.33	0.517
	[0.68]	[1.01]	[1.231]
Female Age	38.86	38.81	-0.057
	[0.64]	[0.91]	[1.142]
Household Size	5.15	5.18	0.033
	[0.11]	[0.16]	[0.197]
Man's number of spouses	1.06	1.08	0.023
	[0.01]	[0.02]	[0.025]
Farm area	3.03	2.96	-0.062
	[0.10]	[0.11]	[0.168]
Wage income (Y/N)	0.59	0.64	0.043
	[0.03]	[0.04]	[0.050]
Any spouse attended FFS	0.83	0.84	0.012
	[0.02]	[0.03]	[0.038]
Any spouse attended gender training	0.9	0.9	-0.004
	[0.02]	[0.03]	[0.031]
Any spouse attended VSLA	0.76	0.83	0.065
	[0.02]	[0.03]	[0.042]
Joint decision-making index	2.06	2.24	0.173*
	[0.06]	[0.07]	[0.099]
Labor index	0.91	0.95	0.040***
	[0.01]	[0.01]	[0.014]
Income control index	0.47	0.52	0.054*
	[0.02]	[0.03]	[0.032]
Distraction treatment	0.5	0.41	-0.093*
	[0.03]	[0.04]	[0.051]
Experiment order	10.27	9.4	-0.871
	[0.37]	[0.57]	[0.669]
N	310	135	445

Significance levels: * < 10% ** < 5% *** < 1%. Standard errors in brackets.
Comparisons between all variables are made using student T-Tests.

3.9 Robustness Checks

The tables follow on the next page.

Table A.3.3: Robustness Check: Main Experiment Results – Mean Values of Outcome Variables by Treatment Group

	Total Cups	Proportion of Risky Cups	Unsorted Cups	Expected Return	Investment Std. Dev.	Payment	Observations
By Treatment Group (Decision-Maker, Laborer)							
Man-Man	5.74	0.46	$1.00^{\mathbf{WW}, \mathit{JW}}$	4413.7^{FM}	0.18	4046.58	73
	[.04]	[.01]	[.03]	[11.56]	[0]	[18.96]	
Man-Woman	5.87^{WM}	$0.49^{\mathit{JM}, \mathrm{JJ}}$	0.65^{WW}	4476^{FM}	$0.2^{\mathrm{FM}, \mathrm{JM}}$	$4338.67^{\mathbf{FM}, \mathbf{JM}}$	75
	[.04]	[.01]	[.02]	[12.13]	[0]	[19.99]	
Woman-Man	$5.03^{\mathrm{MW}, \mathit{WF}, \mathit{JJ}}$	0.43	0.82^{WW}	$4212.33^{\mathrm{MM}, \mathit{MW}, \mathrm{JW}, \mathit{JJ}}$	0.16^{MW}	$3782.19^{\mathbf{MW}, \mathit{WW}, \mathbf{JW}, \mathrm{JJ}}$	73
	[.04]	[.01]	[.02]	[10.14]	[0]	[12.68]	
Woman-Woman	5.53	0.42	$0.35^{\mathbf{MM}, \mathrm{MW}, \mathit{FM}, \mathit{JM}, \mathrm{JJ}}$	4347.3	0.16	$4175.68^{\mathit{FM}, \mathit{JM}}$	74
	[.04]	[.01]	[.01]	[11.08]	[0]	[17.81]	
Joint-Man	5.36	0.37^{MW}	$0.93^{\mathit{WW}, \mathrm{JW}}$	4294.52	0.16^{MW}	$3778.08^{\mathbf{MW}, \mathit{WW}, \mathbf{JW}, \mathit{JJ}}$	73
	[.04]	[.01]	[.02]	[10.99]	[0]	[16.26]	
Joint-Woman	5.97^{FM}	0.44	$0.49^{\mathit{MM}, \mathrm{JM}}$	4433.77^{FM}	0.18	$4342.86^{\mathbf{FM}, \mathbf{JM}}$	77
	[.04]	[.01]	[.01]	[9.80]	[0]	[15.38]	
Joint-Joint	5.86^{FM}	0.37^{MW}	0.66^{WW}	4384.21^{FM}	0.15	$4119.74^{\mathit{FM}, \mathit{JM}}$	76
	[.04]	[.04]	[.02]	[10.29]	[0]	[14.68]	
By Decision-Making Treatment Arm							
Woman	$5.28^{\mathrm{M}, \mathrm{J}}$	0.42	0.59^{M}	4280.27^{M}	0.23	3980.27	147
	[0.25]	[0.04]	[0.11]	[64.46]	[0.02]	[95.10]	
Man	5.8^{W}	0.48^{J}	0.82^{W}	4445.27^{W}	0.27	4194.59	148
	[0.270	[0.04]	[0.13]	[71.96]	[0.02]	[118.85]	
Joint	5.73^{W}	0.37^{M}	0.69	4372.12	0.23	4085.4	226
	[0.21]	[0.03]	[0.09]	[51.76]	[0.02]	[78.53]	
By Labor Treatment Arm							
Woman	5.79^{M}	0.45	$0.5^{\mathbf{M}}$	4419.47^{M}	0.25	$4286.73^{\mathbf{M}}$	226
	[0.21]	[0.03]	[0.07]	[55.07]	[0.02]	[88.81]	
Man	5.37^{W}	3.05	$0.92^{\mathbf{W}}$	4306.85^{W}	0.24	$3868.95^{\mathbf{W}}$	219
	[0.21]	[0.03]	[0.12]	[53.86]	[0.02]	[79.86]	

Superscripts denote which treatment group a given variable's value is significantly different from. For treatment group comparisons in the first panel, superscripts are abbreviated such that the first letter marks the decision-maker and the second letter marks the laborer. For example, FM denotes a female-decision maker and a male laborer, while JW denotes a joint decision-maker and a female laborer. In the second and third panels, comparisons are only made across the decision-making and labor treatment arms.
Bolded superscripts denote a p-values <0.01, italicized superscripts denote p-values < 0.5, and superscripts that are neither bolded nor italicized denote p-values < 0.1

as good or better than their spouse at sorting beans. Coefficients are found by estimating Equation 2.

Table A.3.4: Conditional Differences in Means by Relatively Less Productive Laborers and Decision-Maker

	(1) Total Cups	(2) Proportion of Risky cups	(3) Unsorted Cups	(4) Expected Return	(5) Investment Std. Dev.	(6) Payment
Relatively Less Productive Laborer	-0.0233	-0.190	0.637**	-52.40	-0.0196	-494.5**
	(0.0926)	(0.360)	(0.286)	(150.6)	(0.0365)	(217.1)
Female Decision-Maker	-0.0856	-0.219	-0.201	-152.2	-0.0348	-359.4*
	(0.0753)	(0.246)	(0.291)	(117.5)	(0.0250)	(191.2)
Joint Decision-Maker	0.0328	-0.374	0.0250	-18.71	-0.0242	-104.6
	(0.0681)	(0.252)	(0.245)	(107.6)	(0.0245)	(189.2)
Relatively Less Productive Laborer x Female Decision-Maker	-0.0236	0.000468	-0.336	-27.45	0.0216	506.3*
	(0.137)	(0.475)	(0.437)	(205.1)	(0.0468)	(302.8)
Relatively Less Productive Laborer x Joint Decision-Maker	-0.198	0.176	-0.423	-192.5	0.00613	-54.36
	(0.130)	(0.504)	(0.431)	(198.6)	(0.0488)	(300.5)
Order Controls	Yes	Yes	Yes	Yes	Yes	Yes
Survey Controls	Yes	Yes	Yes	Yes	Yes	Yes
Session Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	445	427	445	445	445	445

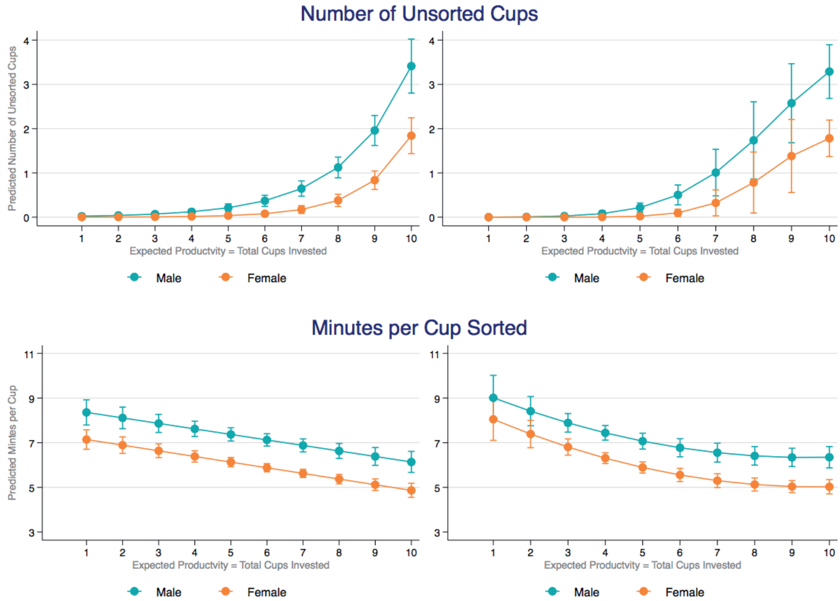
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. Standard errors are clustered at the treatment group – session level. Coefficients are found via estimation Equation 1. The Joint-Joint treatment group is excluded from the sample because the labor decision is endogenous. The coefficients for the total number of cups do not change when the base for the treatment group variables is changed.

Table A.3.5: Female and Male Laborers' Productivity by Decision-Maker Excluding Outliers

	(1) Minutes per Cup Sorted	(2) Minutes per Cup Sorted	(3) Minutes per Cup Sorted	(4) Minutes per Cup Sorted
Female-Female Base				
Male-Female	-0.106	-0.109	-0.121	-0.110
	(0.315)	(0.315)	(0.305)	(0.266)
Joint-Female	-0.110	-0.112	-0.0487	-0.111
	(0.310)	(0.310)	(0.299)	(0.222)
Male-Male Base				
Female-Male	0.145	0.146	0.0600	0.130
	(0.312)	(0.313)	(0.302)	(0.382)
Joint-Male	0.497	0.495	0.397	0.412
	(0.312)	(0.312)	(0.301)	(0.371)
Total Cups	-1.002***	-1.000***	-0.864***	-0.749***
	(0.145)	(0.145)	(0.142)	(0.186)
Total Cups Squared	0.0550***	0.0548***	0.0469***	0.0401***
	(0.0113)	(0.0114)	(0.0111)	(0.0136)
Order Controls	No	Yes	Yes	Yes
Survey Controls	No	No	Yes	Yes
Village Fixed Effects	No	No	No	Yes
N	489	489	489	489

Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. Standard errors in Columns 1-3 are not clustered, and standard errors in Column 4 are clustered at the session-treatment group level.
Coefficients are found via estimation Equation 3. The Joint-Joint treatment group is excluded from the sample because the labor decision is endogenous. The coefficients for the total number of cups do not change when the base for the treatment group variables is changed.

Figure A.3.1: Failure Rates and Productivity by Investment Level and Laborer Gender, Conditional on Controls and Village Fixed Effects



Predictive margins are reported for each investment level. The error bars display the 95% confidence levels. Standard errors are clustered at the treatment-session level.
The panels on the left and right display estimates from Equation 3 without the quadratic term and Equation 3, respectively. The estimations do not include control variables, or village fixed effects.

3.10 The Labor Cost Treatment

Half of the sessions included music and snacks in the bean-sorting area. The intention was that these would provide a distraction or an incentive to not work and therefore, adjust the labor costs of the participants. However, the intervention did not have the intended effect and was too weak to effect any changes. We encourage further research along these lines in real-effort tasks to find ways to exogenously affect labor costs. This is particularly important in gender studies because women tend to have higher marginal labor costs because they have more household duties than men. Table A.3.1 to Table A.3.7 show that the labor cost treatment had no overall effects, no heterogeneous effects by decision-maker, and no heterogeneous effects by laborer. The model estimating effects of the labor cost treatment by the decision-maker assigned is given by:

$$Y_i = \beta_0 + \beta_1 labor\ cost_k + \beta_2 decsion\ maker_i + \beta_3 labor\ cost_k \times decsion\ maker_i + \epsilon_i \qquad (A.1)$$

where k represents the session (as the treatment is given at the session level) and the decision-maker can be the man only, woman only, or both spouses together. The model estimating effects of the labor cost treatment by the laborer assigned is given by:

$$Y_i = \beta_0 + \beta_1 labor\ cost_k + \beta_2 laborer_i + \beta_3 labor\ cost_k \times laborer_i + \epsilon_i \quad \text{(A.2)}$$

where the laborer can be either the man, woman, or an endogenous selection. The results of the analysis are presented below in Table A.3.6 and Table A.3.7, which follow on the next pages.

Table A.3.6: Effect of Labor Cost Treatment on Experiment Outcomes by Decision-Makers

	(1) Total Cups	(2) Proportion of Red Cups	(3) Unsorted Cups	(4) Expected Return	(5) Investment Std. Dev.	(6) Payment
Labor Cost Treatment	0.0436	-0.453	-0.202	-0.0335	-0.0473	173.2
	(0.109)	(0.335)	(0.346)	(0.0355)	(0.0502)	(243.8)
Woman	-0.108	-0.536*	-0.287	-0.0529*	-0.0748*	-161.8
	(0.0888)	(0.297)	(0.245)	(0.0285)	(0.0403)	(237.4)
Joint	-0.0231	-0.478	-0.244	-0.0434	-0.0613	-72.38
	(0.0896)	(0.311)	(0.297)	(0.0319)	(0.0452)	(202.5)
Labor Cost Treatment # Woman	0.0259	0.667*	-0.127	0.0506	0.0715	-116.5
	(0.13)	(0.404)	(0.496)	(0.0375)	(0.053)	(285)
Labor Cost Treatment # Joint	0.0233	0.254	0.156	0.0323	0.0457	-80.28
	(0.134)	(0.432)	(0.449)	(0.0406)	(0.0574)	(253.6)
Order Controls	No	No	No	No	No	No
Survey Controls	No	No	No	No	No	No
Village Fixed Effects	No	No	No	No	No	No
N	521	501	521	521	521	521

Marginal effects reported for Columns 1-3; Significance levels: * p < 0.10, ** p < 0.05, *** p < 0.01. Standard errors in parentheses. Standard errors are estiamted via Poisson regressions in Columns 1-4 and OLS in Columns 5-7. Standard errors are clustered at the session level.
Coefficients are estimated via Equation A.1.

Table A.3.7: Effect of Labor Cost Treatment on Experiment Outcomes by Laborers

	(1)	(2)	(3)	(4)	(5)	(6)
	Total Cups	Proportion of Red Cups	Unsorted Cups	Expected Return	Investment Std. Dev.	Payment
Labor Cost Treatment	0.0101	-0.0401	-0.201	-12.50	-0.00651	113.8
	(0.0976)	(0.287)	(0.239)	(110.0)	(0.0343)	(192.1)
Woman	0.0363	0.187	-0.618**	65.76	0.0177	416.4**
	(0.0702)	(0.252)	(0.273)	(105.7)	(0.0330)	(203.4)
Joint	0.0440	-0.0175	-0.452	21.59	-0.0148	314.3
	(0.0791)	(0.332)	(0.278)	(142.8)	(0.0445)	(258.4)
Labor Cost Treatment # Woman	0.0758	-0.136	0.0408	96.40	0.000756	-6.285
	(0.0951)	(0.371)	(0.428)	(154.0)	(0.0480)	(252.6)
Labor Cost Treatment # Joint	0.0964	-0.471	0.278	131.5	-0.0195	-142.5
	(0.120)	(0.513)	(0.522)	(218.0)	(0.0680)	(297.3)
Order Controls	No	No	No	No	No	No
Survey Controls	No	No	No	No	No	No
Village Fixed Effects	No	No	No	No	No	No
N	521	501	521	521	521	521

Marginal effects reported for Columns 1-3; Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. Standard errors are estiamted via Poisson regressions in Columns 1-4 and OLS in Columns 5-7. Standard errors are clustered at the session level.
Coefficients are estimated via Equation A.2.

Chapter 4

Shocked into Side-Selling? Production Shocks and Organic Coffee Farmers' Marketing Decisions in Peru

Peru is the world's leading exporter of organic coffee. Organic coffee production in Peru is largely dependent on farmers' cooperatives which have helped small coffee farmers transition to organic production, earn price premiums over conventional coffee in more lucrative global specialty coffee markets, and access extension services and finance. However, rising temperatures, increasingly volatile rainfall patterns, and the proliferation of pests and diseases make organic production riskier, as organic farmers cannot rely on agrochemicals to protect their farms against production shocks. If members of organic coffee cooperatives respond to production shocks by increasing their sales to private buyers ('side-selling'), then cooperatives' financial health could be threatened through reduced bargaining power with buyers and a decrease in scale economies. This paper explores the economic incentives (liquidity, production scale, fixed costs to marketing, and risk preferences) for members to side-sell in the event of a production shock and gives empirical evidence of how production shocks influence side-selling using panel data from members of two Peruvian specialty coffee cooperatives in 2013 and 2015. The study period coincides with a widespread production shock – the Coffee Leaf Rust epidemic of 2012/13 that decimated coffee production in Peru and across Latin America in the past decade. We find that there is suggestive, albeit non-causal, evidence that the incidence of Coffee Leaf Rust on farms is correlated with increased side-selling overall. Particularly, members with high risk tolerance and high levels of non-coffee income increase side-sales when affected by production shocks. We contend that rather than alleviating demand for liquidity and reducing side-selling, non-coffee income enables households to incur fixed costs to private marketing when affected by a shock. This paper contributes to a growing literature on the determinants of side-selling in agricultural cooperatives by examining the role of production shocks in side-selling decisions, extending existing theoretical frameworks, and analyzing determinants using panel data methods. The paper underscores the need to understand small farmers' coping mechanisms to production shocks and their potential influence on institutions in the face of climate change.

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4.1 Introduction

Coffee is one of the world's most important agricultural commodities, consisting of 19 billion USD in global exports in 2017 (Voora et al., 2019). Coffee is almost exclusively produced in low and middle income countries and is the main income source for millions of people. Despite its massive global scale, small farms produce 70% of coffee globally (Panhuysen and Pierrot, 2014). Small coffee farmers' incomes and livelihoods are dependent on volatile international coffee prices, which can have detrimental household welfare effects (Mohan et al., 2014). Specialty coffee (e.g. fair-trade, organic coffee), whose market has grown drastically in Europe and the United States in recent decades, offers an alternative to tumultuous markets (The International Trade Centre 2004; Voora et al. 2019). On global markets, specialty coffee prices are higher and less volatile than conventional coffee prices (Bissinger 2019; Simatovic and Remy 2007).

To take advantage of these economic benefits, specialty coffee cooperatives (cooperatives dealing primarily in certified organic and/or fair trade coffee) have taken hold in many producing countries, particularly in Latin America (Linton 2008; Simatovic and Remy 2007). Peru is the world's leading exporter of organic coffee, a position largely achieved through a long history of active coffee cooperatives (USDA 2020; Simatovic and Remy 2007). These cooperatives can help households gain access to certification that would have prohibitively high costs for individual farms, but not for a collective of farmers (Barrett et al., 2001). They also provide technical assistance to farmers who want to make the transition from conventional to organic production (Bissinger, 2019). Further, members benefit from cooperatives' ability to leverage scale economies to reduce transaction costs (Bacon 2005; Stockbridge et al. 2003) and increase bargaining power (Thorp et al., 2005). Extra profits generated by cooperatives are typically channeled to members through price premiums and/or dividends paid to members at the end of the season (Enelow, 2014). Both certification and cooperative membership are generally associated with improved welfare outcomes for small farmers (Bray and Neilson 2017; Grashuis and Ye 2019).[1]

Climate change threatens the benefits offered by organic coffee farming and cooperative membership. Rising temperatures and increasingly volatile climatic patterns threaten coffee production and quality while also creating conditions for the proliferation of pests and diseases that can decimate coffee harvests (DaMatta and Ramalho 2006; Jaramillo et al. 2011). These trends are expected to continue in the foreseeable future (Marengo et al., 2014). Organic farmers are particularly vulnerable to these threats because pesticides and fungicides are often non-organic (Torres Castillo et al., 2020). Such risks can reduce income and reduce capacity to make investments in longer-term organic solutions (e.g. cultivation of new varieties) to building resistance to climate change, pests, and diseases.[2]

[1] More specifically, transitioning to organic farming reduces farmers' reliance on input markets, increases the long-term environmental sustainability of coffee farming (Bissinger, 2019), increases household income over time (Meemken, 2020), and increases household assets (Ruben and Fort, 2012). Membership in agricultural cooperatives has generally been shown to improve farmers' livelihoods through increased technology and input adoption (Abebaw and Haile 2013; Ma and Abdulai 2016; Zhang et al. 2020), improved productivity (Ortega et al. 2019; Verhofstadt and Maertens 2014; Ma and Abdulai 2016), and improved incomes (Wollni and Zeller 2007; Markelova et al. 2009; Ma and Abdulai 2016; Mojo et al. 2017). In a review of peer-reviewed publications, Grashuis and Ye (2019) finds that cooperative membership generally improves members' outcomes across the aforementioned factors; however, there is heterogeneity between large and small farmers and across organizational structures.

[2] Improved varieties are one of the only organic solutions to building resistance to diseases, such as Coffee Leaf Rust. Switching to new varieties takes time, however. Once planted or grafted, coffee trees take 2 to 3 years to

If cooperative members change their marketing strategies through increased side-selling when afflicted with production shocks, then the effects of a changing climate could extend beyond (organic) farms and impact the financial health of specialty coffee cooperatives. While the influence of shocks in cooperative side-selling has yet to be explored, farmers have been shown to disengage from contract farming arrangements when affected by shocks (Barrett et al., 2012). In the context of agricultural cooperatives, such disengagement can be detrimental to the cooperative's ability to offer its members benefits, putting in jeopardy farmers' welfare gains from joining cooperatives (Sexton and Iskow 1988; Mosheim 2008; Grashuis and Ye 2019). Side-selling creates uncertainty in the supply of coffee the cooperative can sell, making it harder to meet contractual obligations and have healthy long-term relationships with buyers (Murray et al., 2006). Lower supplies also reduce revenue and margins for cooperatives, resulting in lower dividends paid to members and decreased capacity to provide access to inputs, extension, and other services. Finally, side-selling presents a free-rider problem where members may extract services from the cooperative, but do not contribute to building cooperative resources (Mujawamariya et al., 2013).

Production shocks can be correlated with side-selling through mechanisms related to scale economies, liquidity, fixed costs to marketing, and risk preferences. Production shocks reduce farm output, which decreases the ability of households to take advantage of scale economies of private markets. Side-selling behavior of organic vegetable growers in South Africa provides evidence of this mechanism – large farmers are the most likely to free-ride (Gadzikwa et al., 2007). Wollni and Fischer (2015) proposes the scale economies mechanisms in a theoretical framework, but also shows that large farmers have the most to benefit from cooperatives' delayed dividends (because they have relatively low discount rates). Small farmers do not have the scale to sell on private markets, and large farmers can afford to wait for cooperative dividends. Consequently, small and large farmers are the most committed members in Costa Rican coffee cooperatives, while medium-sized farmers are the most likely to side-sell (Wollni and Fischer, 2015).

Access to non-coffee liquidity sources can either reduce or facilitate side-selling for farmers affected by production shocks. Cooperative payments and dividends are delayed, and often prefinancing arrangements are not available to relieve farmers' liquidity demand between delivery and payment (Enelow, 2014). Small farmers have higher discount rates than large farmers, and higher demand for liquidity incentivizes farmers to sell on private markets where they receive payment upon delivery (Hazell 2000; Wollni and Fischer 2015). When impacted by production shocks, output decreases and demand for liquidity increases, potentially leading to an increase in side-selling. Being highly dependent on coffee for income and liquidity gives incentives to farmers to side-sell, as they cannot get liquidity through other means. In Ethiopian barley cooperatives, households with a higher percentage of land devoted to barley side-sell more frequently (Alemu et al., 2020). Analogously, having non-coffee sources of liquidity and/or income could diminish liquidity demand and reduce side-selling. For example, households with higher outstanding credit tend to side-sell less (Wollni and Fischer, 2015).[3] However, liquidity can also facilitate side-selling by helping farmers cover fixed costs to private marketing (e.g. search costs). This suggestion is corroborated by Fischer and Qaim (2011), which shows that more diversified farmers tend to side-sell more frequently in Kenyan banana cooperatives.

Risk preferences are likely to be correlated with side-selling decisions for households af-

produce cherries, making changes in varieties a long-term, rather than short-term, solution to to mitigating the effects of Coffee Leaf Rust (Abate et al., 2021)

[3]This result may reflect a member commitment mechanism, however. When credit is given by the cooperative, members may feel more committed to the cooperative and engage in fewer private sales.

fected by shocks. Exposure to climate shocks in production are likely to reduce risk-taking in other domains (Barrett et al., 2012). Since Peruvian specialty cooperatives typically offer greater price stability than private markets, more risk averse farmers may be more likely to sell to the cooperative if affected by a production shock. When cooperatives offer more stable prices, risk aversion is associated with greater sales to the cooperative (Mujawamariya et al., 2013). In other cases, when cooperatives delay payments, farmers may be worried that the cooperative will default on their payments. In such cases, more risk averse farmers are more likely to sell on the private market, even if the cooperative offers a price premium (Woldie, 2010). When there is uncertainty around payment timing, risk aversion is positively associated with side-selling (Arana-Coronado et al., 2019).

Based on theory and evidence of the scale economies, liquidity demand, fixed costs, and risk preferences mechanisms, the correlations between production shocks and side-selling are unclear *a priori*. To date, no study has explored the relationship between production shocks and side-selling, despite the increasing exposure to climate shocks, pests, and diseases (DaMatta and Ramalho 2006; Jaramillo et al. 2011). Further, only one study analyzes the determinants of side-selling in specialty coffee cooperatives (Arana-Coronado et al., 2019). As specialty coffee becomes more prominent in global markets, a greater focus on specialty coffee cooperatives is needed (Voora et al., 2019).

This paper studies the role of production shocks in side-selling decisions using panel data analysis based on household surveys administered to members of two Peruvian specialty coffee cooperatives between 2013 and 2015. The data collection coincides with the Peruvian Coffee Leaf Rust epidemic of 2012-13, which swept Latin America in the early 2010s, allowing for an analysis of production shocks and side-selling behavior. Further, we explore how production shocks influence side-selling through the four mechanisms discussed above: scale economies, liquidity demand, fixed costs to marketing, and risk preferences. These mechanisms are analyzed both theoretically (through extending the models of (Woldie, 2010) and (Wollni and Fischer, 2015)) and empirically.

We find that on average, production shocks (measured via incidence of plant disease on a farm) are positively, but insignificantly, correlated with side-selling across time. However, households with relatively high levels of non-coffee income sell a higher proportion of their coffee to private channels when inflicted with a production shock. This suggests that liquidity (proxied by non-coffee income) likely plays a larger role in covering fixed costs to marketing on private markets than reducing liquidity demand to encourage more sales to cooperatives. Additionally, members that are more risk tolerant are more likely to side-sell than relatively risk-averse farmers, consistent with the idea that exposure to shocks reduces risk-taking for risk averse farmers.

Our findings are consistent with existing theoretical frameworks on side-selling (Woldie 2010; Wollni and Fischer 2015). Empirically, our results are consistent with Wollni and Fischer (2015), which finds a U-Shape relationship between farm size and member commitment. Our findings show that small farmers and larger farmers are more likely to sell through the cooperative than medium-sized farmers. Our results are also consistent with Arana-Coronado et al. (2019), Mujawamariya et al. (2013), Saitone et al. (2018), and Woldie (2010) who find that risk aversion is associated with increased sales through the less risky marketing channel (the cooperative in the context of this paper). However, we do not find significant associations between side-selling and attitudes or demographics in contrast to many papers in the literature (Alemu et al. 2020; Wollni and Fischer 2015; Meier zu Selhausen 2016). This non-finding could be a result of the panel data models being able to control for time-invariant household-level heterogeneity.

We make four contributions to the literature on the determinants side-selling. First, this is the first study to address the role of production shocks in side-selling decisions. Second, the side-selling literature relies on cross-sectional studies, and this is the first paper to use panel data methods to control for fixed individual characteristics while estimating the determinants of side-selling. Third, we extend the theoretical framework of Woldie (2010) and Wollni and Fischer (2015) to understand the role of fixed costs to marketing in side-selling decisions and to assess the liquidity demand and scale economies mechanisms in the context of production shocks. Finally, only one paper to date has focused on side-selling in specialty coffee cooperatives (Arana-Coronado et al., 2019), and we extend the empirical evidence to a new setting.

The rest of the paper is organized as follows. Section 4.2 describes the theoretical framework that builds upon Woldie (2010) and Wollni and Fischer (2015). Then, 4.3 presents the data used in the empirical analysis, and Section 4.4 discusses the empirical methodology used to measure the determinants of side-selling. Section 4.5 presents the main empirical results, and Section 4.6 concludes.

4.2 Theoretical Framework

The theoretical framework explains how farmers make marketing decisions between private and cooperative buyers given an exogenous coffee production quantity. Analytical solutions are derived, and comparative static analysis is used to understand how liquidity demand, scale economies, fixed costs to marketing, and risk preferences influence responses to exogenous production shocks. The model uses the theoretical framework of Woldie (2010) and Wollni and Fischer (2015) as a starting point, but certain assumptions and minor features are adjusted to reflect the Peruvian specialty coffee cooperative context. Wollni and Fischer (2015) proposes that there are two key mechanisms that determine side-selling: liquidity demand and scale economies. Small farmers have a higher discount rate and a higher demand for liquidity (Hazell, 2000). Since the cooperative dividend is paid at a later date, demand for liquidity leads to side-selling. Meanwhile, larger farmers can leverage scale economies to more profitably operate in the private market. We extend the existing models by including price risk in an isoelastic utility function (as opposed to a simple coefficient, as in Woldie 2010 and its exclusion altogether in Wollni and Fischer 2015). This introduces decreasing absolute risk aversion (DARA) to the model, which explains why production shocks may reduce risk taking in marketing decisions. We also include an exogenous cash endowment (i.e. cash from non-coffee sources), which is introduced along with fixed costs to marketing. The theoretical analysis is then extended to explore how the households choose their marketing outlets after experiencing a production shock.

This section first presents the main hypotheses of the theoretical framework. We then introduce the utility function, followed by a presentation of the the private and cooperative marketing channels for farmers' coffee. The optimal shares to private and cooperative buyers are shown with the derivation in Appendix 4.A. Finally, we show the comparative statics of the model with respect to quantity produced, the exogenous cash endowment, and risk/risk preferences to show the main results of model.

4.2.1 Hypotheses

The theoretical model highlights the mechanisms behind coffee farmers' marketing decisions. It first shows that even in the context of cooperative price premiums, the predictions of Wollni and Fischer (2015) hold – side-selling is increased by scale economies and demand for liquidity. Medium-sized farmers side-sell more frequently because small farmers do not have the scale to side-sell and large farmers do not have the demand for liquidity to side-sell. We extend the model to show three propositions with respect to production shocks:

Proposition 1 *Production shocks can increase side-selling through an increase in farmers' discount rates. However, production shocks reduce scale economies and make it less profitable for households to pay fixed costs to marketing on private channels, which can decrease side-selling.*

Proposition 2 *The effect of liquidity from non-coffee sources on side-selling is ambiguous. An exogenous cash endowment can mitigate the increase in side-selling from production shocks by crowding out demand for liquidity from coffee sales on the private market. However, the cash endowment can also facilitate side-selling by giving households a greater capacity to incur fixed marketing costs.*

Proposition 3 *When cooperatives offer more stable prices than private buyers, risk aversion mitigates the increase in side-selling from production shocks because households have decreasing absolute risk aversion.*

4.2.2 The Utility Function

The marketing decision of coffee cooperative members farmers can be thought of as a portfolio problem whereby farmers maximize utility by choosing between a risk-free and risky marketing channel in an isoelastic utility function. The general utility function is given as:

$$U = \frac{(I+E)^{1-\gamma} - 1}{1-\gamma} \text{ for } \gamma \neq 1 \tag{4.1}$$

where I is total income, E is a cash endowment, and γ is the coefficient of relative risk aversion. The cash endowment is assumed to be exogenous (i.e. it is cash from non-coffee sources). We assume that farmers are risk averse, a claim that has been shown by (Vieider et al., 2013). Further, households have decreasing absolute risk aversion (DARA), resulting in the assumption that $0 < \gamma < 1$. This implies that as households have higher incomes (either from coffee or non-coffee sources), then they will be willing to take more risks in marketing.

In the context of the isoelastic utility function, income is derived from a risky income source and a risk-free income source. The proportion of the portfolio allocation going to the risky source is δ and the portion allocated to the risk-free source is $1-\delta$. Let the expected payoff of the risky asset be μ and the payoff of the risk-less asset be r. We assume that the risky source has a higher expected payoff than the risk-free source (i.e. $\mu > r$), otherwise there would be no incentive to allocated sales to the risky source.

Income from the risky source is stochastic and follows a lognormal distribution such that $\log(I) \sim \mathcal{N}(\mu, \sigma^2)$, where μ is the expected income and σ^2 is the variance of income. The log distribution of income is given by:

$$\ln I + E \sim \mathcal{N}(E + r + \delta(\mu - r) - \frac{\delta^2\sigma^2}{2}, \delta^2\sigma^2) \tag{4.2}$$

Because e is the inverse of ln, and the expected log-normal income is $r+\delta(\mu-r)-\frac{\delta^2\sigma^2}{2}$, the expected income and the cash endowment can be inserted into the utility and the maximization problem Equation 4.A.4. Appendix 4.A shows how this maximization problem becomes:

$$\max E + r + \delta(\mu - r) - \frac{1}{2}\delta^2\sigma^2\gamma \,\forall\, \gamma \neq 1 \tag{4.3}$$

In Appendix 4.A, we see that taking the derivative and solving for δ, we get the general solution to the portfolio decision problem:

$$\delta^* = \frac{(\mu - r)}{\sigma^2\gamma} \tag{4.4}$$

4.2.3 Marketing Channels

The quantity of organic coffee produced is given by Q and assumed to be exogenous. Farmers can choose to sell a proportion, δ, of their quantity produced on the private market and a proportion, $1 - \delta$ to cooperatives. They receive price, p_p for each unit sold to private buyers and price, p_c, for each unit sold to the cooperative. In Peru, cooperatives offer higher sales prices and cooperative dividends. For this reason, we assume that there is a premium, such that $p_c = p_p + x_c$, where x_c the price premium cooperatives gain from selling specialty coffee. However, the cooperative offers delayed prices, while private prices are paid on the spot. In the model, private payments are not discounted while cooperative payments have a discount rate, $\beta(Q, E)^{t_p}$. Following Wollni and Fischer (2015), the discount rate is a decreasing function of quantity because smaller farmers tend to have higher discount rates than larger farmers (Hazell, 2000). The discount rate is also a function of the cash endowment. t_p represents the time delay in payment. Households are assumed to be price takers and their individual decisions do not affect the viability of the cooperative.[4] Revenues from private and cooperative sales are respectively given by:

$$\begin{aligned} R_p &= p_p\delta Q \\ R_c &= (p_p + x_c)(1 - \delta)Q\beta(Q, E)^{t_p} \end{aligned} \tag{4.5}$$

Side-selling is possible under the assumption that $x_c < x^*$, where x^* is the premium at which the household is indifferent between private and cooperative sale and is defined as $x_c^* = \frac{p_p}{\beta(Q,E)^{t_p}} - p_p$. Intuitively, this means that a cooperative price premium must be sufficiently high to compensate for the delay in payment in order for no side-selling to occur.

At the end of the season, cooperatives offer dividend payments, d_c.[5,6] Following Wollni and Fischer (2015), the cooperative dividend is based on international prices and the total quantity sold to the cooperative. Since the cooperative leverages economies of scale, the cooperative dividend rate is a an increasing function of total quantity sold:

$$R_d = (1 - \delta)Q(p_x - p_c)^{\alpha}\left(\sum_{j=1}^{N}(1 - \delta_j)Q_j\right)^{(\alpha-1)}\beta(Q, E)^{t_d} \tag{4.6}$$

[4] This assumption may be not be realistic because it assumes the viability of the cooperative is exogenous. Farmers may note that the cooperative is able to fail and reduce their side-selling in an effort to maintain the cooperative as a viable institution. Further, the presence of a cooperative affects prices offered on private markets, but this is assumed to not occur in the model.

[5] The model can be mirrored by letting the private market have a price premium, as is the case in other settings (e.g. Costa Rica, Wollni and Fischer 2015). However, we have chosen to express the model in terms of the Peruvian context, instead of a more general framework.

[6] Peruvian cooperatives typically set a delivery price at the beginning of the season, (i.e. p_c), and determine the dividend at the end of season, taking into account international prices.

where p_x is the export price received by the cooperative, the α parameter imposes decreasing marginal returns to both profit margins and quantity sold by the cooperative on dividends and implies differential returns for each factor (prices and quantity). Total quantity sold to the cooperative is given by $\sum_{j=1}^{N}(1-\delta_j)Q_j$, following Wollni and Fischer (2015).[7] Each farmer is paid a dividend proportional to their sales to the cooperative with a delay of t_d. Intuitively, this shows that the cooperative dividend an individual farmer receives is a function of international price margins, the quantity sold by all members to the cooperative (economies of scale), and an individual's discount rate. Total revenue is the sum of R_p, R_c, and R_d. These assumptions reflect the context described in Section 4.3.

Private sales also assumed to be more volatile than cooperatives' prices, reflecting the lower volatility in specialty (particularly, fair trade) coffee markets (Bacon, 2013). To simplify the model, we assume that cooperative payments are risk-free, while private payments are log-normally distributed with mean p_p and variance σ^2 (i.e there is a risk premium). However, private buyers offer quicker payments than cooperatives. The marketing risk premium is given by:

$$\text{private risk premium} = \delta^2\sigma^2 \tag{4.7}$$

In terms of revenue, the advantage of selling to private buyers versus specialty coffee co-operatives is quicker payment times. The extent to which households prefer quicker, but lower and riskier, payments is determined by their discount rates, which are a decreasing function of quantity.

Selling on each marketing channel carries variable and fixed costs as well. Variable costs are accounted for by reducing the unit sale price in a given marketing channel. Fixed costs are only observed for a marketing channel if a household sells a positive quantity of coffee on that channel. If the household does not sell on a particular channel, fixed costs are not incurred. Fixed costs for the cooperative channel can come for example, from membership fees (usually paid at the onset of membership) or time spent participating in cooperative activities. Fixed costs to the private channel can result from search costs to finding traders and building trust in traders. Since cooperatives dominate the organic coffee sector in Peru, the search costs for finding a private organic coffee trader may be high.[8]

Farmers can exploit economies of scale in delivering coffee to both cooperatives and private buyers. However, economies of scale should be more important in private markets where buyers can facilitate transport (rather than farmers delivering to pickup points) or other cost-reducing measures with large farmers. In cooperatives, all farmers are treated equally, so no such measures exist for large farmers. Therefore, the economies of scale parameter is assumed to be zero for cooperative sales and only exists for private sales. The costs of selling to private and cooperative buyers are respectively given by:

[7] For ease of presentation, we have not included i subscripts to denote the representative household of interest, but use the j subscript to represent quantity of another household

[8] Cooperatives can leverage their scale to offer organic certification. Therefore, to sell organic coffee outside of the cooperative (as organic coffee and not conventional coffee), the household would need to find a trader with sufficient scale to be in the organic value chains. This is not the typical trader (otherwise, the cooperative's comparative advantage would be diminished). In addition to the rare organic trader, households may potentially also sell to other, further away, cooperatives (which may include costs of membership as well as arranging for transportation across large distances), or through other farmers within the cooperative (which would also require finding willing farmers and costs of arranging marketing deals). All of these mechanisms require fixed costs and can be thought of as selling on the private channel.

$$\begin{cases} C_p = c_1^p \delta_i Q - \frac{c_2^p}{2}(\delta_i Q)^2 + f_p & \text{if } \delta > 0 \\ C_p = 0 & \text{if } \delta_i = 0 \\ C_c = c_1^c(1-\delta)Q + f_c & \text{if } \delta < 1 \\ C_c = 0 & \text{if } \delta_i = 1 \end{cases} \tag{4.8}$$

where c_1^p and c_1^c are the linear costs for private and cooperative sales, respectively. c_2^p is the economy of scale term for private buyers (and can be thought of as the private scale economies premium over the cooperative scale economies parameter). f_p and f_c are the fixed costs associated with selling to private buyers and the cooperative, respectively. f_p and f_c are only incurred if the household respectively sells to private buyers and/or the cooperative. Fixed costs can be paid for out of a cash endowment, which is introduced in the next section.

4.2.4 Optimal Shares

In terms of the utility framework, the private profits are μ (the risky payoff) and the cooperative profits are r (the safe payoff). This means that the maximization problem with the cash endowment becomes:

$$\begin{aligned} &\max\, [E + p_p\delta Q + (p_p + x_c)(1-\delta)Q\beta(Q,E)^{t_p} + R_d] \\ &- [c_1^p\delta Q - \frac{c_2^p}{2}(\delta Q)^2 + c_1^c(1-\delta_i)Q] \\ &- \frac{1}{2}\delta^2\sigma^2\gamma \\ &\forall\, \gamma \neq 1 \end{aligned} \tag{4.9}$$

The optimization first solves for an interior solution, and then checks whether this solution gives higher utility than either of the two corner solutions. To find the interior solution, utility is maximized by setting the marginal utility of private (and by default cooperative) sales to zero. Appendix 4.A shows the derivation of the optimal share (the interior solution) sold to private markets, which is given by:

$$\begin{aligned} &\delta^* = \frac{p_p - (p_p + x_c)Q\beta(Q,E)^{t_p} + \frac{\partial R_d}{\partial \delta} - c_1^p Q - c_1^c Q}{c_2^p Q^2 + \sigma^2\gamma} \\ &\text{where} \\ &\frac{\partial R_d}{\partial \delta} = -Q(p_x - p_c)^\alpha (\sum_{j=1}^{N}(1-\delta_j)Q_j)^{(\alpha-1)}\beta(Q,E)^{t_d} \end{aligned} \tag{4.10}$$

The household then evaluates whether the interior solution yields a higher utility than the corner solutions by evaluating the value function at each of the three possible cost regimes from Equation 4.8. Households choose to use their endowment following whichever regime maximizes utility from the following possibilities:

$$\begin{cases} U(I(\delta^*) + E - f_p) & \text{if } \ \delta = 1 \\ U(I(\delta^*) + E - f_c) & \text{if } \ \delta = 0 \\ U(I(\delta^*) + E - f_p - f_c) & \text{if } \ < \delta < 1 \end{cases} \tag{4.11}$$

Intuitively, the household chooses a δ^* between 0 and 1 if utility is higher from selling on both the private market and to the cooperative (and incurring the fixed costs of both) than selling (and incurring the fixed costs) on only one channel. The household will sell through only one channel if the utility after incurring fixed costs is higher than selling on two channels.

Selling to the private market becomes profitable when the optimal solution yields a utility higher than that of the solution when only selling to the cooperative. Similarly, selling the cooperative is only profitable when the optimal solution yields a utility that is higher than the utility from only selling to the private market. These threshold values change based on the parameters, and we explore three key parameters: the quantity of coffee produced, the level of the cash endowment, and risk preferences.

4.2.5 Comparative Statics

This section displays the comparative statics of the optimal side-selling share solution, δ^*, in the context of the propositions put forth above. We first discuss the mechanisms at play in isolation and then discuss how these mechanisms affect responses to production shocks. Scale economies and liquidity demand create an inverse U-shape side-selling response in relation to farm size – the main hypothesis in Wollni and Fischer (2015). Cash from non-coffee sources can reduce side-selling by relieving liquidity demands or increase side-selling by helping hosueholds incur fixed costs to marketing. Since cooperatives offer more stable prices, risk aversion is associated with lower side-selling.

When inflicted with a shock, side-selling increases through heightened liquidity demand. Additionally, widespread shocks (such as the Coffee Leaf Rust epidemic) reduce the cooperative dividend through decreased deliveries to the cooperative (such that scale economies are reduced at the cooperative level). On the other hand, shocks reduce farmers' scale economies and the profitability of incurring fixed costs to marketing on private markets. In the event of a production shock, cash from non-coffee sources can either alleviate liquidity demands or help households cover fixed costs to marketing, creating an ambiguous effect. Risk aversion reduces side-selling when households face production shocks. Since households have decreasing absolute risk aversion, a decrease in quantity produced discourages risk-taking on private markets.

Scale Economies and Liquidity: Liquidity demand and scale economies drive side-selling, creating an inverse U-shape side-selling curve with respect to size – small and large farmers are more likely to sell to the cooperative, while midsize farmers are more likely to side-sell. Liquidity demands and scale economies incentivize side-selling in spite of the price premiums and reduced price risk offered by cooperatives, but work in opposite directions. Appendix 4.B shows the derivation of the comparative static of δ^* with respect to quantity, Q. Equation 4.12 shows the rearranged comparative static such that the left-hand side is the percent change in side-selling from changes in liquidity demand mechanism and the right-hand side is the percent change in side-selling from the scale economies mechanisms. If the liquidity effect outweighs the scale economies effect, then an increase in quantity will increase side-selling, while if the scale economies effect outweighs the liquidity effect, then an increase in quantity will decrease side-selling.

For small farmers, the scale economies effect is likely to be smaller than the liquidity demand effect (as Q^2 is in the denominator of the right-hand side of Equation 4.12). Increases in quantity will incentive side-selling. Conversely, the scale economies mechanism is likely to play a larger role for large farmers, and an increase in the quantity of organic coffee produced will decrease side-selling. As a result, side-selling is driven by medium-sized farmers, and there is an inverse U-shape pattern with respect to side-selling, as in (Wollni and Fischer, 2015).

$$\frac{[-(p_p+x_c)t_p\beta(Q,E)^{t_p-1}\frac{\partial\beta'(Q,E)}{\partial Q}+\frac{\partial R_d}{\partial\delta\,\partial Q}-c_1^p-c_1^c]}{[p_p-(p_p+x_c)Q\beta(Q,E)^{t_p}+\frac{\partial R_d}{\partial\delta}-c_1^pQ-c_1^cQ]}\lesseqgtr\frac{[2c_2^pQ]}{[c_2^pQ^2+\sigma^2\gamma]}$$
$$\text{where }\frac{\partial R_d}{\partial\delta\,\partial Q}=[-(p_x-p_c)^\alpha(\sum_{j=1}^{N}(1-\delta_j)Q_j)^{\alpha-1}][\beta(Q,E)^{t_d}-Qt_d\beta(Q,E)^{t_d-1}\frac{\partial\beta(Q,E)}{\partial E}] \tag{4.12}$$

Cash from non-coffee sources: Cash from non-coffee sources (i.e. the cash endowment) can reduce side-selling through the liquidity demand mechanism or increase side-selling through the fixed costs mechanism. In terms of liquidity, Equation 4.13 shows that the comparative static of side-selling is negative with respect to the cash endowment. Since the discount rate, $\beta(Q,E)$ is a decreasing function of both quantity, Q, and the cash endowment, E, then higher values of the cash endowment result in lower discount rates and higher discounted returns on cooperative sales. As a result, side-selling decreases.

$$\begin{aligned}\frac{\partial\delta^*}{\partial E}=&-(p_p+x_c)t_pQ\beta(Q,E)^{t_p-1}\frac{\partial\beta(Q,E)}{\partial E}\\&-Qt_d(p_x-p_c)^\alpha(\sum_{j=1}^{N}(1-\delta_j)Q_j)^{(\alpha-1)}\beta(Q,E)^{t_d-1}\frac{\partial\beta(Q,E)}{\partial E}\end{aligned} \tag{4.13}$$

In the comparing the interior solution and the corner solutions (Equation 4.11), the endowment plays a role in increasing utility and (potentially) covering fixed costs. At minimum, coffee-producing households must participate in either the private market (Case 1 in Equation 4.8) or the cooperative market (Case 2 in Equation 4.8). To demonstrate how the endowment can increase side-selling, assume $f_c<f_p<E<f_c+f_p$, such that the endowment can cover either the fixed cost to the cooperative or the fixed costs to private markets, but not both. If the endowment increases, such that $E\geq f_c+f_p$, then the household can participate in both markets, and potentially increase utility (depending on the interior solution, δ^*).[9] Generally, we assume that households are more likely to sell to the cooperative by default and only sell to the private market if costs permit.[10] Intuitively, the cash endowment can give households the ability to cover fixed marketing costs to private sellers and increase side-selling.

Risk Preferences: Risk aversion and risk decrease side-selling. Equation 4.14 shows that the comparative static of δ^* with respect to γ is negative. When risk aversion increases, side-selling to the risky channel decreases. Since all farmers are assumed to be risk averse, households have a risk-based disincentive to sell on the private market. The results can be also interpreted in terms of risk, σ^2, as well – an increase in price risk on the private market results in in a decrease in sales to the private market. An analogous comparative static and interpretation holds for price risk, σ^2.

$$\frac{\partial\delta^*}{\partial\gamma}=-\frac{(p_p-(p_p+x_c)Q\beta(Q,E)^{t_p}+\frac{\partial R_d}{\partial\delta}-c_1^pQ-c_1^cQ)(\sigma^2\gamma)}{(c_2^pQ^2+\sigma^2\gamma)^2}<0 \tag{4.14}$$

[9] This process can also occur through changes in income (and therefore, quantity), as income can be used to cover fixed costs.

[10] This assumption is based on the relatively low rates of selling to private markets compared to cooperative sales and the fact that cooperatives offer both monetary and non-monetary benefits.

Proposition 1: Production shocks can increase side-selling by increasing the liquidity effect, decreasing the fixed cost effect, and decreasing cooperative dividends. Only the increase in the scale economies effect can reduce side-selling in the event of a shock. These Effects are mediated by risk aversion and outside liquidity.

Equation 4.14 shows the comparative static with respect to risk preferences. When discussing the inverse U-Shape of side-selling with respect to quantity, these results are discussed in terms of an increase in quantity, but a production shock is just the opposite. When quantity decreases, the liquidity demand effect increases (the left-hand side of Equation 4.14 increases) and the scale economy effect decreases (the right hand side of Equation 4.14 becomes smaller), causing respective decreases and increases in side-selling.

Shocks affect two other mechanisms – the fixed cost effect and the cooperative dividend. Following the logic of Proposition 3, the household has less cash to pay for fixed costs, and is therefore more likely to sell to the cooperative. Further, if the shock is widespread (as is the case with Coffee Leaf Rust), then overall sales to the cooperative decrease (a decrease in $Q_j \; \forall \; j$), resulting in lower returns to scale for the cooperative. In this event, the cooperative dividend decreases, along with the returns from selling to the cooperative. By assuming that δ_j is exogenously determined (for simplicity), this mechanism can be seen from the comparative static of $\frac{\partial R_d}{\partial \delta}$ with respect to Q_j:

$$\frac{\partial R_d}{\partial \delta \, \partial Q_j} = -Q(1-\delta_j)(\alpha-1)(p_x-p_c)^{\alpha}(\sum_{j=1}^{n}(1-\delta_j)Q_j)^{\alpha-2}\beta(Q,E)^{t_d} < 0 \tag{4.15}$$

In other words, when total quantity sold to the cooperative increases (decreases), then side-selling with respect to the cooperative dividend will decrease (increase). During a shock, the dividend decreases and side-selling increases. The overall effect of a shock will depend on the relative importance of each of these mechanisms. If sum of the liquidity, fixed costs, and cooperative dividend effects is larger than the scale economies effect, then side-selling will increase, and vice versa. The scale economies effect will only outweigh the other effect in the case of large farmers, so we expect that shocks will generally increase side-selling.

Proposition 2: Equation 4.15 shows that the cash endowment decreases (increases) the liquidity effect of increases (decreases) in Q in Equation 4.15 (because the discount rate is also a function of E). This means that when there is a shock to quantity (i.e. Q decreases), the outside cash endowment reduces the resulting increase in liquidity demand and reduces side-selling on the market. On the other hand, the fixed costs effect can also be in play and E could increase the ability of households to sell on private markets during a production shock.

Proposition 3: It is trivial to note that the right-hand side of Equation 4.12 decreases when the risk parameters increase. This is tantamount to an increase (decrease) in the relative effects of liquidity when quantity increases (decreases). For all farmers, a decrease in quantity produced increases the liquidity effect and side-selling, but risk aversion mitigates this increase because households become more risk averse when quantity decreases due to their decreasing absolute risk aversion.

4.3 Data and Study Context

4.3.1 Data Source

The empirical analysis uses a original panel dataset of Peruvian coffee farmers, who are members of one of two specialty coffee cooperatives in the northern part of the Cajamarca region

– Cooperativa Agraria Cafetalera La Frontera (Frontera) and the Cooperativa Agraria Cafetalera La Prosperidad de Chirinos (Chirinos). In 2013, 200 households were randomly selected from lists of 316 and 573 eligible farmers in Frontera and Chirinos, respectively. A household questionnaire was administered to each of the selected households to understand household demographics, farm characteristics, cooperative involvement, marketing decisions, and other respondent characteristics such as risk aversion. The survey was administered in January 2014 and January 2016.

The attrition rate from the first to second wave was 13.5%, as 29 farmers were not interviewed in the second round. Appendix 4.C shows the differences characteristics of those participating in two rounds and those who dropped out of the study and confirms that there is no attrition bias – only one variable (expenditure on labour) in 23 variables tested shows a statistically significant difference. The reasons why households dropped out of the sample is unclear. While it may be possible that these households switched to non-organic farming – in Mexico, there is evidence that after leaf rust outbreaks, farmers applied chemical fungicides to fight the disease (Valencia et al., 2018) – this switch would not have precluded them from participating in the second wave.

4.3.2 Data Measurement

The primary outcome variable is the percent of organic coffee sold to outside buyers. We focus on organic coffee because cooperatives do not purchase conventional coffee. This data is derived from survey questions concerning the amount of organic coffee sold to the cooperative and to private buyers. The main empirical specifications relate to the intensive margin – the share of coffee side-sold. Focusing on shares creates consistency with the theoretical framework and other studies (Wollni and Fischer 2015; Arana-Coronado et al. 2019). However, our theoretical framework extends Wollni and Fischer (2015) and Woldie (2010) to include fixed costs of marketing. The decision to incur these fixed costs is a decision that is made on the extensive margin. To understand these decisions better, an alternative outcome variable is used – an indicator for whether a member side-sells *any* organic coffee. Results related to this outcome variable are presented in Appendix 4.F.

The main explanatory variables are the percent of the farm affected by plant diseases, organic farm size, risk aversion , and the log of outside (non-coffee) annual income (which proxies non-coffee liquidity, albeit endogenously and imperfectly). For the exposure to Coffee Leaf Rust, farmers were asked how many organic trees were affected by plant diseases in the past year.[11] The measure of exposure to coffee plant diseases is the percentage of organic trees affected by diseases in a given year. Organic farm size is measured by asking farmers to recall the size in acres of their organic coffee farms. As a robustness check we also use farmer recall of the number of productive organic coffee trees on their farm and the total farm area (organic area, non-organic area, and non-coffee area). Risk attitudes were measured by asking respondents how much they would be willing to pay to participate in a standard raffle with potential winnings of 50, 100, and 1000 soles.[12] A higher willingness to pay indicates less risk aversion. Non-Coffee Income is measured as the log of self-reported total (in Soles) annual income from non-coffee sources.

The literature indicates that demographic factors, economic factors, and attitudes may be driving side-selling. The demographic variables measured are the sex, age, and number of

[11] While this measure encompasses all potential plant diseases, the context suggests that Coffee Leaf Rust was dominant plant disease during the study period

[12] 1 sol $\approx$ 0.35 USD in January, 2014

years of education of the household head, which have all been shown to influence side-selling (Alemu et al. 2020; Wollni and Fischer 2015; Meier zu Selhausen 2016). Economic variables include log expenditures on coffee installations and hired labor (in soles) (Enelow, 2014). Log loan amount (as a less common source of non-coffee liquidity), an indicator for whether a household's plots are organically certified or not, and an indicator for whether respondents are aware of fair-trade are also used as controls. Log outstanding loan amount is used as an alternative proxy for liquidity in robustness checks. The percentage of resistant coffee varieties on each farm is included as a control since resistant varieties are a source of heterogeneity in the propensity to be affected by leaf rust. Finally, a measure for distance in kilometers from the household to the cooperative is also used to proxy transaction costs of selling to the cooperative. Since data is not available to geo-locate each household, the center point of each household's *centro poblado* (the lowest administrative unit) is used.

A series of questions were asked concerning farmers' perception of and identification with the cooperative based on a Likert scale, as these factors have also been shown to influence side-selling (Arana-Coronado et al. 2019; Wollni and Fischer 2015; Fischer and Qaim 2011). Concerning the perception of the cooperative, respondents were asked five questions about the capacity of the cooperative to provide commercialization, technical assistance, inputs, credit, and improvements in coffee quality. For the identification with the cooperative, respondents were asked about whether they felt the cooperative was theirs, if other members felt the cooperative belonged to them, if they felt proud to be a part of the cooperative, if they felt committed to the cooperative, and if they shared the same values as the cooperative. A simple average of the five questions about perceptions and identification are calculated to create a perception and identification index, respectively. Alternative measures of attitudes towards cooperatives are used in Appendix 4.F. These measures are satisfaction with the cooperative and beliefs about the cooperative's effectiveness and are measured using Likert scales analogous to the perception and identification indices used in the main specification.

Finally, respondents were asked about historical side-selling and plant diseases from 2009 to 2012 in the first wave and 2014 in the second wave. These variables are used to describe side-selling and plant disease trends before and during the study period (Figure 4.2), but not in any main specifications.

4.3.3 The Cooperative Environment

Sales to the cooperatives analyzed in this study are characterized by three key features – price premiums, more stable prices, and delays in payment. The specialty coffee cooperatives focus on organic, fair-trade coffee, which yields higher prices than conventional coffee (Bissinger, 2019). While individual farmers can sell certified organic coffee on the private market, fair trade certification is given at the cooperative level, allowing cooperatives to offer a price premium over private buyers. According to the surveys in 2014 and 2016, these prices premiums are estimated to be 4.8% and 5.6% respectively (Table 4.1). Further, specialty coffee prices are less volatile on the international market than conventional coffee, and because of this, cooperatives can offer more stable prices than private buyers.

While farmers can benefit from these incentives offered by cooperatives, it comes at a cost – cooperatives' payments to members are delayed. Qualitative interviews with cooperative managers suggest that cooperative payment delays in recent years have been reduced from months to cooperatives offering 80% of the sale price upon delivery and the remaining 20% months later. However, this contradicts the delays reported by farmers. Respondents were asked about payment delays from 2009 to 2015. These questions were not asked for each marketing chan-

Table 4.1: Cooperative Price Premiums

	2013	2015
Outside Buyer Price/Kg	1.04	1.43
	(42)	(28)
Cooperative Price/Kg	1.09	1.51
	(172)	(141)
Cooperative Premium	4.8%	5.6%

Observations in parentheses
These are rough calculations based on farmers' responses to selling prices in the survey. The sample sizes are low for prices of organic coffee on private markets, but still show evidence of a price premium. The presence of price premiums is consistent with other studies on fair trade coffee (Bacon, 2013)

nel, but rather they were asked in general, regardless of whether the respondent sold to the cooperative or to private buyers. As a result, these payment delays are excluded from the empirical analysis, but are still useful in understanding the cooperative context. For respondents not engaged in side-selling (and therefore reporting cooperative payment times), the cooperatives took 12 days to deliver payments in 2009 on average. These times were reduced to 6 days by 2013 and 3.4 days in 2015. This decrease has largely been the result of cooperatives gaining access to external capital. According to cooperative managers, the improved payment times have helped increase 'fidelity' to the cooperative (i.e. reduced side-selling). In another study of side-selling in Peruvian cooperatives, the delay in the delivery payment is generally 1-2 weeks (Enelow, 2014). In a study of Mexican specialty coffee cooperatives, delays can extend into months (Arana-Coronado et al., 2019). While the delays in our study are short, they can still make a big difference – especially for farmers who face severe liquidity constraints. For example, a study in Indonesia shows that farmers discount a payment delay of one week by 32% (de Zegher et al., 2018).[13]

Despite these advancements in cooperative capacity, side-selling still exists. From the survey data, 23% of farmers side-sold at least some of their organic coffee in 2013 and 19% in 2015.[14] Table 4.2 shows that when farmers side-sold in 2013, they sold an average of 50% of their coffee, while this figure was only 34% in 2013. These figures are non-negligible – losing 10% of sales in a business dependent on scale economies can undoubtedly reduce organizational capacity.

Further, the cooperatives do not have any regulations prohibiting members from selling on the private market, where payments are made in full upon delivery. The cooperative dividend is distributed at the end of the season, so members must wait a full season to receive dividend payments, and pre-financing is generally not available.

[13] There is also evidence that farmers sometimes prefer payment delays because the delays can serve as a savings mechanism (Casaburi and Macchiavello, 2019).

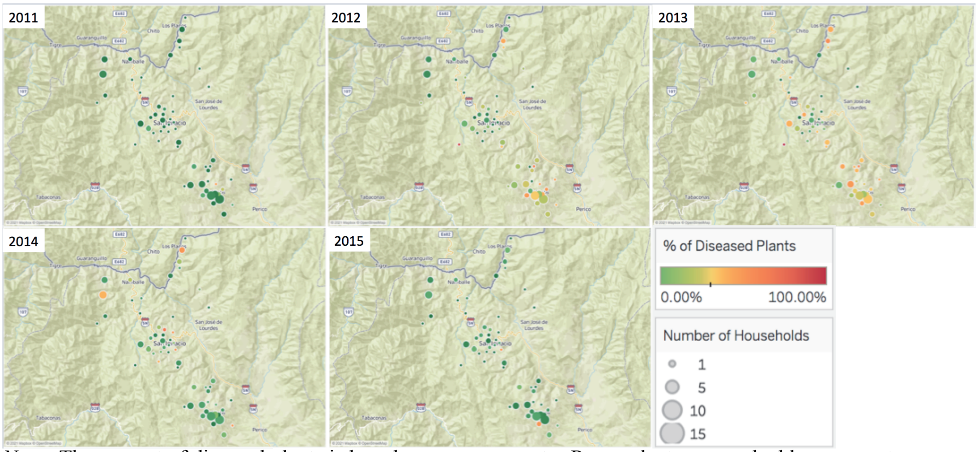
[14] We focus on organic coffee because the cooperatives' is on organic coffee. Only 17 of 200 farmers do not grow organic coffee at all, and these farmers are excluded from the sample

4.3.4 Coffee Leaf Rust

Coffee Leaf Rust develops from a fungus called Hemileia vastatrix, which develops in settings of decreased moisture and temperatures between 10 and 35 degrees Celsius. The disease inhibits the ability for leaves to photosynthesize and produce fruits, drastically reducing yields (Arneson, 2000). The disease's impact can be mitigated by planting improved varieties or using fungicides (often copper-based). Organic farmers have greater difficulties in fighting coffee rust because fungicides are often non-organic (Torres Castillo et al., 2020). Further, switching to new varieties takes time. Once planted or grafted, coffee trees take 2 to 3 years to produce cherries, making changes in varieties a long-term, rather than short-term, solution to to mitigating the effects of Coffee Leaf Rust (Abate et al., 2021).

In the last decade, Coffee Leaf Rust has devastated yields in numerous Latin American countries, including Peru where its impacts peaked in 2013 (Avelino et al., 2015). Despite other Latin American countries experiencing outbreaks of Coffee Leaf Rust before Peru, the epidemic was unexpected and few precautions were taken to prevent the disease from spreading in Peru (Avelino et al., 2015). As a result, Coffee Leaf Rust affected about 60% of the value of coffee harvests in 2013, amounting to 290 million USD in lost value (Julca Otiniano et al., 2019). About 76% of farmers in our survey reported having at least one tree with plant diseases in 2013 (up from 10% in 2009). 25% of the median farm was infected in 2013, but the leaf rust subsided in 2015 with the median farm having only 8% of trees infected. The disease was distributed geographically and temporally across the sample, as shown in Figure 4.1.

Figure 4.1: Geographic Distribution of Plant Diseases (2011-2015)



Note: The percent of diseased plants is based on survey reports. Respondents were asked how many trees were infected in each year from 2009 to 2013 in the first survey wave and 2014 and 2015 in the second wave. GPS coordinates were not recorded for individual farms, but we obtained the GPS coordinates for each *centro poblado* (the lowest administrative level), which are plotted above. Data for 2009 and 2010 are not shown because plant diseases were not prevalent. The size of each marker reflects the number of households in the corresponding *centro poblado*. The average percentage of trees infected across households in each *centro poblado* is displayed using a color scale where green represents low incidences of plant diseases and red represents high incidences.

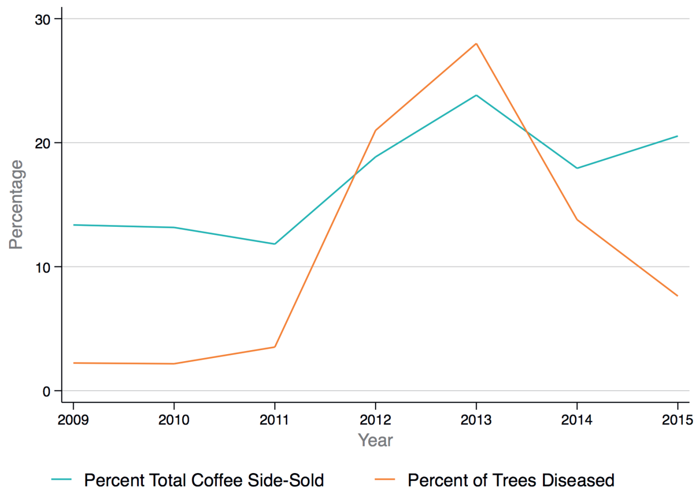
Figure 4.1 above shows there is some correlation with location and plant diseases – households in the south are slightly more likely to have plant diseases in 2013, but appear less likely to have them in 2015. Controlling for individual fixed effects in the within estimations and cooperative and district fixed effects in between estimations helps alleviate concerns arising from the somewhat uneven geographic distribution of plant diseases (Section 4.4).

While the effects of the outbreak were widespread, they were not homogeneous. Organic farmers are unable to stop the spread of Coffee Leaf Rust, but several farm characteristics and farm management practices can help mitigate the impacts of the disease. For example, using agronomic best practices builds up the health of trees and this can reduce the impacts of Coffee Leaf Rust. Farms with older trees are more susceptible to Coffee Leaf Rust, so farmers who continuously rejuvenate their farms are less susceptible (Ehrenbergerová et al., 2018). Finally, certain varieties are resistant to Coffee Leaf Rust (although they can still get the disease) (Borjas-ventura et al., 2020). In the study area, the *Catimor* variety is resistant to Coffee Leaf Rust, while other common varieties – *Pache*, *Typica*, *Caturra*, and *Bourbon* – are not resistant to Coffee Leaf Rust (World Coffee Research, 2019). The median farm in our study is comprised of 50% *Catimor* trees.

4.3.5 Summary Statistics

Figure 4.2 plots the average values for the percent of total coffee side-sold and the percent of trees diseased. The percent of total coffee side-sold increased over the period, going from around 15% in 2009 to 20% in 2013. A possible explanation for this trend is the rise in plant diseases (due to the Coffee Leaf Rust epidemic). In 2012, over 20% of coffee trees were infected with plant diseases on the average farm. This figure rose to nearly 30% by 2013 and dropped off in the following two years. The rise in side-selling appears to be correlated with plant diseases. Only the period from 2014 to 2015 shows a divergence in trends between the two figures. While our empirical analysis is unable to explore these longer-term trends, they provide motivation to study the correlation between production shocks and side-selling.

Figure 4.2: Side-Selling, Plant Diseases, and Number of Days for Coop. Payment 2009-2013)



Note: Data is derived from survey questions regarding the amount of coffee side-sold and the number of diseased coffee trees from 2009 to 2013 in the first survey wave and 2014 and 2015 in the second survey wave. Households in the sample do not necessarily only grow organic coffee, and the questions regarding historic plant disease and side-selling behavior are not limited to only organic coffee in this figure. However, most households are primarily organic farmers and these data points are still useful in descriptive analysis, even if not used in the main empirical specifications.

While Figure 4.2 provides a simple graphical representation of the correlation of side-selling and plant diseases, exploration of the proposed mechanisms and controlling for other factors is important for a proper empirical analysis. The descriptive statistics of the variables used in the empirical analysis are shown in Table 4.2 for each year. In both years, around twenty percent of households in the sample side-sold any coffee. Conditional on side-selling, households side-sold about 51% of their organic coffee in 2013 and 34% of their organic coffee in 2015. This difference is statistically significant. Households in 2013 also experienced more Coffee Leaf Rust with the average farm having about 28% of coffee trees infected in 2013, compared to only 8% in 2015 (graphically seen in Figure 4.1). Further, area devoted to organic coffee production and expenditure on coffee installations are lower in 2015 than in 2013, but all farmers in the sample had become organically certified by 2015.[15]

Farmers in the sample are highly dependent on organic coffee for their income. While growing and selling organic coffee does not mean that farmers cannot also grow conventional coffee, most households only grow organic coffee – on average, 97% and 99% of coffee growing area was devoted to organic production in 2013 and 2015, respectively. Further, in 2013 the average household received 84% of their income from coffee. In 2015, 81% of income came from coffee for the average household. These figures underscore the importance of organic coffee sales for the sample and show that the Coffee Leaf Rust epidemic did not lead to a shift away from organic farming or a shift away from coffee as an income source from 2013 to 2015.

In both years, average expenditure on labor was extremely low, reflecting the low reliance on outside labor – most farms are family farms. On average, the center-points of households' *centro poblados* are about 10km away from cooperatives. Despite, the focus of cooperatives on specialty coffee, only about 60% of respondents were aware of fair trade coffee.[16]

In terms of demographics and socio-economics, the average household head has nearly seven years of education and is in their late forties/early fifties. Very few households are headed by women, and the typical households has about four members. Non-coffee income is fairly common and is larger than expenditures on coffee installations and labor. Further, non-coffee income appears to be the main source of non-coffee liquidity, as it was more than three times the size of outstanding loan values in 2013 and two times the size of outstanding loan values in 2015.

Behaviorally, the average respondent in both waves expressed a favorable opinion on four out of five questions related to the capacity of the cooperative to provide adequate services. Additionally, most respondents identify with their cooperative on nearly four out of five measures. In terms of risk-taking, respondents are generally risk averse, and are willing to pay only small amounts to play in standard lotteries. While risk preferences generally trend towards risk aversion, there are also farmers who are willing to pay large amounts to participate in the lotteries. Further, it should be noted that all farmers in the sample have taken on some level of risk in adopting organic coffee.

[15] Households may engage in organic production without certification. Households that cannot afford or do not have access to agrochemicals are organic farmers by default, but this does not necessarily mean they have certification.

[16] Since all respondents are members of cooperatives that sell fair-trade coffee, this measure may not be accurate and could reflect a lack of understanding in the survey question.

Table 4.2: Descriptive Statistics

Variable	2013	2015	Diff
Side-Selling Indicator	0.23	0.19	-0.042
	(0.00)	(0.00)	(0.359)
% Organic Coffee Side-Sold	51.16	34.03	-17.127**
	(0.00)	(0.00)	(0.049)
% Trees with Leaf Rust	28.33	8.05	-20.281***
	(0.00)	(0.00)	(0.000)
Non-Coffee Incomes (soles)	4644.78	2709.62	-1935.151
	(0.00)	(0.00)	(0.241)
	(0.00)	(0.00)	(0.965)
50 Sol Lottery	5.61	5.66	0.052
	(0.00)	(0.00)	(0.891)
100 Sol Lottery	10.07	10.40	0.326
	(0.00)	(0.00)	(0.715)
1000 Sol Lottery	26.50	28.07	1.569
Organic Hectares	2.76	2.40	-0.359*
	(0.00)	(0.00)	(0.073)
Total Organic Trees	10131.36	9036.33	-1095.035
	(0.00)	(0.00)	(0.181)
% Organic Coffee	0.97	0.99	0.02**
	(0.01)	(0.00)	(0.010)
% Resistant Variety	53.57	59.01	5.438
	(0.00)	(0.00)	(0.131)
% Income from Coffee	0.84	0.81	-0.024
	(0.02)	(0.03)	(0.033)
Exp. on Coffee Installations (soles)	1434.20	594.62	-839.587***
	(0.00)	(0.00)	(0.000)
Exp. on Labour (soles)	18.99	12.17	-6.822
	(0.00)	(0.13)	(0.501)
Outstanding Loan Value (soles)	2155.50	1545.67	-609.829
	(0.01)	(0.00)	(0.522)
Distance to Coop. (km)	10.24	10.04	-0.197
	(0.00)	(0.00)	(0.834)
Organic Certification	0.84	1.00	0.160***
	(0.00)	(.)	(0.000)
Knowledge of Fair Trade	0.57	0.58	0.008
	(0.00)	(0.00)	(0.876)
HH Head Years of Edu.	6.92	6.67	-0.244
	(0.00)	(0.00)	(0.587)
HH Head Age	47.14	50.56	3.418**
	(0.00)	(0.00)	(0.015)
Female HH Head	0.15	0.12	-0.039
	(0.00)	(0.00)	(0.271)
Household Size	4.20	4.47	0.273
	(0.00)	(0.00)	(0.173)
Perception of Coop. Services	0.78	0.81	0.029
	(0.00)	(0.00)	(0.821)
Identification with Coop.	3.82	3.82	-0.004
	(0.00)	(0.00)	(0.714)
N	200	173	373

[1] Significance levels: $^{*} < 10\%$ $^{**} < 5\%$ $^{***} < 1\%$
[2] P-Values in parentheses
[3] % of Organic Coffee Side-Sold is conditional on side-selling any organic coffee.

4.4 Empirical Predictions and Methodology

4.4.1 Empirical Predictions

The econometric approach is designed to uncover the mechanisms at play in Section 4.2. Table 4.3 summarizes the linkages between the propositions in Section 4.2 and the econometric approach. While the theoretical model discusses causal links, the econometric specifications do not. Only risk aversion and the interaction of risk aversion and production shocks are theoretically predicted to have a uniform direction across all households, while changes in the other variables could theoretically increase or decrease sales to the private market.

Table 4.3: Empirical Hypotheses

Mechanisms and Propositions	**Variable**	**Theoretical Relationship**	**Hypotheses**	**Primary Empirical Correlation Tested**
Inverse U-Shape Curve	Hectares and Hectares Squared	+/-	Inverse U-Shape	Within
Liquidity from Non-Coffee Sources	Non-Coffee Income	+/-	+	Within
Risk Preferences	Willingness to Play in Lottery	-	-	Between
Proposition 1	% Plants Diseased	+/-	+/-	Within
Proposition 2	% Plants Diseased × Non-Coffee Income	+/-	-	Interaction of Within
Proposition 3	% Plants Diseased × Risk Aversion	-	-	Interaction of Within and Between

While the theoretical relationships are ambiguous in terms of the effect on side-selling, we propose separate empirical hypotheses for each of the theoretically ambiguous propositions. First, the predominance of the fixed costs effect or the liquidity effect will determine whether non-coffee income is positively or negatively correlated side-selling in Proposition 2. Reported average payment delays are six days in 2013 and 3.4 days in 2015 – far from the months-long delays reported in Arana-Coronado et al. (2019) and the weeks-long delays reported in Enelow (2014). These shorter time periods may make weaken liquidity mechanism. Meanwhile, most farmers have two hectares or fewer (considered smallholders by Lowder et al. 2016). These small farm sizes may preclude households from reaching the production scale necessary to be able to incur fixed costs. Non-coffee income can make up for this deficiency. It is likely that the fixed costs mechanism predominates the liquidity mechanism and non-coffee income enables more side-selling. This logic extends to Proposition 2.

Additionally, production shocks (plant diseases) will be positively correlated with side-selling if the liquidity and risk mechanisms predominate, while they will be negatively correlated with side-selling if the fixed costs effect is larger than the combined liquidity and risk mechanisms. It is unclear *a priori* which mechanism will be stronger and we do not offer an empirical hypothesis for Proposition 1.

4.4.2 Econometric Model

The empirical estimation strategy takes advantage of the available panel data and uses the within-between estimator (Bell and Jones, 2015), also known as a hybrid model (Allison, 2009). This estimator builds on the decomposed panel models first proposed in Mundlak (1978), which introduced the correlated random effects model.

Since panel data is used in the analysis, there exists heterogeneity in data points across time within individual respondents and across (or between) respondents. The standard approach in economic analyses is to employ a fixed effects model, which controls for the heterogeneity between respondents and gives estimates of 'within effects' (i.e. the differences across time within individual respondents). Less commonly applied, but still a textbook approach, is the random effects model, which assumes that errors are uncorrelated with covariates. The RE model estimates 'between effects' (i.e. heterogeneity across individual respondents). To choose which model is most appropriate, the standard approach is to estimate the coefficients of both models and apply a Huasman test to test whether the coefficients are different. If the coefficients are not significantly different, then a RE model is chosen because it is more efficient than FE. If the coefficients are significantly different, then a FE model is chosen because the RE model will give biased estimates (Hausman, 1978).

RE and FE models have several weaknesses that make them unsuitable for our study. First, RE models assume that between and within effects are equivalent. This assumption does not hold theoretically. For example, the effects on side-selling of being exposed to a production shock in one period is likely different than the effect of being exposed to production shocks at an above average rate over time. Further, the RE model assumes that errors are uncorrelated with covariates. As with most economic studies, this assumption is unlikely to hold, making RE an inappropriate specification (Wooldridge, 2013). FE models can solve the latter issue by controlling for individual-level heterogeneity – time invariant characteristics are controlled for and consistent estimators of within effects are found. However, the FE solution brings forth another problem. Propositions 3 concerns a time-invariant measure, risk aversion (which is only measured in the first wave of data collection). Applying a FE estimation would come at the cost of not being able to answer our research questions, and a methodology that cannot answer the research question surely cannot be the correct methodology (Bell and Jones, 2015).

Following the standard approach, we estimate RE and FE models and run Hausman tests to determine which model is more appropriate (Appendix 4.D). The Huasman tests are run using models with only main explanatory variables and models with both main explanatory variables and controls. Out of the seven tests run, the Hausman test suggests RE to be used in two of the specifications and FE in five of the specifications. These variable results are concerning because it suggests that the propositions cannot be tested in a single coherent framework. Further, the assumptions underlying both models are either methodologically problematic (as in RE) or cannot answer the research questions (as in FE).

The solution to these issues lies in the hybrid estimator, which can provide the within effects estimates equivalent to those estimated by FE models and between effects estimates that do not rest on the assumption made in RE models that within and between effects are equivalent (Allison, 2009). Let X_{it} be a k-length vector of time-varying variables for individual i and $\bar{X}_i$ be a k-length vector of the means (over time) of each element of X_{it}. X_{it} and $\bar{X}_i$ can include interaction terms as well as standard covariates. Each element, k, of $\bar{X}_i$ can be given by $\bar{x}_{i,k} = \frac{(\sum_{t=1}^{T} x_{it,k})}{T}$, where k is the variable for indivudal i in time t, and T is the total number of panels (2 in this study). Let C_i be an h-length vector of time invariant variables. Following (Schunck, 2013), the estimator is then given by:

$$y_{it} = \beta_0 + \beta_1(X_{it} - \bar{X}_i) + \beta_2 C_i + \beta_3 \bar{X}_i + \mu_i + \epsilon_{it} \tag{4.16}$$

where y_{it} is the outcome for individual i at time t, μ_i is the time-invariant error term, and ϵ_{it} is the time variant error term. β_1 is a k-length vector of coefficients of the within effects, and these terms are equivalent to the coefficients for time-varying variables estimated by FE (Schunck, 2013). β_2 is an h-length vector of coefficients for variables, C_i, that only vary between individuals (but not across time). β_3 is a k-length vector of coefficients of the between effects for time-varying variables. The within-effects coefficients, β_1, do not rely on the assumption that $E(\mu_i|X_{it}, C_i) = 0$ to be unbiased (as with the FE approach). However, the estimates of the between effects, β_2 an β_3, are only unbiased if $E(\mu_i|X_{it}, C_i) = 0$ (as in the RE approach), and this assumption is unlikely to hold.[17]

One of the key advantages of the hybrid approach is the ability to include interaction terms between time-variant and time-invariant variables (Bell and Jones, 2015). The model can be easily extended to include these interaction terms. The interaction terms follow the same interpretation as they would in a standard FE or RE model.

The hybrid formulation combines the advantages of FE and RE, but it does not imply causal interpretations. Bias in the within effects estimation can arise if $E(\epsilon_{it}|x_{it} \neq 0)$. This is likely to occur if there are omitted time-varying variables. While we attempt to control for all relevant time-varying characteristics possible, this condition is still unlikely to hold, and therefore we abstain from making causal interpretations in the analysis. The absence of causal interpretations is standard in the literature on the determinants of side-selling, which solely relies on cross-section analysis. While causality is not claimed, this panel approach removes some of the endogeneity in the estimation and is an improvement over cross-sectional approaches.

Only the coefficient for the within effect of the percentage of plants infected in a given year could be reasonably assumed to be a causal effect. Plant diseases are commonly thought of as a 'production shock' (Jezeer et al., 2019). A recent study on the resilience of smallholder farmers uses coffee plant diseases as an exogenous shock (Serfilippi et al., 2020). Coffee Leaf Rust was a shock to Peruvian farmers – national authorities were under-prepared to fight the Coffee Leaf Rust epidemic, despite its outbreak in other Latin American countries (Avelino et al., 2015). Further, organic coffee farmers were unable to change their practices to effectively fight the disease because copper-based fungicides that eliminate Coffee Leaf Rust are inorganic and cultivating new resistant varieties takes two to three years to generate yields. However, out of an abundance of caution we do infer causality even in this coefficient because the number of plants infected (as opposed to only exposed) to the disease is dependent on time-varying farm practices (Ehrenbergerová et al., 2018). Further, Coffee Leaf Rust affected households in 2012, before our study began. Some of the correlation between shocks and side-selling observed in our study could be spillovers from previous shocks.

[17] This assumption is also implicit in cross-sectional models, and all studies in the literature surrounding the determinants of side-selling use cross-sectional analysis which does not account for endogeneity. Therefore, this weakness in part of our econometric specification is a standard weakness in the literature.

4.5 Results

The empirical results provide suggestive evidence for the mechanisms at play in Section 4.2. This section first addresses whether shocks have a positive or negative relationship with side-selling. We then discuss whether farm size, income from non-coffee sources, and risk preferences are correlated with side-selling decisions. Then, we test Propositions 2 and 3 by including an interaction terms between the percentage of trees affected by leaf rust and non-coffee income and risk preferences. Although we cannot present causal evidence, the correlational evidence shows that production shocks may influence side-selling decisions, but with heterogeneity based on liquidity and risk preferences.

Proposition 1: The within estimates in Table 4.4 show that increases in the percent of coffee trees infected with plant diseases are correlated with increases in side-selling, but this relationship is not statistically significant either with (Column 1) or without controls (Column 5). This lack of a significant relationship may reflect the competing mechanisms at play. Shocks increase liquidity demand and encourage side-selling while also reducing scale economies and the profitability of covering fixed costs to side-selling. The between estimates show that households experiencing more intense production shocks on average are more likely to side-sell, conditional on controlling for other covariates (Column 5) and cooperatives and district indicators (Column 6). This suggests that there is household-level heterogeneity in marketing responses to production shocks.

Inverse U-Shape Curve: Side-selling follows an inverse U-Shape pattern with respect to farm size, reflecting the liquidity demand and scale economies mechanisms for small farmers and large farmers (Wollni and Fischer, 2015). These results hold for both the within and between estimations. The within estimations in Column 2 of Table 4.4, show that farmers are more likely to side-sell when they they have moderate amounts of land producing organic coffee.[18] Figure 4.3 shows the within-estimation of the inverse U-shape side-selling curve graphically. The smallest farmers – households with 1 hectare or fewer of organic coffee production – are not predicted to side-sell any coffee. When households have 2 to 7 hectares of organic coffee production, they tend to side-sell small amounts of their organic coffee (less than 20% on average). These estimates confirm the idea that the smallest farmers do not have the scale economies and/or the cash to pay fixed costs of side-selling, while larger farmers sell to the cooperative because they have lower discount rates and do not need liquidity from private markets.

The between estimation corroborates these results, but has a slightly different interpretation. The between estimator shows that members with small and larger organic farms, on average across time, are less likely to side-sell. Only the within estimates are robust to the inclusion of control variables (Column 5). Table 4.A.6 in Appendix 4.F shows the results using the number of organic coffee trees as a measure of farm size, and the results are similar. Since the size of organic farms (whether measured by trees or area) can be endogenous to side-selling, an additional robustness check is run using total farm area (organic coffee area, non-organic coffee area, and non-coffee area) as the measure of farm size in Table 4.A.8 in Appendix 4.F. The results are robust to the use of total farm area.

A potential mechanism that reduces the inverse U-shape, not included in the theoretical framework, is that larger farmers have a higher capacity to purchase fungicides *ex post* and may transition to non-organic coffee after their farms are affected by CLR in an attempt to reduce

[18] Land devoted to coffee production does vary between years. Table 4.2 shows that area of organic coffee production is 0.359 hectares less on average in 2015 than 2013. This difference does not appear to be driven by attrition (Appendix 4.C). Further, the inclusion of a year indicator does not explain the statistically significant inverse U-Shape (Table 4.A.3 in Appendix 4.D).

losses. Since this reduces large farmers' ability to leverage scale economies of organic coffee sales, it may reduce their side-selling. Meanwhile, small farmers who cannot afford fungicides will see their liquidity demand increase as a result of the shock. The transition from organic to non-organic may therefore diminish the inverse U-shape pattern, as small farmers increase side-selling and large farmers reduce organic side-selling. While, we do not have data on fungicides used, we have data on the percent of organic coffee trees on the farm. Appendix 4.E shows that the percent of organic trees is lower when farmers are affected by CLR, suggesting that farmers transition to non-organic production *ex post*. However, this relationship does not change across farm sizes.

Non-Coffee Income: Non-coffee income is positively correlated with side-selling when looking at the within estimation in Column 3 of Table 4.4. A one percent increase in outside income is associated with a one percentage point increase in side-selling. This suggests that the fixed cost mechanism is playing a larger role on average than the demand for liquidity mechanism (which would imply a negative coefficient of non-coffee income). When households have outside income, they may be using it to cover their fixed costs of marketing on private markets, as suggested in Section 4.2. The results are robust to the inclusion of controls (Column 5), but the between estimation does not show the same pattern. The between estimation suggests that households with higher average outside incomes do not have different side-selling behaviors than those with lower average outside incomes. This indicates that it is likely the liquidity from outside income that is important in households' decision-making rather than features inherent to households with outside income (e.g. larger social networks or more entrepreneurial tendencies). These results are not robust to using the log outstanding loan amount as a proxy for liquidity (4.F). This may be because few households have outstanding loans (only 26% in both years) and outstanding loan amounts are about half the size of non-coffee incomes (Table 4.2). Further, as with non-coffee income, the outstanding loan amount does not necessarily translate to liquidity, as households can have the outstanding loan amounts tied up in non-liquid investments.

Table 4.A.5 in Appendix 4.F shows that the results for non-coffee income hold when analyzing the extensive margin. The same model is used as in Equation 4.16, but an indicator for whether a household sells *any* organic coffee rather than the portion of organic coffee side-sold. A one percentage increase in non-coffee income is associated with 1.8% increase in the probability of selling coffee through non-cooperative channels. This suggests that the fixed cost mechanism is at play – the results in Table 4.4 could be largely driven by households' decisions to side-sell on the extensive margin.

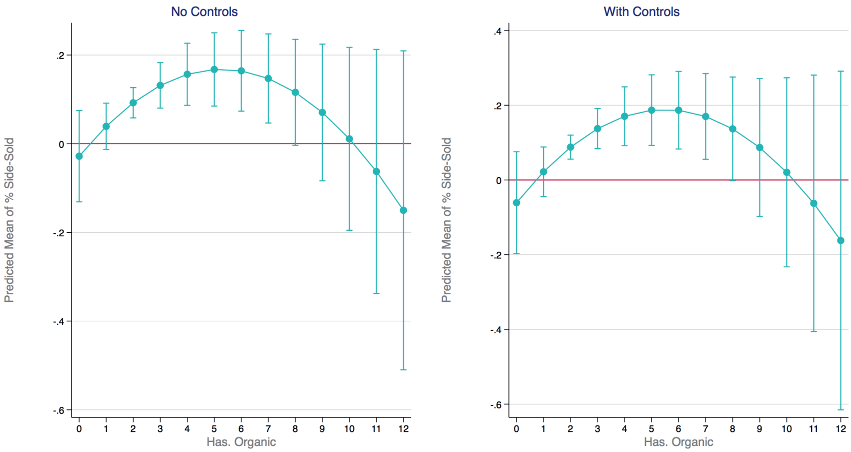
Risk Preferences: Equation 4.14 shows that risk-taking (risk aversion) increases (decreases) side-selling. Column 4 in Table 4.4 provides the between estimations of Equation 4.16 for risk. Members with a higher preference to take risks side-sell more than their more risk averse counterparts, providing evidence of the risk mechanism. A one percentage point increase in the willingness to take risks is correlated with a 0.4 percentage point increase in the quantity of coffee sold on the private market. This positive and significant relationship is robust to the inclusion of controls (Column 5) and the inclusion of cooperative and district fixed effects (Column 6). Appendix 4.F shows that the results are robust to using risk-taking measures from a 50 soles lottery, but not a 1000 soles lottery (Table 4.A.6). In the robustness checks, the latter has a positive, but insignificant relationship. These results are consistent with Woldie (2010) in that risk-averse households sell to the less risky channel; however, the less risky channel in this case is the cooperative as opposed to the private market.

Table 4.4: Hybrid Model: Base Results

	(1) % Organic Coffee Side-Sold	(2) % Organic Coffee Side-Sold	(3) % Organic Coffee Side-Sold	(4) % Organic Coffee Side-Sold	(5) % Organic Coffee Side-Sold	(6) % Organic Coffee Side-Sold
Within Estimation						
% Trees with Leaf Rust	0.0432				0.0973	0.0973
	(0.0840)				(0.107)	(0.108)
Organic Hectares		0.0743**			0.0910**	0.0910**
		(0.0329)			(0.0425)	(0.0428)
Organic Hectares ×Organic Hectares		-0.00704**			-0.00828*	-0.00828*
		(0.00335)			(0.00435)	(0.00438)
Non-Coffee Income			0.0125**		0.0138*	0.0138*
			(0.00580)		(0.00715)	(0.00720)
HH Head Years of Edu.					0.00233	0.00233
					(0.0176)	(0.0177)
HH Head Age					0.00346	0.00346
					(0.00910)	(0.00916)
Female HH Head					-0.0215	-0.0215
					(0.112)	(0.113)
Household Size					-0.0135	-0.0135
					(0.0104)	(0.0105)
Log Expenditure on Coffee Installments					-0.00318	-0.00318
					(0.00472)	(0.00475)
Log Loan Amount					0.00922	0.00922
					(0.00723)	(0.00728)
% Resistant Variety					-0.0000577	-0.0000577
					(0.000760)	(0.000765)
Organic Certification					-0.0888	-0.0888
					(0.159)	(0.160)
Between Estimation						
% Trees with Leaf Rust	0.0709				0.139*	0.215**
	(0.0862)				(0.0842)	(0.0902)
Organic Hectares		0.0444**			0.0309	0.00902
		(0.0216)			(0.0215)	(0.0205)
Organic Hectares ×Organic Hectares		-0.00355*			-0.00268	-0.00107
		(0.00199)			(0.00176)	(0.00158)
Non-Coffee Income			-0.00184		-0.00348	-0.00294
			(0.00481)		(0.00514)	(0.00521)
100 Sol Lottery				0.00448**	0.00617***	0.00582***
				(0.00202)	(0.00215)	(0.00207)
[1em] HH Head Years of Edu.					0.00725*	0.00512
					(0.00437)	(0.00434)
HH Head Age					0.000613	0.00000875
					(0.00134)	(0.00129)
Female HH Head					0.0575	0.0664
					(0.0642)	(0.0626)
Household Size					-0.00484	-0.00407
					(0.00895)	(0.00857)
Log Expenditure on Coffee Installments					0.00247	-0.000186
					(0.00631)	(0.00659)
Log Loan Amount					0.00870	0.00895
					(0.00531)	(0.00570)
% Resistant Variety					0.000259	0.000618
					(0.000514)	(0.000488)
Organic Certification					-0.107	-0.0781
					(0.0722)	(0.0682)
Distance to Coop. (km)					0.00332**	0.00190
					(0.00169)	(0.00129)
Perception of Coop. Services					-0.0116	-0.00172
					(0.0126)	(0.0140)
Identification with Coop.					-0.0277	-0.0223
Constant	0.0838***	0.0152	0.105***	0.0526***	0.0402	0.0747
	(0.0228)	(0.0384)	(0.0266)	(0.0204)	(0.116)	(0.108)
District Indicators	No	No	No	No	No	Yes
Cooperative Indicators	No	No	No	No	No	Yes
Observations	323	330	330	330	315	315

[1] Within and between correlations are estimated using the hybrid model in Equation 4.16. The within estimation is identical to the fixed effects estimation presented in Table 4.A.2 in Appendix 4.D.
[2] Heteroskedastic robust standard errors are clustered at the *Centro Poblado* (lowest administrative unit) level and reported in parentheses.
[3] * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$

Figure 4.3: Within Correlations: Inverse U-Shape Side-Selling Curve



The left panel corresponds to the results in Column 2 of Table 4.4, and the right panel corresponds to the results in Column 5 of Table 4.4. The graphs were generated using the correlated random effects model, which gives the same results as the hybrid model, but can be used within Stata's margins framework (while the hybrid model cannot) (Schunck, 2013). The plot displays the predicted marginal effect (y-axis) for each farm size on the x-axis.

Proposition 2: Non-Coffee Income is correlated with increases in side-selling when households are affected by production shocks. Table 4.4 above shows that outside income likely plays a larger role in facilitating sales to the private market through the fixed cost mechanism. When households experience a production shock, they demand liquidity more (since their production is lower), but they are also less able to sell on the private market because they are less able to pay for fixed costs to marketing (Section 4.2). Columns 1-3 show that Non-Coffee Income is not significantly correlated with side-selling for households not experiencing shocks, but is correlated with increased side-selling in households affected by shocks. A one percentage point increase in Coffee Leaf Rust on a farm combined with a 1% increase in outside income, is correlated with a 5 percentage point increase in side-selling, conditional on other covariates. In other words, households with higher outside income are more likely to side-sell during shocks. These results are shown graphically in Figure 4.4. In the left panel, the relationship is not statistically significant, but shows a clear upward trend. In the right panel, shocks are positively and significantly correlated with side-selling for households with the highest non-coffee income, but are not significantly correlated with side-selling in households with low non-coffee incomes. As above in Proposition 2, these correlations are present in within estimates, not between estimates, suggesting that liquidity is playing a large role, not individual household characteristics that are linked with having outside income.

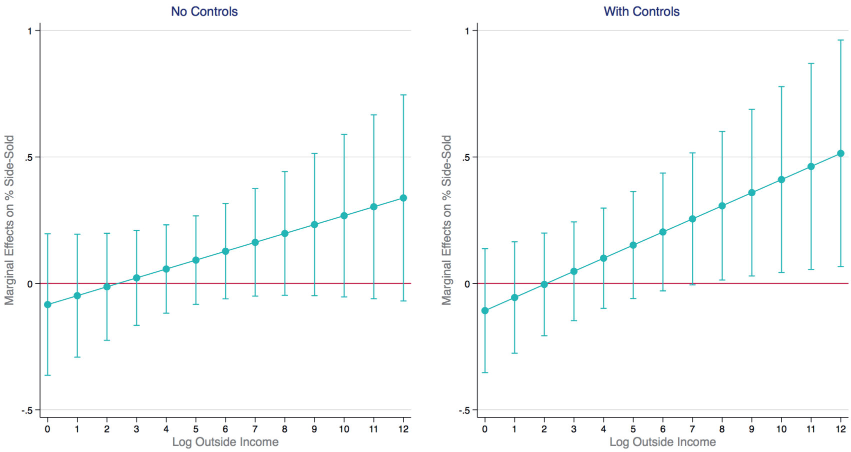
Proposition 3: When households experience a production shock, higher tolerance for risk-taking is correlated with an increase in side-selling. Table 4.4 shows that households do not significantly change their side-selling behavior when affected by a shock, but households that are willing to take more risks side-sell more often when affected by a shock. A one percentage point increase in the number of trees infected with leaf rust and a one percentage point increase in the willingness to take risks are correlated with a 2.5 percentage point increase in side-selling. This relationship is only significant at the 90% confidence level, but when controls are included, the relationship becomes significant at the 95% confidence level (Column 5). The results are robust to the inclusion of district and cooperative indicators (Column 6). Figure 4.5 shows the marginal effects of this relationship graphically. For households that are extremely risk averse (i.e. not willing to pay high amounts to participate in the lottery), production shocks are not significantly correlated with side-selling (and are likely negatively correlated). However, for households that are willing to pay 15 soles or more to participate in the lottery, side-selling increases as the intensity of production shocks increases. These relationships are only significant at the 90% confidence level when no controls are included (Panel 1 of Figure 4.5), but at the 95% confidence level when controls are included (Panel 2 of Figure 4.5). These results corroborate the theoretical model's prediction that risk aversion mitigates any increases in side-selling that may occur from production shocks. The between estimates do not show a significant relationship. Appendix 4.F shows that these results are robust to measuring risk preferences with 50 Soles lottery, but not a 1000 soles lottery.

Table 4.5: Hybrid Model: Interaction Results

	(1) % Organic Coffee Side-Sold	(2) % Organic Coffee Side-Sold	(3) % Organic Coffee Side-Sold	(4) % Organic Coffee Side-Sold	(5) % Organic Coffee Side-Sold	(6) % Organic Coffee Side-Sold
Within Estimation						
% Trees with Leaf Rust	-0.0838	-0.108	-0.108	-0.191	-0.150	-0.152
	(0.143)	(0.125)	(0.126)	(0.138)	(0.152)	(0.154)
Non-Coffee Income	0.00764	0.00552	0.00552		0.0143**	0.0143**
	(0.00520)	(0.00637)	(0.00641)		(0.00725)	(0.00731)
Non-Coffee Income ×% Trees Leaf Rust	0.0351	0.0518**	0.0518**			
	(0.0250)	(0.0234)	(0.0236)			
100 Sol Lottery ×% Trees Leaf Rust				0.0254*	0.0267**	0.0269**
				(0.0136)	(0.0126)	(0.0128)
Organic Hectares		0.106**	0.106**		0.0813*	0.0812*
		(0.0449)	(0.0452)		(0.0421)	(0.0424)
Organic Hectares ×Organic Hectares		-0.00961**	-0.00961**		-0.00762*	-0.00761*
		(0.00450)	(0.00453)		(0.00424)	(0.00428)
HH Head Years of Edu.		0.00524	0.00524		0.00580	0.00583
		(0.0154)	(0.0155)		(0.0168)	(0.0170)
HH Head Age		0.00248	0.00248		0.00447	0.00448
		(0.00873)	(0.00879)		(0.00867)	(0.00872)
Female HH Head		-0.0235	-0.0235		-0.00865	-0.00855
		(0.106)	(0.107)		(0.108)	(0.109)
Household Size		-0.0151	-0.0151		-0.0183	-0.0183
		(0.0100)	(0.0101)		(0.0113)	(0.0114)
Log Expenditure on Coffee Installments		-0.00295	-0.00295		-0.00344	-0.00344
		(0.00488)	(0.00492)		(0.00467)	(0.00471)
Log Loan Amount		0.00916	0.00916		0.0128*	0.0128*
		(0.00676)	(0.00680)		(0.00742)	(0.00747)
% Resistant Variety		-0.000309	-0.000309		0.0000299	0.0000306
		(0.000769)	(0.000775)		(0.000742)	(0.000748)
Organic Certification		-0.0721	-0.0721		-0.0950	-0.0950
		(0.161)	(0.162)		(0.157)	(0.158)
Between Estimation						
% Trees with Leaf Rust	0.0366	0.0707	0.206*	0.0289	0.0922	0.190
	(0.119)	(0.126)	(0.114)	(0.146)	(0.147)	(0.156)
Non-Coffee Income	-0.00381	-0.00607	-0.00255		-0.00309	-0.00243
	(0.00667)	(0.00716)	(0.00643)		(0.00516)	(0.00533)
Non-Coffee Income ×% Trees Leaf Rust	0.0130	0.0203	0.00548			
	(0.0240)	(0.0279)	(0.0245)			
100 Sol Lottery				0.00347	0.00533*	0.00549*
				(0.00295)	(0.00320)	(0.00312)
100 Sol Lottery ×% Trees Leaf Rust				0.00261	0.00230	0.0000343
				(0.0125)	(0.0130)	(0.0124)
Organic Hectares		0.0330	0.0105		0.0336	0.0115
		(0.0210)	(0.0194)		(0.0217)	(0.0208)
Organic Hectares ×Organic Hectares		-0.00256	-0.000970		-0.00300*	-0.00137
		(0.00188)	(0.00169)		(0.00175)	(0.00158)
HH Head Years of Edu.		0.00720	0.00458		0.00674	0.00466
		(0.00488)	(0.00474)		(0.00433)	(0.00432)
HH Head Age		0.00142	0.000628		0.000481	-0.000119
		(0.00150)	(0.00140)		(0.00133)	(0.00127)
Female HH Head		0.0515	0.0606		0.0562	0.0655
		(0.0676)	(0.0659)		(0.0612)	(0.0597)
Household Size		-0.00467	-0.00481		-0.00402	-0.00277
		(0.00918)	(0.00869)		(0.00866)	(0.00853)
Log Expenditure on Coffee Installments		0.000946	-0.00168		0.00162	-0.00110
		(0.00646)	(0.00671)		(0.00600)	(0.00632)
Log Loan Amount		0.00852	0.00865		0.00853*	0.00900*
		(0.00549)	(0.00572)		(0.00494)	(0.00527)
% Resistant Variety		0.000259	0.000681		0.000219	0.000600
		(0.000555)	(0.000495)		(0.000515)	(0.000487)
Organic Certification		-0.122	-0.0965		-0.104	-0.0738
		(0.0744)	(0.0695)		(0.0745)	(0.0710)
Distance to Coop. (km)		0.00278	0.00107		0.00328*	0.00198
		(0.00194)	(0.00152)		(0.00175)	(0.00127)
Perception of Coop. Services		-0.00766	0.00184		-0.0102	-0.000582
		(0.0127)	(0.0139)		(0.0123)	(0.0137)
Identification with Coop.		-0.0103	-0.00808		-0.0290*	-0.0236
		(0.0182)	(0.0179)		(0.0174)	(0.0179)
Constant	0.0964***	0.0216	0.0687	0.0502	0.0600	0.0815
District Indicators	No	No	Yes	No	No	Yes
Cooperative Indicators	No	No	Yes	No	No	Yes
	(0.0357)	(0.129)	(0.115)	(0.0367)	(0.126)	(0.117)
Observations	315	315	315	315	315	315

Marginal effects; Standard errors in parentheses
(d) for discrete change of dummy variable from 0 to 1
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 4.4: Within Correlations: Interaction of Outside Income and Plant Disease



The left panel corresponds to the results in Column 4 of Table 4.5, and the right panel corresponds to the results in Column 5 of Table 4.5. The graphs were generated using the correlated random effects model, which gives the same results as the hybrid model, but can be used within Stata's margins framework (while the hybrid model cannot) (Schunck, 2013)

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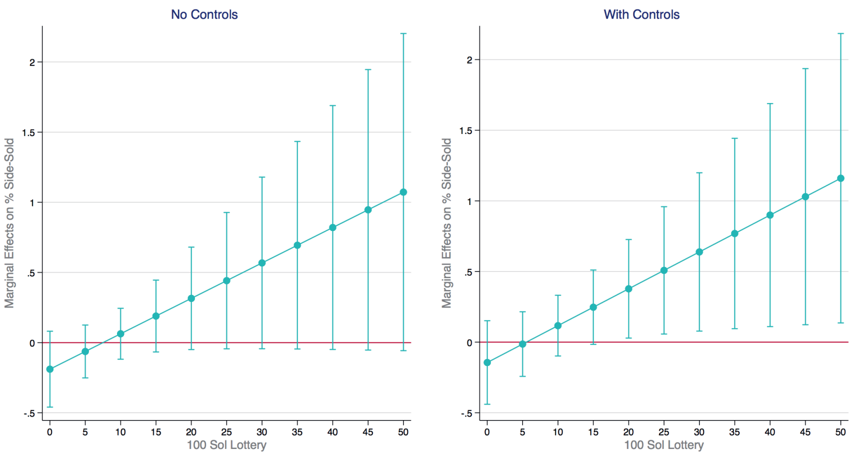
Figure 4.5: Within Correlations: Interaction of Risk and Plant Disease



The left panel corresponds to the results in Column 1 of Table 4.5, and the right panel corresponds to the results in Column 2 of Table 4.5. The graphs were generated using the correlated random effects model, which gives the same results as the hybrid model, but can be used within Stata's margins framework (while the hybrid model cannot) (Schunck, 2013).

4.6 Discussion and Conclusion

Side-selling potentially threatens the financial viability of farmers' cooperatives, and there have been many efforts to understand the determinants of side-selling in a diverse set of contexts (Sexton and Iskow, 1988). However, no studies to date have explored the role of production shocks in influencing side-selling decisions, despite the increasing vulnerability of small farmers, particularly organic farmers, to climate change. Since *Arabica* coffee is sensitive to temperature increases, pests, and diseases, cooperatives, and other institutions involved in coffee marketing, should understand the potential consequences of shock-induced marketing decisions (DaMatta and Ramalho 2006; Jaramillo et al. 2011).

Previous studies have used cross-sectional studies to uncover the correlations of various household and cooperative characteristics with side-selling. This paper contributes to the existing literature by exploring the role of production shocks in side-selling decisions, extending existing theoretical frameworks to show how non-coffee liquidity can both reduce and facilitate side-selling, and implementing panel data methods to understand the determinants of side-selling while controlling for individual-level effects. We use panel data from members of two Peruvian specialty coffee cooperatives during the 2012/13 Coffee Leaf Rust epidemic to understand these dynamics.

We find that Coffee Leaf Rust incidence may increase side-selling, but the evidence for this is weak and the correlations are heterogeneous. Shocks may increase side-selling through farmers' increased demand for liquidity from private buyers, but also decrease farmers' ability to incur fixed costs to private marketing and reduce farmers' gains from scale economics on private markets. Further, risk aversion may lead farmers to sell to the relatively safer cooperative in the event of a production shock. These competing mechanisms may be the reason why we only find weak correlations between Coffee Leaf Rust incidence and side-selling. However, households with relatively high levels of non-coffee income and risk tolerance increase their side-selling behavior in the event of a shock. These results suggest that mechanisms related to fixed costs to marketing play a larger role than liquidity demand for households coping with production shocks. This could be reflective of the fairly short delays in payment offered by cooperatives (6 days in 2013 and 3.4 days in 2015).

This study shows that marketing responses to production shocks are heterogeneous and likely dependent on broader contextual factors (such as cooperative payment times). Overall, side-selling is a concern for cooperatives as around 20% of respondents side-sell in each year, and when they do, they side-sell significant portions of their coffee (50% in 2013 and 33% in 2015). While these figures may not be an imminent threat to cooperative health, over time, side-selling should be carefully monitored as a large spike may cause serious problems in any given year. For other cooperatives who have large delays in payments, the liquidity demand mechanism may play a larger role and production shocks could be devastating for cooperative financial health through both reductions in coffee production and increases in side-selling to meet liquidity needs. Relieving liquidity constraints is an intuitive policy for cooperatives to reduce incentives to side-sell in these instances, but may have unintended consequences, as suggested in this study.

There are several limitations to our study. First, we are unable to show causal effects of production shocks or the mechanisms through which production shocks influence side-selling. Our findings are suggestive – although external validity is improved by the inclusion of a theoretical framework (Garcia and Wantchekon, 2010) – and should be interpreted with caution. Second, the study has a limited contextual scope. Only two cooperatives are included in the study. Both cooperatives have benefited from external finance in the past years which allow them to offer faster payment times, which mitigate (and possible remove) the role of liquidity demand in side-selling. Other specialty cooperatives, such as those analyzed in (Arana-Coronado et al., 2019) do not necessarily have the same features. Third, the sample size and data available is limited and other coping mechanisms, such as farmers discontinuing organic cultivation altogether, are unable to be explored. Such behavior also threatens the financial viability of specialty coffee cooperatives and deserves attention.

Further research should continue to explore the determinants of side-selling and organic farmers' coping mechanisms to climate change. For descriptive studies, such as ours, longer panels should be considered to better understand dynamic changes to side-selling behavior and to explore members entry and/or exit from cooperative engagement. Further, panel analysis can help uncover how organic farmers respond to other production shocks, such as aberrations in rainfall. For causal inference, experimental studies should be considered to better understand the determinants of side-selling. Finally, larger scale studies should be conducted to show to what extent members' behavior affects cooperative-level outcomes.

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Appendix 4

4.A Solving the Utility Maximization Problem

4.A.1 General Utility Function

Utility is given by:

$$U = \frac{(I+E)^{1-\gamma} - 1}{1-\gamma} \text{ for } \gamma \neq 1 \tag{4.A.1}$$

Let the total income be given by:

$$I = (1-\delta)r + \delta\mu = r - \delta(\mu - r) \tag{4.A.2}$$

The variance of income is given by:

$$V = \delta^2\sigma^2 \tag{4.A.3}$$

Income follows a log-normal distribution. The expected return of a log-normal variable is given by $\mathrm{e}^{r-\delta(\mu-r)+\frac{\sigma^2\delta^2}{2}}$. Therefore we can maximize the expected return. The log distribution of income and the cash endowment is then:

$$\ln I + E \sim \mathcal{N}(r + E\delta(\mu - r) - \frac{\delta^2\sigma^2}{2}, \delta^2\sigma^2) \tag{4.A.4}$$

We plug this expected return, its variance, and the cash endowment into the utility function:

$$E[U(\delta)] = \frac{\mathrm{e}^{(1-\gamma)(E+r+\delta(\mu-r)-\frac{\delta^2\sigma^2}{2})+\frac{1}{2}\delta^2\sigma^2(1-\gamma)^2} - 1}{1-\gamma} \; \forall\, \gamma \neq 1 \tag{4.A.5}$$

Since e is a constant, we can simply maximize the expression in the exponent. This is equivalent to maximizing:

$$\max E + r + \delta(\mu - r) - \frac{\delta^2\sigma^2}{2} + \frac{1}{2}\delta^2\sigma^2(1-\gamma) \; \forall\, \gamma \neq 1 \tag{4.A.6}$$

Simplifying:

$$\max E + r + \delta(\mu - r) - \frac{1}{2}\delta^2\sigma^2\gamma \; \forall\, \gamma \neq 1 \tag{4.A.7}$$

The FOC becomes:

$$\frac{\partial E[U(\delta)]}{\partial\delta} = (\mu - r) - \delta\sigma^2\gamma = 0 \tag{4.A.8}$$

We now solve for δ:

$$\boxed{\delta^* = \frac{(\mu - r)}{\sigma^2\gamma}} \tag{4.A.9}$$

We have now solved for the optimal share in the risky channel.

4.A.2 Explicit Utility Function

This section solves for the explicit solution to the utility maximization problem.

$$\begin{aligned}
\max U = & [E + p_p\delta Q + (p_p + x_c)(1-\delta)Q\beta(Q,E)^{t_p} + R_d] \\
& - [c_1^p\delta Q - \frac{c_2^p}{2}(\delta Q)^2 + c_1^c(1-\delta_i)Q] \\
& - \frac{1}{2}\delta^2\sigma^2\gamma \\
& \forall\, \gamma \neq 1 \\
& \text{where } R_d = (1-\delta)Q(p_x - p_c)^\alpha(\sum_{j=1}^{N}(1-\delta_j)Q_j)^{(\alpha-1)}\beta(Q,E)^{t_d}
\end{aligned} \tag{4.A.10}$$

Taking the first order condition with respect to δ, we get:

$$\frac{\partial U}{delta} = p_p - (p_p + x_c)Q\beta(Q,E)^{t_p} + \frac{\partial R_d}{\partial \delta} - c_1^p Q - c_2^p\delta Q^2 - c_1^c Q - \delta\sigma^2\gamma = 0 \tag{4.A.11}$$

Rearranging:

$$p_p - (p_p + x_c)Q\beta(Q,E)^{t_p} + \frac{\partial R_d}{\partial \delta} - c_1^p Q - c_1^c Q = \delta(c_2^p Q^2 + \sigma^2\gamma) \tag{4.A.12}$$

The optimal solution is given by:

$$\begin{aligned}
& \delta^* = \frac{p_p - (p_p + x_c)Q\beta(Q,E)^{t_p} + \frac{\partial R_d}{\partial \delta} - c_1^p Q - c_1^c Q}{c_2^p Q^2 + \sigma^2\gamma} \\
& \text{where} \\
& \frac{\partial R_d}{\partial \delta} = -Q(p_x - p_c)^\alpha(\sum_{j=1}^{N}(1-\delta_j)Q_j)^{(\alpha-1)}\beta(Q,E)^{t_d}
\end{aligned} \tag{4.A.13}$$

4.B Selected Comparative Statics

$\frac{\partial \delta^*}{\partial Q}$: Take partial derivative of δ^*:

$$\begin{aligned}
& \frac{[-(p_p + x_c)t_p\beta(Q,E)^{t_p-1}\frac{\partial \beta'(Q,E)}{\partial Q} - c_1^p - c_1^c][c_2^p Q^2 + \sigma^2\gamma]}{(c_2^p Q^2 + \sigma^2\gamma)^2} - \\
& \qquad \frac{[p_p - (p_p + x_c)Q\beta(Q,E)^{t_p} + \frac{\partial R_d}{\partial \delta} - c_1^p Q - c_1^c Q][c_2^p]}{(c_2^p Q^2 + \sigma^2\gamma)^2}
\end{aligned} \tag{4.A.14}$$

Only the numerator will determine whether the comparative static is positive or negative:

$$[-(p_p + x_c)t_p\beta(Q,E)^{t_p-1}\frac{\partial\beta'(Q,E)}{\partial Q} - c_1^p - c_1^c][c_2^pQ^2 + \sigma^2\gamma] - [p_p - (p_p + x_c)Q\beta(Q,E)^{t_p} + \frac{\partial R_d}{\partial\delta} - c_1^pQ - c_1^cQ][2c_2^pQ] \lesseqgtr 0 \tag{4.A.15}$$

Rearranging:

$$\begin{aligned}[-(p_p + x_c)t_p\beta(Q,E)^{t_p-1}\frac{\partial\beta'(Q,E)}{\partial Q} - c_1^p - c_1^c][c_2^pQ^2 + \sigma^2\gamma] &\lesseqgtr \\ [p_p - (p_p + x_c)Q\beta(Q,E)^{t_p} + \frac{\partial R_d}{\partial\delta} - c_1^pQ - c_1^cQ][2c_2^pQ]&\end{aligned} \tag{4.A.16}$$

Rearranging:

$$\frac{[-(p_p + x_c)t_p\beta(Q,E)^{t_p-1}\frac{\partial\beta'(Q,E)}{\partial Q} - c_1^p - c_1^c]}{[p_p - (p_p + x_c)Q\beta(Q,E)^{t_p} + \frac{\partial R_d}{\partial\delta} - c_1^pQ - c_1^cQ]} \lesseqgtr \frac{[2c_2^pQ]}{[c_2^pQ^2 + \sigma^2\gamma]} \tag{4.A.17}$$

The comparative static of δ^* with respect to p_x is negative. Intuitively, this means that In Equation 4.A.17, the first term in the numerator represents the change in quantity sold to the private market based on cooperative premiums in delivery price – if delivery price premiums increase, then side-selling decreases. The second term shows the change in side-selling with respect to the cooperative dividend. Holding international prices constant, delivery price premium increases decrease the dividend (because the cooperative's margins decrease). However, this effect is less than the delivery price premium effect because cooperative dividends are more delayed (i.e. $t_d > t_p$), and therefore more steeply discounted. Therefore, the overall effect of a price premium in delivery prices on side-selling is negative.

$$\frac{\partial\delta^*}{\partial x_c} = \frac{-Q\beta(Q,E)^{t_p} - [\alpha Q(p_x - (p_p + x_c)^{\alpha-1}][(\sum_{j=1}^{N}(1-\delta_j)Q_j)^{(\alpha-1)}\beta(Q,E)^{t_d}]}{c_2^pQ^2 + \sigma^2\gamma} < 0 \tag{4.A.18}$$

4.C Attrition Tests

Table 4.A.1: Test for Attrition Bias

Variable	Incomplete Cases	Complete Cases	Difference
Side-Selling Indicator	0.27	0.23	-0.038
	(0.01)	(0.00)	(0.671)
% Organic Coffee Side-Sold	0.09	0.13	0.039
	(0.01)	(0.00)	(0.498)
% Trees with Leaf Rust	0.29	0.28	-0.011
	(0.00)	(0.00)	(0.840)
Organic Hectares	3.33	2.97	-0.362
	(0.00)	(0.00)	(0.407)
Total Organic Trees	13125.00	10732.62	-2392.376
	(0.00)	(0.00)	(0.198)
% Resistant Variety	47.38	54.22	6.842
	(0.00)	(0.00)	(0.337)
Exp. on Coffee Installations (soles)	1330.58	1514.69	184.111
	(0.00)	(0.00)	(0.709)
Exp. on Labour (soles)	61.15	13.04	-48.109**
	(0.12)	(0.01)	(0.013)
Outstanding Loan Value (soles)	903.85	2465.61	1561.759
	(0.06)	(0.02)	(0.534)
Distance to Coop. (km)	11.68	9.89	-1.793
	(0.00)	(0.00)	(0.364)
Organic Certification	0.81	0.90	0.090
	(0.00)	(0.00)	(0.182)
Knowledge of Fair Trade	0.50	0.57	0.073
	(0.00)	(0.00)	(0.488)
HH Head Years of Edu.	5.69	6.93	1.238
	(0.00)	(0.00)	(0.171)
HH Head Age	43.50	47.70	4.201
	(0.00)	(0.00)	(0.137)
Female HH Head	0.08	0.17	0.095
	(0.16)	(0.00)	(0.221)
Household Size	3.92	4.24	0.319
	(0.00)	(0.00)	(0.476)
Non-Coffee Incomes (soles)	1371.92	5247.71	3875.784
	(0.03)	(0.01)	(0.400)
Perception of Coop. Services	0.54	0.82	0.277
	(0.01)	(0.00)	(0.284)
Identification with Coop.	3.85	3.85	0.006
	(0.00)	(0.00)	(0.973)
Risk: 50 Sol Lottery	5.25	5.56	0.307
	(0.00)	(0.00)	(0.683)
Risk: 100 Sol Lottery	8.06	10.39	2.334
	(0.00)	(0.00)	(0.188)
Risk: 1000 Sol Lottery	16.85	28.28	11.437
	(0.00)	(0.00)	(0.188)
N	26	157	183

[1] Significance levels: $^{*} < 10\%$ $^{**} < 5\%$ $^{***} < 1\%$
[2] P-Values in parentheses

4.D Hausman Tests

Table 4.A.2: Fixed Effects

	(1) % Organic Coffee Side-Sold	(2) % Organic Coffee Side-Sold	(3) % Organic Coffee Side-Sold	(4) % Organic Coffee Side-Sold	(5) % Organic Coffee Side-Sold	(6) % Organic Coffee Side-Sold	(7) % Organic Coffee Side-Sold	(8) % Organic Coffee Side-Sold
Organic Hectares	0.0743**			0.0910**	0.0700**			0.0882**
	(0.0328)			(0.0414)	(0.0312)			(0.0432)
Organic Hectares × Organic Hectares	-0.00704**			-0.00828*	-0.00677**			-0.00809*
	(0.00334)			(0.00423)	(0.00331)			(0.00433)
Non-Coffee Income		0.0125**		0.0138*		0.0120**		0.0134*
		(0.00579)		(0.00696)		(0.00586)		(0.00724)
% Trees with Leaf Rust			0.0432	0.0973			-0.0433	0.0761
			(0.0839)	(0.104)			(0.0908)	(0.123)
HH Head Years of Edu.				0.00233				0.00252
				(0.0171)				(0.0173)
HH Head Age				0.00346				0.00418
				(0.00885)				(0.00987)
Female HH Head				-0.0215				-0.0220
				(0.109)				(0.110)
Household Size				-0.0135				-0.0132
				(0.0101)				(0.00987)
Log Expenditure on Coffee Installments				-0.00318				-0.00384
				(0.00459)				(0.00448)
Log Loan Amount				0.00922				0.00919
				(0.00704)				(0.00702)
% Resistant Variety				-0.0000577				-0.0000544
				(0.000739)				(0.000741)
Organic Certification				-0.0888				-0.0809
				(0.155)				(0.149)
Year = 1					-0.0235	-0.0287	-0.0491	-0.0153
					(0.0278)	(0.0311)	(0.0340)	(0.0429)
Constant	-0.0303	0.0474**	0.0874***	-0.176	-0.0112	0.0623**	0.126***	-0.201
	(0.0562)	(0.0222)	(0.0162)	(0.510)	(0.0519)	(0.0276)	(0.0279)	(0.532)
Time Indicator	No	No	No	No	Yes	Yes	Yes	Yes
Observations	330	330	323	315	330	330	323	315

1 Within correlations are estimated using a fixed effects model. Columns 1 - 4 respectively correspond with Columns 2, 3, 1, and 5 in Table 4.4. Between correlations cannot be estimated using the traditional fixed effects model. Columns 5-8 include the year indicator and these models are used in the time fixed effect test in Table 4.A.3 below.

2 Heteroskedastic robust standard errors are clustered at the *Centro Poblado* (lowest administrative unit) level and reported in parentheses.

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

Table 4.A.3: Hausman Tests and Breusch and Pagan Lagrange Multiplier Tests

Explanatory Variables	Year Indicators	Control Variables	Hausman Chi-Squared	Hausman P-Value	Time Fixed Effect F-Test	Time Fixed Effects P-Value
Hectares and Hectares-Squared	No	No	0.69	0.71		
Hectares and Hectares-Squared	Yes	No	7.34	0.06	0.68	0.41
Non-Coffee Income	No	No	5.26	0.02		
Non-Coffee Income	Yes	No	11.32	0.00	0.63	0.43
Coffee Leaf Rust	No	No	1.08	0.30		
Coffee Leaf Rust	Yes	No	9.35	0.01	1.21	0.27
All Explanatory Variables	Yes	Yes	17.74	0.09	0.58	0.45

[1] The models are run with the percentage of organic coffee sold as the dependent variable, following Equation 4.16 in Section 4.4. Year indicators are indicator variables for the wave to which each observation belongs, and the control variables follow from Section 4.3.

[2] The Hausman test is run after estimating both fixed and random effects models. The null hypothesis of the Hausman test is that there is no systematic difference between coefficients in the Fixed Effects and Random Effects models. Rejection of the null hypothesis suggests that only Fixed Effects models are consistent, while Random Effects provides inconsistent results. Failure to reject the null hypothesis suggests that random effects is both consistent and efficient, while fixed effects is efficient, but inconsistent.

[3] The time fixed-effects F-Test tests jointly whether the year indicators are equal to zero. Since there are only two panels, this test is equivalent to the test of whether the year indicator is equal to zero in Table 4.A.2.

[4] For all tests, P-Values ≤ 0.10 are considered as statistically signicant.

4.E Tests for Farmers' Shift to Non-Organic Production

Table 4.A.4: Hybrid Model: Results for Extensive Margins

	(1) Side-Selling Indicator	(2) % of Organic Coffee Trees	(3) % of Organic Coffee Trees	(4) % of Organic Coffee Trees	(5) % of Organic Coffee Trees	(6) % of Organic Coffee Trees
Within Estimation						
% Trees with Leaf Rust	-0.0725	-0.127*	-0.127*	-0.146	-0.194	-0.194
	(0.0649)	(0.0662)	(0.0667)	(0.153)	(0.170)	(0.172)
Total Has.		0.00759	0.00759	0.00309	0.00228	0.00228
		(0.0171)	(0.0173)	(0.0192)	(0.0221)	(0.0222)
Total Has. $\times$Total Has. $\times$% Trees with Leaf Rust				0.0306	0.0288	0.0288
				(0.0415)	(0.0467)	(0.0471)
Log Outside Income		-0.00412	-0.00412		-0.00396	-0.00396
		(0.00705)	(0.00710)		(0.00706)	(0.00711)
HH Head Years of Edu.		0.00499	0.00499		0.00641	0.00641
		(0.0129)	(0.0129)		(0.0142)	(0.0143)
HH Head Age		-0.00223	-0.00223		-0.00158	-0.00158
		(0.00339)	(0.00342)		(0.00313)	(0.00315)
Female HH Head		0.0594	0.0594		0.0648	0.0648
		(0.0793)	(0.0798)		(0.0824)	(0.0830)
Household Size		-0.00636	-0.00636		-0.00797	-0.00797
		(0.0106)	(0.0107)		(0.0114)	(0.0115)
Log Expenditure on Coffee Installments		0.0000943	0.0000943		-0.000341	-0.000341
		(0.00372)	(0.00374)		(0.00400)	(0.00403)
Log Loan Amount		0.00148	0.00148		0.00146	0.00146
		(0.00412)	(0.00415)		(0.00393)	(0.00396)
% Resistant Variety		-0.00107**	-0.00107**		-0.00102**	-0.00102**
		(0.000460)	(0.000463)		(0.000467)	(0.000470)
Organic Certification		-0.149	-0.149		-0.151	-0.151
		(0.0984)	(0.0991)		(0.100)	(0.101)
Between Estimation						
% Trees with Leaf Rust	0.0838	0.0567	0.0421	0.0518	0.0231	-0.00254
	(0.0536)	(0.0552)	(0.0564)	(0.0718)	(0.0818)	(0.0868)
Total Has.		-0.000750	-0.000175	-0.00434	-0.00296	-0.00315
		(0.00651)	(0.00691)	(0.00713)	(0.00780)	(0.00861)
Total Has. $\times$Total Has. $\times$% Trees with Leaf Rust				0.0103	0.0111	0.0149
				(0.0170)	(0.0182)	(0.0201)
Log Outside Income		0.00116	0.00258		0.00136	0.00285
		(0.00359)	(0.00363)		(0.00363)	(0.00369)
100 Sol Lottery		-0.00206**	-0.00210**		-0.00209**	-0.00214**
		(0.000946)	(0.000955)		(0.000948)	(0.000964)
HH Head Years of Edu.		0.000165	-0.000405		0.000170	-0.000395
		(0.00293)	(0.00296)		(0.00294)	(0.00297)
HH Head Age		0.000163	0.0000842		0.000148	0.0000650
		(0.000621)	(0.000659)		(0.000620)	(0.000657)
Female HH Head		-0.00820	-0.00861		-0.00750	-0.00768
		(0.0385)	(0.0400)		(0.0385)	(0.0399)
Household Size		-0.00459	-0.00349		-0.00456	-0.00355
		(0.00591)	(0.00518)		(0.00588)	(0.00517)
Log Expenditure on Coffee Installments		0.00161	0.00195		0.00159	0.00191
		(0.00321)	(0.00337)		(0.00320)	(0.00334)
Log Loan Amount		0.000363	0.0000107		0.000373	0.0000653
		(0.00395)	(0.00408)		(0.00396)	(0.00410)
% Resistant Variety		-0.000712	-0.000571		-0.000707	-0.000561
		(0.000578)	(0.000580)		(0.000580)	(0.000582)
Organic Certification		-0.0230	-0.0176		-0.0240	-0.0189
		(0.0483)	(0.0492)		(0.0491)	(0.0501)
Distance to Coop. (km)		-0.00197	-0.00112		-0.00199	-0.00117
		(0.00176)	(0.00195)		(0.00177)	(0.00196)
Perception of Coop. Services		0.000463	-0.000238		0.000767	0.000151
		(0.0104)	(0.0107)		(0.0106)	(0.0108)
Identification with Coop.		0.0158	0.0163		0.0157	0.0160
		(0.0128)	(0.0110)		(0.0128)	(0.0110)
Constant	0.933***	0.981***	0.959***	0.946***	0.989***	0.969***
	(0.0195)	(0.104)	(0.107)	(0.0291)	(0.103)	(0.104)
District Indicators	No	No	Yes	No	No	Yes
Cooperative Indicators	No	No	Yes	No	No	Yes
Observations	315	315	315	315	315	315

[1] Between correlations are estimated using the random effects model in Equation 4.16. Within correlations cannot be estimated using the traditional random effects model.
[2] Heteroskedastic robust standard errors are clustered at the *Centro Poblado* (lowest administrative unit) level and reported in parentheses.
[3] * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$

4.F Robustness Checks

Table 4.A.5: Hybrid Model: Results for Extensive Margins

	(1) Side-Selling Indicator	(2) Side-Selling Indicator	(3) Side-Selling Indicator	(4) Side-Selling Indicator	(5) Side-Selling Indicator	(6) Side-Selling Indicator
Within Estimation						
% Trees with Leaf Rust	-0.0319 (0.152)				0.125 (0.196)	0.125 (0.198)
Organic Hectares		0.134** (0.0534)			0.140* (0.0751)	0.140* (0.0757)
Organic Hectares $\times$ Organic Hectares		-0.0139** (0.00589)			-0.0142* (0.00812)	-0.0142* (0.00818)
Non-Coffee Income			0.0183** (0.00923)		0.0186* (0.0106)	0.0186* (0.0106)
HH Head Years of Edu.					0.0315 (0.0234)	0.0315 (0.0235)
HH Head Age					0.00539 (0.0122)	0.00539 (0.0123)
Female HH Head					-0.153 (0.115)	-0.153 (0.115)
Household Size					-0.0199 (0.0203)	-0.0199 (0.0205)
Log Expenditure on Coffee Installments					-0.0109 (0.00955)	-0.0109 (0.00961)
Log Loan Amount					0.0120 (0.0109)	0.0120 (0.0109)
% Resistant Variety					0.000728 (0.00112)	0.000728 (0.00112)
Organic Certification					-0.00610 (0.212)	-0.00610 (0.214)
Between Estimation						
% Trees with Leaf Rust	-0.0769 (0.152)				0.0281 (0.130)	0.110 (0.135)
Organic Hectares		0.105*** (0.0370)			0.0974*** (0.0358)	0.0677* (0.0369)
Organic Hectares $\times$ Organic Hectares		-0.00829** (0.00329)			-0.00700** (0.00305)	-0.00484 (0.00304)
Non-Coffee Income			0.00248 (0.00794)		0.000834 (0.00806)	0.000591 (0.00845)
100 Sol Lottery				0.00650** (0.00286)	0.00979*** (0.00340)	0.00977*** (0.00333)
HH Head Years of Edu.					0.0140 (0.0102)	0.0108 (0.0101)
HH Head Age					-0.00226 (0.00231)	-0.00293 (0.00239)
Female HH Head					0.0605 (0.0746)	0.0690 (0.0742)
Household Size					-0.00433 (0.0130)	0.000130 (0.0133)
Log Expenditure on Coffee Installments					-0.000358 (0.0101)	-0.00305 (0.00992)
Log Loan Amount					0.0104 (0.00749)	0.00930 (0.00699)
% Resistant Variety					-0.000350 (0.000988)	-0.000126 (0.000970)
Organic Certification					-0.394*** (0.138)	-0.353*** (0.135)
Distance to Coop. (km)					0.00604*** (0.00216)	0.00468*** (0.00179)
Perception of Coop. Services					-0.0438** (0.0177)	-0.0272 (0.0186)
Identification with Coop.					-0.0135 (0.0316)	0.00236 (0.0309)
dist=2						0.180** (0.0819)
Constant	0.239*** (0.0478)	0.0270 (0.0722)	0.215*** (0.0441)	0.155*** (0.0306)	0.340 (0.229)	0.387* (0.221)
District Indicators	No	No	No	No	No	Yes
Cooperative Indicators	No	No	No	No	No	Yes
Observations	315	315	315	330	315	315

Marginal effects; Standard errors in parentheses
(d) for discrete change of dummy variable from 0 to 1
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[1] Within and between correlations are estimated using the hybrid model in Equation 4.16. The within estimation is identical to the fixed effects estimation presented in Table 4.A.2 in Appendix 4.D.
[2] Heteroskedastic robust standard errors are clustered at the *Centro Poblado* (lowest administrative unit) level and reported in parentheses.
[3] * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$

Table 4.A.6: Hybrid Model: Robustness for Base Results

	(1) % Organic Coffee Side-Sold	(2) % Organic Coffee Side-Sold	(3) % Organic Coffee Side-Sold	(4) % Organic Coffee Side-Sold	(5) % Organic Coffee Side-Sold	(6) % Organic Coffee Side-Sold	(7) % Organic Coffee Side-Sold	(8) % Organic Coffee Side-Sold	(9) % Organic Coffee Side-Sold
Within Estimation									
% Trees with Leaf Rust	0.0432				0.0264	0.0219		0.0225	0.0219
	(0.0840)				(0.109)	(0.110)		(0.109)	(0.110)
Total Organic Trees		0.00169			0.00182	0.00182		0.00182	0.00182
		(0.00104)			(0.00126)	(0.00128)		(0.00126)	(0.00128)
Org. Trees × Org. Trees		-0.00000295			-0.00000329	-0.00000325		-0.00000326	-0.00000325
		(0.00000253)			(0.00000302)	(0.00000304)		(0.00000301)	(0.00000304)
Log Loan Amount			0.00888		0.00898	0.00918		0.00912	0.00918
			(0.00595)		(0.00702)	(0.00703)		(0.00699)	(0.00703)
HH Head Years of Edu.					-0.000342	-0.000363		-0.000357	-0.000363
					(0.0176)	(0.0175)		(0.0174)	(0.0175)
HH Head Age					0.00435	0.00446		0.00445	0.00446
					(0.0102)	(0.0102)		(0.0101)	(0.0102)
Female HH Head					-0.0271	-0.0261		-0.0264	-0.0261
					(0.120)	(0.121)		(0.120)	(0.121)
Household Size					-0.0143	-0.0143		-0.0143	-0.0143
					(0.0118)	(0.0120)		(0.0119)	(0.0120)
Log Expenditure on Coffee Installments					-0.00454	-0.00463		-0.00462	-0.00463
					(0.00437)	(0.00451)		(0.00436)	(0.00451)
Non-Coffee Income					0.0139*	0.0138*		0.0138*	0.0138*
					(0.00752)	(0.00766)		(0.00755)	(0.00766)
% Resistant Variety					-0.0000210	-0.0000495		-0.0000412	-0.0000495
					(0.000760)	(0.000761)		(0.000759)	(0.000761)
Organic Certification					-0.0578	-0.0610		-0.0600	-0.0610
					(0.149)	(0.149)		(0.150)	(0.149)
Between Estimation									
% Trees with Leaf Rust	0.0709				0.132	0.218**		0.145	0.218**
	(0.0862)				(0.0928)	(0.0964)		(0.0935)	(0.0964)
Total Organic Trees		0.000742**			0.000639	0.000350		0.000714*	0.000350
		(0.000375)			(0.000396)	(0.000387)		(0.000383)	(0.000387)
Org. Trees × Org. Trees		-0.000000962*			-0.000000945*	-0.000000525		-0.00000106*	-0.000000525
		(0.000000566)			(0.000000567)	(0.000000544)		(0.000000569)	(0.000000544)
Log Loan Amount			0.00743		0.00814	0.00816		0.00753	0.00816
			(0.00560)		(0.00523)	(0.00566)		(0.00521)	(0.00566)
1000 Sol Lottery				0.000419		0.000289	0.000419	0.000607	0.000289
				(0.000430)		(0.000395)	(0.000430)	(0.000416)	(0.000395)
50 Sol Lottery					0.00864**	0.00778*			0.00778*
					(0.00401)	(0.00466)			(0.00466)
HH Head Years of Edu.					0.00610	0.00424		0.00552	0.00424
					(0.00449)	(0.00422)		(0.00453)	(0.00422)
HH Head Age					0.00103	0.000116		0.000817	0.000116
					(0.00135)	(0.00123)		(0.00133)	(0.00123)
Female HH Head					0.0628	0.0705		0.0605	0.0705
					(0.0659)	(0.0640)		(0.0660)	(0.0640)
Household Size					-0.00578	-0.00459		-0.00793	-0.00459
					(0.00918)	(0.00931)		(0.00939)	(0.00931)
Log Expenditure on Coffee Installments					0.00206	-0.00102		0.000871	-0.00102
					(0.00645)	(0.00701)		(0.00633)	(0.00701)
Non-Coffee Income					-0.00167	-0.000869		-0.000451	-0.000869
					(0.00524)	(0.00516)		(0.00500)	(0.00516)
% Resistant Variety					0.000206	0.000578		0.000350	0.000578
					(0.000522)	(0.000518)		(0.000541)	(0.000518)
Organic Certification					-0.142**	-0.102		-0.140**	-0.102
					(0.0721)	(0.0671)		(0.0706)	(0.0671)
Distance to Coop. (km)					0.00294*	0.00151		0.00320*	0.00151
					(0.00177)	(0.00148)		(0.00185)	(0.00148)
sat_index					-0.0101	-0.00349		-0.00526	-0.00349
					(0.0193)	(0.0184)		(0.0191)	(0.0184)
fuerz_index					0.0172	0.0124		0.0138	0.0124
					(0.0200)	(0.0196)		(0.0201)	(0.0196)
Constant	0.0838***	0.0385	0.0822***	0.0863***	-0.0462	-0.00399	0.0863***	-0.0115	-0.00399
	(0.0228)	(0.0305)	(0.0210)	(0.0165)	(0.118)	(0.116)	(0.0165)	(0.114)	(0.116)
District Indicators	No	No	No	No	No	Yes	No	No	Yes
Cooperative Indicators	No	No	No	No	No	Yes	No	No	Yes
Observations	323	330	330	330	315	315	330	315	315

[1] Within and between correlations are estimated using the hybrid model in Equation 4.16. The within estimation is identical to the fixed effects estimation presented in Table 4.A.2 in Appendix 4.D.
[2] Heteroskedastic robust standard errors are clustered at the *Centro Poblado* (lowest administrative unit) level and reported in parentheses.
[3] * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$

Table 4.A.7: Hybrid Model: Robustness for Interaction Results

	(1) % Organic Coffee Side-Sold	(2) % Organic Coffee Side-Sold	(3) % Organic Coffee Side-Sold	(4) % Organic Coffee Side-Sold	(5) % Organic Coffee Side-Sold	(6) % Organic Coffee Side-Sold	(7) % Organic Coffee Side-Sold	(8) % Organic Coffee Side-Sold	(9) % Organic Coffee Side-Sold
Within Estimation									
% Trees with Leaf Rust	0.0564	0.0200	0.0178	-0.347**	-0.374**	-0.371**	-0.0756	-0.0857	-0.0914
	(0.0980)	(0.127)	(0.130)	(0.136)	(0.154)	(0.155)	(0.108)	(0.113)	(0.114)
Log Loan Amount	0.00945	0.00900	0.00936		0.0134*	0.0135*		0.0107	0.0109
	(0.0108)	(0.0108)	(0.0106)		(0.00702)	(0.00704)		(0.00701)	(0.00702)
Log Loan Amount × % Trees Leaf Rust	-0.00698	0.000709	-0.000548						
	(0.0473)	(0.0424)	(0.0423)						
Total Organic Trees		0.00182	0.00182		0.00191	0.00190		0.00188	0.00188
		(0.00127)	(0.00129)		(0.00117)	(0.00118)		(0.00121)	(0.00122)
Org. Trees × Org. Trees		-0.00000325	-0.00000324		-0.00000345	-0.00000342		-0.00000308	-0.00000305
		(0.00000304)	(0.00000306)		(0.00000295)	(0.00000296)		(0.00000291)	(0.00000291)
50 Sol Lottery × % Trees Leaf Rust				0.0794***	0.0878***	0.0862***			
				(0.0242)	(0.0260)	(0.0262)			
1000 Sol Lottery × % Trees Leaf Rust							0.00545	0.00561	0.00561
							(0.00368)	(0.00355)	(0.00356)
HH Head Years of Edu.		-0.000357	-0.000373		0.00230	0.00223		0.00143	0.00141
		(0.0174)	(0.0175)		(0.0178)	(0.0177)		(0.0173)	(0.0173)
HH Head Age		0.00450	0.00462		0.00175	0.00190		0.00512	0.00528
		(0.0100)	(0.00999)		(0.00999)	(0.00996)		(0.00989)	(0.00984)
Female HH Head		-0.0261	-0.0256		-0.0571	-0.0556		-0.0105	-0.00948
		(0.121)	(0.122)		(0.112)	(0.113)		(0.111)	(0.111)
Household Size		-0.0143	-0.0143		-0.0133	-0.0134		-0.0158	-0.0158
		(0.0120)	(0.0122)		(0.0121)	(0.0122)		(0.0122)	(0.0124)
Log Expenditure on Coffee Installments		-0.00468	-0.00476		-0.00333	-0.00344		-0.00410	-0.00423
		(0.00419)	(0.00435)		(0.00464)	(0.00477)		(0.00443)	(0.00457)
Non-Coffee Income		0.0138*	0.0137*		0.0143*	0.0142*		0.0128*	0.0127*
		(0.00744)	(0.00755)		(0.00750)	(0.00763)		(0.00739)	(0.00750)
% Resistant Variety		-0.0000394	-0.0000587		-0.0000460	-0.0000712		0.0000528	0.0000285
		(0.000734)	(0.000737)		(0.000691)	(0.000693)		(0.000730)	(0.000731)
Organic Certification		-0.0597	-0.0614		-0.0802	-0.0826		-0.0721	-0.0746
		(0.154)	(0.153)		(0.144)	(0.144)		(0.145)	(0.145)
Between Estimation									
% Trees with Leaf Rust	0.0829	0.124	0.207*	0.0406	0.123	0.225	-0.0400	0.00307	0.0831
	(0.0903)	(0.104)	(0.111)	(0.127)	(0.136)	(0.146)	(0.102)	(0.0995)	(0.104)
Log Loan Amount	0.00540	0.00626	0.00702		0.00876*	0.00893*		0.00684	0.00711
	(0.00650)	(0.00633)	(0.00678)		(0.00486)	(0.00526)		(0.00511)	(0.00545)
Log Loan Amount × % Trees Leaf Rust	0.00589	0.00636	0.00424						
	(0.0257)	(0.0257)	(0.0271)						
Total Organic Trees		0.000710*	0.000429		0.000671*	0.000359		0.000744*	0.000453
		(0.000387)	(0.000379)		(0.000382)	(0.000376)		(0.000382)	(0.000366)
Org. Trees × Org. Trees		-0.00000103*	-0.000000597		-0.000000928	-0.000000438		-0.00000107*	-0.000000629
		(0.000000583)	(0.000000559)		(0.000000566)	(0.000000540)		(0.000000553)	(0.000000518)
50 Sol Lottery				0.00705	0.00926	0.0109*			
				(0.00507)	(0.00583)	(0.00582)			
50 Sol Lottery × % Trees Leaf Rust				0.000180	-0.00529	-0.00918			
				(0.0188)	(0.0210)	(0.0227)			
1000 Sol Lottery							-0.000296	-0.000185	-0.000124
							(0.000380)	(0.000342)	(0.000308)
1000 Sol Lottery × % Trees Leaf Rust							0.00501**	0.00531**	0.00506**
							(0.00255)	(0.00258)	(0.00238)
HH Head Years of Edu.		0.00562	0.00398		0.00586	0.00415		0.00464	0.00295
		(0.00467)	(0.00455)		(0.00449)	(0.00432)		(0.00447)	(0.00428)
HH Head Age		0.00119	0.000417		0.000764	0.00000289		0.000485	-0.000239
		(0.00138)	(0.00129)		(0.00128)	(0.00118)		(0.00135)	(0.00126)
Female HH Head		0.0571	0.0639		0.0697	0.0776		0.0543	0.0604
		(0.0670)	(0.0652)		(0.0648)	(0.0629)		(0.0661)	(0.0646)
Household Size		-0.00638	-0.00500		-0.00324	-0.000913		-0.00893	-0.00720
		(0.00855)	(0.00808)		(0.00923)	(0.00897)		(0.00871)	(0.00831)
Log Expenditure on Coffee Installments		0.000266	-0.00282		0.0000967	-0.00278		0.00212	-0.000895
		(0.00618)	(0.00663)		(0.00618)	(0.00679)		(0.00594)	(0.00641)
Non-Coffee Income		-0.000798	-0.000133		-0.00114	-0.000670		0.0000709	0.000714
		(0.00505)	(0.00497)		(0.00522)	(0.00526)		(0.00494)	(0.00483)
% Resistant Variety		0.000274	0.000645		0.000186	0.000532		0.000183	0.000521
		(0.000558)	(0.000526)		(0.000519)	(0.000503)		(0.000519)	(0.000481)
Organic Certification		-0.139*	-0.101		-0.135*	-0.0953		-0.148**	-0.108
		(0.0717)	(0.0681)		(0.0718)	(0.0684)		(0.0726)	(0.0682)
Distance to Coop. (km)		0.00267	0.00105		0.00287	0.00141		0.00304	0.00152
		(0.00187)	(0.00152)		(0.00175)	(0.00134)		(0.00186)	(0.00150)
Satisfaction Index		-0.00555	-0.000332		-0.0145	-0.00841		-0.00695	-0.000877
		(0.0201)	(0.0189)		(0.0185)	(0.0173)		(0.0188)	(0.0177)
Effectiveness Index		0.0143	0.0107		0.0128	0.00856		0.0118	0.00772
		(0.0206)	(0.0202)		(0.0181)	(0.0176)		(0.0202)	(0.0198)
Constant	0.0681**	-0.00484	0.0246	0.0489	-0.0300	-0.00420	0.0883***	0.0550	0.0854
	(0.0278)	(0.114)	(0.113)	(0.0382)	(0.121)	(0.120)	(0.0239)	(0.119)	(0.119)
District Indicators	No	No	No	No	No	Yes	No	No	Yes
Cooperative Indicators	No	No	No	No	No	Yes	No	No	Yes
Observations	315	315	315	315	315	315	315	315	315

Marginal effects; Standard errors in parentheses
(d) for discrete change of dummy variable from 0 to 1
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[1] Within and between correlations are estimated using the hybrid model in Equation 4.16. The within estimation is identical to the fixed effects estimation presented in Table 4.A.2 in Appendix 4.D.
[2] Heteroskedastic robust standard errors are clustered at the *Centro Poblado* (lowest administrative unit) level and reported in parentheses.
[3] * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$

Table 4.A.8: Hybrid Model: Results using Total Farm Area

	(1) % Organic Coffee Side-Sold	(2) % Organic Coffee Side-Sold	(3) % Organic Coffee Side-Sold
Within Estimation			
Total Has.	0.0449**	0.0449*	0.0449*
	(0.0222)	(0.0233)	(0.0234)
Total Has. $\times$Total Has.	-0.000337**	-0.000330*	-0.000330*
	(0.000171)	(0.000170)	(0.000171)
Log Outside Income		0.0139**	0.0139**
		(0.00687)	(0.00692)
% Trees with Leaf Rust		0.0656	0.0656
		(0.0997)	(0.100)
HH Head Years of Edu.		0.000793	0.000793
		(0.0178)	(0.0179)
HH Head Age		0.00222	0.00222
		(0.00855)	(0.00861)
Female HH Head		-0.00704	-0.00704
		(0.122)	(0.123)
Household Size		-0.0147	-0.0147
		(0.0106)	(0.0106)
Log Expenditure on Coffee Installments		-0.00334	-0.00334
		(0.00446)	(0.00450)
Log Loan Amount		0.00980	0.00980
		(0.00710)	(0.00715)
% Resistant Variety		-0.000157	-0.000157
		(0.000746)	(0.000751)
Organic Certification		-0.122	-0.122
		(0.160)	(0.161)
Between Estimation			
Total Has.	0.0370***	0.0358***	0.0222
	(0.0135)	(0.0135)	(0.0152)
Total Has. $\times$Total Has.	-0.000260***	-0.000263***	-0.000185**
	(0.0000785)	(0.0000755)	(0.0000826)
Log Outside Income		-0.000947	-0.000480
		(0.00471)	(0.00490)
% Trees with Leaf Rust		0.149	0.225**
		(0.0965)	(0.102)
HH Head Years of Edu.		0.00509	0.00339
		(0.00449)	(0.00450)
HH Head Age		0.00101	0.000381
		(0.00136)	(0.00128)
Female HH Head		0.0586	0.0663
		(0.0661)	(0.0646)
Household Size		-0.00600	-0.00560
		(0.00904)	(0.00854)
Log Expenditure on Coffee Installments		-0.000252	-0.00266
		(0.00644)	(0.00666)
Log Loan Amount		0.00872	0.00896
		(0.00560)	(0.00597)
% Resistant Variety		0.000378	0.000790
		(0.000583)	(0.000520)
Organic Certification		-0.123	-0.0946
		(0.0756)	(0.0709)
Distance to Coop. (km)		0.00220	0.000957
		(0.00178)	(0.00138)
Perception of Coop. Services		-0.00647	0.00198
		(0.0122)	(0.0137)
Identification with Coop.		-0.0108	-0.00859
		(0.0171)	(0.0169)
Constant	0.00721	0.0208	0.0431
	(0.0337)	(0.113)	(0.104)
District Indicators	No	No	Yes
Cooperative Indicators	No	No	Yes
Observations	315	315	315

Marginal effects; Standard errors in parentheses
(d) for discrete change of dummy variable from 0 to 1
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[1] Within and between correlations are estimated using the hybrid model in Equation 4.16. The within estimation is identical to the fixed effects estimation presented in Table 4.A.2 in Appendix 4.D.

[2] Heteroskedastic robust standard errors are clustered at the *Centro Poblado* (lowest administrative unit) level and reported in parentheses.

[3] * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$

Table 4.A.9: Hybrid Model: Results Including Time Indicators

	(1) % Organic Coffee Side-Sold	(2) % Organic Coffee Side-Sold	(3) % Organic Coffee Side-Sold
Within Estimation			
Has. Organic	0.0820*	0.0747*	0.0960**
	(0.0455)	(0.0451)	(0.0476)
Has. Org. ×Has. Org.	-0.00765*	-0.00715	-0.00895*
	(0.00459)	(0.00449)	(0.00476)
Log Outside Income	0.0126	0.0133*	0.00372
	(0.00764)	(0.00778)	(0.00676)
% Trees with Leaf Rust	0.0278	-0.195	-0.196
	(0.130)	(0.165)	(0.139)
Risk ×% Trees Leaf Rust		0.0257**	
		(0.0123)	
Log Outside Income ×% Trees with Leaf Rust			0.0541**
			(0.0236)
HH Head Years of Edu.	0.00296	0.00617	0.00609
	(0.0177)	(0.0171)	(0.0154)
HH Head Age	0.00582	0.00627	0.00512
	(0.00991)	(0.00951)	(0.00946)
Female HH Head	-0.0232	-0.0105	-0.0255
	(0.115)	(0.111)	(0.108)
Household Size	-0.0123	-0.0172	-0.0138
	(0.0108)	(0.0115)	(0.0105)
Log Expenditure on Coffee Installments	-0.00535	-0.00511	-0.00541
	(0.00442)	(0.00443)	(0.00466)
Log Loan Amount	0.00912	0.0126*	0.00903
	(0.00718)	(0.00746)	(0.00665)
% Resistant Variety	-0.0000467	0.0000353	-0.000308
	(0.000770)	(0.000749)	(0.000790)
Organic Certification	-0.0631	-0.0749	-0.0423
	(0.155)	(0.152)	(0.158)
Between Estimation			
Has. Organic	0.0112	0.0122	0.00999
	(0.0194)	(0.0205)	(0.0209)
Has. Org. ×Has. Org.	-0.00117	-0.00151	-0.00128
	(0.00166)	(0.00156)	(0.00162)
Log Outside Income	-0.000863	-0.00199	-0.00447
	(0.00493)	(0.00523)	(0.00686)
% Trees with Leaf Rust	0.209**	0.172	0.179
	(0.0990)	(0.149)	(0.155)
100 Sol Lottery		0.00535*	0.00637*
		(0.00309)	(0.00330)
Risk ×% Trees Leaf Rust		0.000672	-0.00205
		(0.0122)	(0.0122)
Log Outside Income ×% Trees with Leaf Rust			0.00999
			(0.0229)
HH Head Years of Edu.	0.00416	0.00458	0.00559
	(0.00469)	(0.00436)	(0.00449)
HH Head Age	0.000635	-0.0000506	0.000269
	(0.00130)	(0.00127)	(0.00140)
Female HH Head	0.0602	0.0655	0.0664
	(0.0643)	(0.0594)	(0.0624)
Household Size	-0.00434	-0.00258	-0.00304
	(0.00864)	(0.00855)	(0.00870)
Log Expenditure on Coffee Installments	-0.00263	-0.00171	-0.00119
	(0.00668)	(0.00647)	(0.00660)
Log Loan Amount	0.00872	0.00909*	0.00937*
	(0.00576)	(0.00525)	(0.00543)
% Resistant Variety	0.000703	0.000606	0.000627
	(0.000505)	(0.000488)	(0.000486)
Organic Certification	-0.0865	-0.0660	-0.0633
	(0.0715)	(0.0721)	(0.0700)
Distance to Coop. (km)	0.00106	0.00202	0.00218
	(0.00146)	(0.00127)	(0.00133)
Perception of Coop. Services	0.00305	-0.00000996	-0.00101
	(0.0141)	(0.0138)	(0.0141)
Identification with Coop.	-0.0103	-0.0248	-0.0234
	(0.0173)	(0.0178)	(0.0180)
Constant	0.0871	0.0939	0.0714
	(0.108)	(0.116)	(0.123)
District Indicators	Yes	Yes	Yes
Cooperative Indicators	Yes	Yes	Yes
Year Indicators	Yes	Yes	Yes
Observations	315	315	315

Marginal effects; Standard errors in parentheses
(d) for discrete change of dummy variable from 0 to 1
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[1] Within and between correlations are estimated using the hybrid model in Equation 4.16. The within estimation is identical to the fixed effects estimation presented in Table 4.A.2 in Appendix 4.D.
[2] Heteroskedastic robust standard errors are clustered at the *Centro Poblado* (lowest administrative unit) level and reported in parentheses.
[3] * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$

Chapter 5

Feeding Instability: Understanding the Effects of Cereal Prices on Conflict and Unrest in Ethiopia

The number of people fleeing conflict and the number of internally displaced persons has globally reached an all-time high. One potential cause for the increase in conflict and displacement is volatility in food prices, sometimes linked to effects of global warming on agriculture which is expected to become more important over time. However, effects of food prices are not yet well understood and research in this area has mostly focused on cross-country analysis, missing important intra-country issues and failing to make a distinction between types of conflicts. Using a unique dataset of monthly cereal prices and detailed conflict events in Ethiopia - the second most populous country in Africa and where conflicts have been on the rise -, we examine what the impact of domestic food prices has been on conflict and unrest over the last 15 years. We find that higher cereal prices cause increases in protests and riots, conflict with local aims, and small-scale violent events, but do not cause conflicts with national aims and large-scale battles. We also show significant context specific and heterogeneous effects, with differential effects seen over time and by local level of cereal production. Our results show that different theoretical mechanisms have been at play. The opportunity cost mechanism has reduced price effects on national conflict while the predation effect has exacerbated price effects on local conflict. This paper highlights the importance of within-country studies in a growing literature concerning the impact of economic conditions on conflict and unrest.

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5.1 Introduction

Conflict and unrest are on the rise globally, despite the international community's commitment to promoting peace and stability within the Sustainable Development Goals (SDGs). Since the establishment of the SDGs in 2015, the number of people fleeing conflict has reached an all-time high (UNHCR, 2020), and the number of internally displaced persons (IDPs) has increased from 200 million in 2015 to 325 million in 2019 (IPDM, 2020). The trends in conflict and unrest are leading not only to a humanitarian crisis, but also to a development crisis, as progress on virtually every SDG is undermined by conflict and unrest - in both the short and long runs. The costs of conflict can be devastating in terms of human life, psychological effects (O'Neil, 2015), the deterioration of institutions (Hoeffler and Reynal-Quero, 2003), the provision of public services (Fafchamps and Minten, 2009), economic welfare (Hess, 2003), and economic growth (De Groot, 2010). Understanding the causes of conflict and unrest is crucial for developing policy to reduce the incidence and impacts of conflict and unrest.

Economic conditions have historically been an important driver of conflict and unrest in Sub-Saharan Africa (SSA) (Miguel et al. 2004; Bruckner and Ciccone 2010). Previous research has demonstrated relationships between conflict and economic growth (Miguel et al., 2004), climate (Maystadt and Ecker 2014; Mach et al. 2019) oil prices (Dube and Vargas, 2013), other commodity prices (Bruckner and Ciccone, 2010), and food prices (McGuirk and Burke 2020; De Winne and Peersman 2019; Fjelde 2015; Hendrix and Haggard 2015). Food prices are of particular interest to policymakers because 65% of the labor force in SSA works in agriculture and food expenditure typically makes up over 50% of household budgets in countries in SSA (Chauvin et al., 2012). Cereals comprise of the majority of diets in SSA and are the most important food group for African consumers and producers (Chauvin et al., 2012). Cereal prices' central role in African economies means that changes in prices can incite unrest and conflict, as seen across the continent during the 2007-8 food riots (Berazneva and Lee, 2013). However, the mechanisms through which cereal prices can incite conflict are unclear because various actors with diverse interests are involved in cereal markets.

Economic theory and empirical evidence have shown that food prices, and by extension cereal prices, impact conflict through four primary economic agents: consumers, producers, governments, and organized armed groups (McGuirk and Burke, 2020). Because changing food prices simultaneously impact various actors with diverse interests, the effect on conflict is theoretically ambiguous. Each agent has a different set of interests and responds to changes in economic conditions through their own mechanisms: the relative deprivation, opportunity cost, state capacity, and predation effects for consumers, producers, governments, and non-government groups, respectively.

The relative deprivation and opportunity costs mechanisms have direct household-level effects. Relative deprivation suggests that when cereal prices increase, net consumers lose purchasing power, leading to increased incentives to engage in conflict and unrest to either appropriate resources or simply demand changes to the political and/or economic environment (Dreze and Sen, 1990). For example, the waves of food riots that swept SSA in 2007-8 after global food prices soared are an example of how the relative deprivation effect can lead to unrest (Berazneva and Lee, 2013). For producers, increases in food prices improve economic conditions and increase the opportunity cost of engaging in conflict and unrest. Consequently, conflict declines (McGuirk and Burke, 2020).

The predation and state-capacity mechanisms directly affect organizations, rather than households.[1] The predation mechanism takes effect when cereal prices increase, causing the value of land to increase along with the incentives for organized armed groups to violently take domestic land (Hirshleifer 1991; Grossman 1999). However, the state's tax revenues also increase from higher prices, giving the state more capacity to maintain peace and eliminate non-state, violent actors (Besley and Persson, 2010).

The empirical evidence, like the economic theory, has found ambiguous net effects of food prices on conflict and unrest. Analyzing the impact of food prices on conflict is particularly difficult because conflict and prices have a simultaneous relationship, causing OLS regressions to give biased estimates. To overcome this simultaneous relationship, researchers try to find exogenous causes of local prices to proxy or instrument for local prices. For small open economies, such as Ethiopia, international prices are a popular exogenous variable used to identify price effects on conflict and unrest.

Several studies using international prices as an exogenous regressor find that increases in international food prices cause increases in social unrest, particularly in urban areas.[2] Increases in national food price indices - instrumented by international food prices - were found to increase urban unrest in forty-seven African countries between 1990 and 2012 (Smith, 2014). Corroborating evidence can be found in Hendrix and Haggard (2015), where the authors use the FAO international food price index as an exogenous regressor and find that increases in food prices led to increases in urban social unrest from 1961-2010. Political institutions are found to play a significant role in the severity of price effects on unrest. Using a different approach, Bellemare (2015) uses natural disasters as instruments for food prices (determined by the FAO international food price index) and also finds that food-related unrest was shown to increase across Africa from 1990-2011. In terms of mechanisms, the focus on urban consumers only allows for testing the relative deprivation hypothesis and fails to give a complete analysis of the effects of food prices on conflict and unrest.

Because rural populations make up the majority of SSA (World Bank, 2019), the literature has evolved to investigate beyond urban and consumer effects and into rural and producer effects. Fjelde (2015) divides all of Africa into 55 km by 55 km grids and measures the effects of changes in the value of agricultural production on armed conflict. Agricultural value is determined by a producer price index comprised of international price series. The production percentages for various agricultural goods in each cell are used as index weights. Exogenous, international price series are used as components of the producer price index. Using the exogenous producer price index as an independent variable, Fjelde (2015) implements a fixed effects model to identify price effects (following Bruckner and Ciccone 2010). Price increases have a negative effect on armed conflict incidence, giving empirical support to the opportunity cost hypothesis.

McGuirk and Burke (2020) combines the consumer and producer mechanisms - relative deprivation, predation, and opportunity cost - into a comprehensive theoretical model which suggests that increased food prices simultaneously disincentivize producers to engage in conflict and unrest (through the opportunity cost mechanism) and incentivize them to engage in conflict (through the predation mechanism). Meanwhile, increased prices push consumers to engage in more conflict and unrest through the relative deprivation mechanism. Empirically, the division between what we call unrest and conflict is made using the terms 'output conflict' and 'factor

[1] However, these mechanisms can have indirect effects on households. For example, households may be paid more to participate in conflict when organisations' conditions improve (Hidalgo et al., 2010)

[2] Many studies have focused on urban social unrest. This focus has been influenced by the 2007-8 food riots (Berazneva and Lee, 2013), and the Arab Spring, where food prices played a prominent role (Sternberg 2012; Malik and Awadallah 2013)

conflict'. Specifically, output conflict consists of events in the Armed Conclict Events Location Database (ACLED) labelled as violence against civilians, riots, or protests (Raleigh et al., 2010), while Factor Conflict refers to events appearing in the Upsalla Conflict Data Prorgam (Sundberg and Melander, 2013). To appear in the UCDP dataset, conflicts must have over twenty-five battle deaths per year, and each event must consist of at least one battle death. In making these distinctions, McGuirk and Burke (2020) shows that increases in food prices can simultaneously increase output conflict and reduce factor conflict across Africa. They confirm these results using household data from Afrobarometer. These claims are partially supported by De Winne and Peersman (2019), which also uses the distinction between factor and output conflict to establish the mechanisms through which prices impact conflict. As an identification strategy, De Winne and Peersman (2019) uses a unique dataset of global quarterly production changes and harvest shocks to instrument for international prices. The authors find that price increases lead to increases in both output and factor conflict.

The literature has advanced our understanding of the effects of food prices on conflict and unrest, but is still lacking in three key areas. First, existing papers establishing causality focus on the effects of international prices or measures derived from international prices. However, if these prices are exogenous, then national governments, by definition, cannot control them. The effect of *domestic* prices on conflict and unrest would provide much more actionable information to decision-makers because governments have various policy tools at their disposal to influence domestic market prices (e.g. buffer stocks, price controls, and trade policy). Second, the distinctions between factor and output conflict illuminate the mechanisms of consumer and producer dynamics, but do not help in distinguishing between the aims of actors or the scale at which they operate. Understanding whether actors' aims are local or national and whether they operate via small-scale events or large-scale battles is relevant in informing policymakers, especially in federal government systems. Finally, Hendrix and Haggard (2015) notes that within-country studies are lacking. Country-specific governance structures, agricultural policies, and conflict dynamics may result in price effects that are different from the macro results found in cross-country studies (e.g. Dube and Vargas 2013).[3] To our knowledge, there are no within-country studies with a causal identification strategy for the effect of local food prices on conflict and unrest.

To overcome these shortfalls, this paper uses Ethiopia - home to nearly 115 million people - as a case study. Like other countries in SSA, Ethiopia is largely agrarian with 80% of the population working in agriculture (FAO, 2020) and highly dependent on cereals with 73% of agricultural land dedicated to cereal production (Seyoum Taffesse et al., 2013). 72% of the average Ethiopian diet and 46% of the average household's spending consists of cereals (Berhane et al., 2013). Naturally, both government and non-government actors are heavily involved in the cereals sector - cereals are crucial for the Ethiopian economy and affect the entire population.

Conflict and unrest in Ethiopia have been present throughout its history. However, November 2015 marked the beginning of an unrelenting uptick in conflict, unrest, and instability. By the end of 2019, Ethiopia had the 10th most IDPs in the world (IPDM, 2020) and was the origin to eighty-three thousand asylum seekers and ninety-five thousand refugees (UNHCR, 2020). 2020 was marked by another wave of internal unrest and conflict, which eventually led to a civil

[3] Dube and Vargas (2013) perform a case study of Colombia, and find that increases in commodity prices impact different types of conflict differently. They distinguish between guerrilla and paramilitary kidnappings, attacks, and massacres to test for the presence of the opportunity and predation effects. However, Dube and Vargas (2013) uses a producer-price index similar to Hendrix and Haggard (2015) that weights a single, national price point. Further, commodities are typically exported, while cereals (the focus of our paper) are generally consumed domestically (Abate et al., 2015).

war in the Tigray Region (Al Jazeera 2020; Gebremedhin 2020). The international community has been unable to ignore the situation - in 2017, the UN established a humanitarian response plan for Ethiopia, which by 2020 required 1.19 billion USD in annual funding (OCHA, 2020). The current situation in Ethiopia is not unfamiliar to observers of conflict and unrest in SSA and is contributing to the global increase in conflict and unrest in recent years.

This paper uses an instrumental variable approach using a unique dataset of monthly cereal prices from 96 Ethiopian retail markets, the Armed Conflict and Location Events Database (ACLED) (Raleigh et al., 2010), and the Uppsala Conflict Data Program (UCDP) (Pettersson and Öberg, 2020) from January 2007 to October 2018. We instrument local cereal prices with the FAO international cereal price index to identify the local price effects on conflict and unrest in an approach similar to Dube and Vargas (2013). The reduced form estimates of these specifications show the international price effects - the standard estimation in the existing literature. We use monthly prices and measures of conflict in all specifications, and therefore focus on short-run outcomes. We divide conflict and unrest into five separate categories: protests and riots, violent events involving ethnic militia, violent events involving rebel groups, violent events involving political militia, and large-scale battles for territory. These divisions in dependent variables allow us to distinguish between price effects on unrest and conflict and conflict's scope (local or national) and scale (small-scale violent events versus large-scale battles). Similar to McGuirk and Burke (2020), to test for mechanisms, we interact cereal prices with the average area of each market's zone (second administrative level in Ethiopia) under cereal cultivation from 2007 to 2015. The interaction term in each of these specifications gives evidence of whether the opportunity cost or predation effect predominates for producers. Finally, we use the recent wave of conflict and unrest in Ethiopia to test for temporal heterogeneity in the results. We test for temporal heterogeneity by including an interaction term between cereal prices and an indicator variable equal to one for dates after November 2015 and zero for dates before.

We find that both international prices and local prices increase the probability and incidence of protests and riots, conflict involving actors with local aims (e.g. ethnic militia), and small-scale violent events (e.g. attacks on civilians and bombings) involving actors with political motivations. Local price effects are nearly twice as large as international price effects. However, we find no significant relationships between cereal prices and battles involving groups with national motivations (e.g. rebel groups), and large-scale battles in ongoing conflicts from the UCDP database. These findings suggest that cereal prices have an influence on unrest, local conflict, and small-scale events, but not on larger civil conflicts.

Testing for heterogeneous results with respect to cereal production shows that the opportunity cost mechanism outweighs the predation effect for every type of conflict and unrest. Without evidence for the predation effect, the overall increases in conflict and unrest we find in the main results must stem from the relative deprivation effect. Our analysis concludes that consumers engage in more conflict as a result from higher prices as their economic situation worsens, while cereal producers engage in conflict less as their economic situation improves. These results indicate that policymakers should work to improve the economic conditions of both producers and consumers to reduce conflict and unrest.

Since heightened levels of unrest and conflict began in November 2015, the price effects have changed. Food prices have had an aggravating effect on local conflict involving ethnic militia, but a negative effect on large-scale battles in ongoing conflicts. The growing influence of ethnic federalism (discussed in Section 5.2) and the recent change in government policy towards the two largest rebel groups in Ethiopia are possible explanations for the changes in price effects. As ethnic tensions grow, food pricing policy is becoming an increasingly important policy tool for curbing local conflict.

This paper adds to a growing literature concerning the effects of food prices on conflict and unrest. Our findings corroborate existing empirical evidence for the opportunity cost mechanism (Fjelde 2015; McGuirk and Burke 2020; De Winne and Peersman 2019) and the relative deprivation mechanism (Raleigh et al. 2015; Hendrix and Haggard 2015; Smith 2014; Bellemare 2015). We do not find evidence that cereal prices are impacting large-scale conflict in general, but do find a significant and negative impact since November 2015. The latter result is consistent with McGuirk and Burke (2020), but contrasts with De Winne and Peersman (2019). Our paper shows that the predation and opportunity cost mechanisms can operate simultaneously, but at different scopes of conflict - local and national, respectively.

Our paper is the first truly meso-economic study analyzing the relationship between food/commodity prices and conflict and unrest. We are the first to use sub-national market prices to test the *causal* effects of market prices on conflict and unrest. Consequently, we are the first to show the difference in effects between local and international price effects. This paper is also the first to propose using different measures of conflict to measure the effects of cereal prices on the scope and scale of conflict. By making these distinctions, we are able to show that the predation and opportunity cost mechanisms are both key mechanisms in determining price effects on conflict in Ethiopia, but at different levels of conflict. Finally, our paper is only the second country case study concerning this topic (after Dube and Vargas 2013) - a contribution called for in Hendrix and Haggard (2015). Through these contributions, we are able to provide specific and targeted analysis to both researches and policymakers interested in understanding food price effects in a contemporary situation involving conflict and unrest.

The paper is organized as follows: Section 5.2 gives a brief, qualitative overview of conflict in Ethiopia during the study period, January 2007 to September, 2018. In Section 5.4, we propose an empirical methodology to identify local and international price effects, corresponding economic mechanisms, and the role of recent unrest in influencing price effects. Section 5.3 describes the data and variable definitions used in the econometric specifications, and Section 5.5 demonstrates the results of the empirical analysis. Finally, we conclude with a brief discussion of potential policy implications and areas for further research in Section 5.6.

5.2 The Ethiopian Context

5.2.1 Violence and Conflict

Conflict and unrest in Ethiopia are characterized by a diverse set of actors, methods, and goals. Most conflict and unrest events during the study period are explicitly about issues other than food prices – only one protest recorded in the ACLED data during the study period was directly about food. Rather, as some authors have claimed was the case in the Arab Spring, food prices can be a contributing factor to conflict and unrest, either implicitly or explicitly (Sternberg 2012; Malik and Awadallah 2013).

An important underlying issue of Ethiopian conflict and unrest is ethnicity. Ethiopia is home to more than eighty ethnic groups and is one of the most ethnically diverse countries in Africa (Posner, 2004). Based on the widely-used Ethno-Linguistic Fractionalization measure (ELF),[4] Ethiopia has an ELF score of 0.79 (Minnesota Population Center 2015; Ethiopia Central Statistical Agency 2007). Intuitively, the ELF Index shows that the probability of two randomly selected individuals being from different ethnic groups is 0.79. While Ethiopia as a whole is

[4] ELF is the Herfindahl–Hirschman Index subtracted from one: $ELF = 1 - \sum_i s_i^2$ where s_i is the is the proportion of the population belonging to group i.

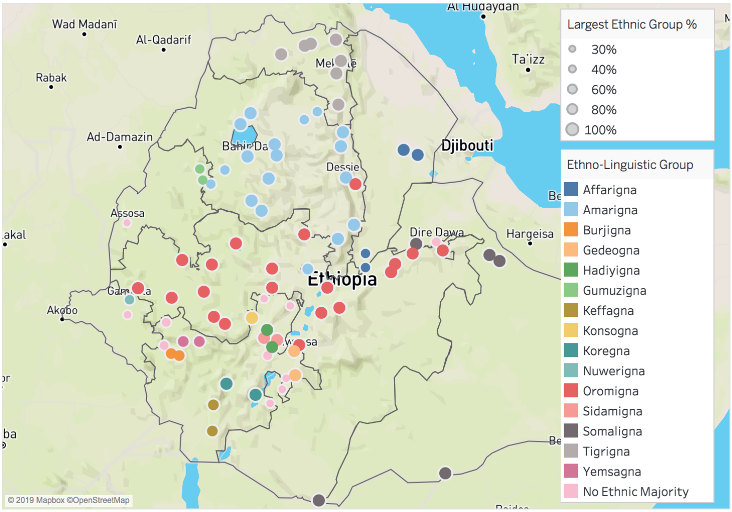

Figure 5.1: Ethnicity by Market

extraordinarily diverse, its regions and sub-regions tend to be ethnically homogeneous (Table 5.A.1 in Appendix 5.A). From the ninety-six markets in the study, most have overwhelming ethnic majorities, which can be seen in Figure 5.1.

Ethnic fractionalization is both a historical and contemporary phenomenon and features prominently in the current constitution, which outlines an ethnic-based federalist governance structure known as 'Ethnic Federalism' (Abbink, 2011). In brief, the constitution establishes five ethnic-based regions - Amhara, Tigray, Oromia, Somali, and Afar.[5] The remaining regions are either special regions (such as Addis Ababa) or non-ethnic based regions. Each region has its own governance systems, working language, and identity.

Section 5.3 defines conflict involving rebel groups, political militia, and large-scale battles as having national goals (e.g. rebellion against the national government).[6] From 2007 to 2018, the two largest *internal* conflicts with national aims were the insurgency in the Ogaden (1994 - 2018) and the Oromo Conflict (1972 - Present). In 2006, Ethiopia launched an invasion of neighboring Somalia. The intervention in the ongoing Somali Civil War led to increased tensions in the Somali region of southeastern Ethiopia (also referred to as the Ogaden). The Ogaden National Liberation Front (ONLF), a militia group in the Somali Region fighting for self-determination, was openly opposed to the Ethiopian invasion and carried out military operations against the Ethiopian military in the region (Vaughan, 2018). The Ethiopian Government put an embargo on the region, banning any trade in or out of the Somali region (Human Rights Watch, 2008).[7] The conflict between the ONLF and the Ethiopian government in the region consisted of both military operations against one another and atrocities against civilians com-

[5] Sidama became the sixth ethnic region after a referendum in November 2019. Sidama was formerly part of the Southern Nations Nationalities and Peoples Region (SNNPR) - the most ethnically diverse region in Ethiopia - and was home to the largest ethnic group in SNNPR (Minnesota Population Center 2015; Gebremedhin 2020)

[6] Large-scale battles can also have local goals; however, the majority of large-scale conflicts during the study period involved rebel groups with national goals.

[7] As seen in Section 5.5.1, international rates do not sufficiently pass through to Somali markets to be included in the instrumental variable analysis. This embargo may be a reason for these weak instruments. To our knowledge, it is the only such embargo during the study period.

mitted by both sides. The spikes in large-scale battles and conflict involving rebel groups seen from 2006 to 2009 are largely a result of this conflict.[8] Conflict continued in the Ogaden from 2010 to 2015, but slowed considerably until 2018 when a peace treaty was signed between the ONLF and the Ethiopian Government. While this conflict is important in terms of geopolitics, humanitarian crises, and internal politics, the Somali region accounts for about 6% of the total population (Ethiopia Central Statistical Agency, 2007), and is in many ways isolated from the rest of country.

The other major conflict during the study period is the Oromo Conflict. Oromia is home to about 36% of the country's population, and the Oromo ethnic group is the largest ethnic group in Ethiopia (Ethiopia Central Statistical Agency, 2007). However, many Oromo feel they have been historically marginalized (Kelbessa, 2005). Since the 1970s, the Oromo Liberation Front (OLF) and its military arm, the Oromo Liberation Army (OLA), have sought independence from the Ethiopian government. While some of the national conflict from 2007-2015 can be attributed to this conflict, the Oromo conflict exploded in late 2015 and has continued in recent years. Protests, riots, and violent conflict were sparked by a plan that would extend Addis Ababa into Oromia (ESRI, 2020). The opposition has been lead by the OLF and other groups, such as the Qeerroo. The protests against the Addis Ababa expansion plans soon turned into a movement generally opposing the central government. This movement has components of unrest, small-scale violence (e.g. violence involving political militia) and large-scale conflict (e.g. open battles between the OLA and Ethiopian Defence Forces) (BBC, 2019). The opposition soon spread from Oromia to other regions, such as SNNPR and Amhara.

By early 2018, the widespread opposition had led to the resignation of then prime minister, Hailemariam Desalegn - the first time an Ethiopian head of state had ever stepped down from office. Desalegn's resignation and the subsequent appointment of Abiy Ahmed - an Oromo - contributed to another spike in conflict and unrest. Thus far, Ahmed has implemented sweeping reforms in the military, legalized groups such as OLF and OLNF, signed a peace treaty with Eritrea, and made other social and economic reforms. Despite international support and winning the Nobel Peace Prize, Ahmed has been a controversial figure within Ethiopia, evidenced by calls for his resignation, military protests (BBC, 2018b) an attempted assassination (BBC, 2018a). The ongoing civil war in Tigray (which started in 2020) has heightened the controversy around Ahmed.

In terms of social unrest, the largest spike in protests and riots was in late 2015 with upticks in the subsequent years as well. Before November 2015, levels of social unrest were relatively low. The first spike in unrest can be seen around 2010, when Ethiopia had parliamentary elections. The opposition only won two out of 547 total seats. Opposition to the government continued for the next few years with particular opposition being aimed at an anti-terrorism law that allowed for the detention of journalists and opposition leaders (according to ACLED event entries). Protests over the next few years opposed the detention of journalists, the marginalization of Muslims in the Ethiopian government, student opposition to the national agenda, and general economic grievances (such as squatter rights). Often, the protests were met with violence from Ethiopian security forces. The wave of protests and riots from 2015 to late 2018 were largely related to the Oromo conflict, but were also related to other local concerns (ACLED).

Underneath the layer of national conflicts, there are a series of conflicts that are locally motivated. These local conflicts are typically driven by security concerns, territorial disputes between regions, and economic conditions (Yusuf, 2019). Arguably, these local conflicts are propelled by the ethnic nationalism stemming from ethnic federalism (Berhane et al. 2013;

[8] In 2010, the Ethiopia-Eritrea border dispute flared into skirmishes as well, contributing to the small peak in large-scale battle conflict seen in 2010. We do not discuss this conflict because it is not an internal conflict.

Taye 2017). First, ethnic-based militias have essentially engaged in an arms race to protect themselves from potential threats. The Amhara, Oromo, and Tigray regions have long-standing disputes with one another over territorial and political concerns. Elites from each of the ethnic groups have voiced their motivations to increase military strength backed by the reasoning that other groups had done so (Yusuf, 2019). The perceived lack of security and the consequent build up of ethnic militias have prompted raids into other ethnic territories. In some cases, these conflicts have been brought on by tensions between minority groups and regional majority groups, such as the conflict between the Qemant and Amhara over zonal autonomy in the Amhara region (Swart, 2020).

Territorial disputes have led to numerous ethnic-based conflicts as well. In some cases, the drawn borders are unclear and ethnic groups fight for control over these areas. Groups may take advantage of unclear borders to partake in land-grabbing to extract economic rents (Rueters, 2019). For example, the boundaries between Benishangul-Gumuz and Oromia are unclear. Oroma and Amhara farmers have migrated to contested areas, and some Oromo farmers in disputed areas refused to pay taxes to the Benishangul-Gumuz regional government. The Oromo region even made plans to incorporate the disputed Asosa area in the Oromo region. The disputes led to ethnic conflict, specifically between Gumuz and Oromo ethnic militia. Similar disputes over territory have arisen between the Oromo and Guju (SNNPR), Amhara and Tigray, Amhara and Oromo, Somali and Oromo, and others (Yusuf, 2019).

5.2.2 The Agricultural Economy

Economic conditions can add fuel to the fire for these conflicts. Ethiopia had 9.9% GDP growth from 2007 to 2018 (World Bank, 2020), but unemployment, inflation, and poverty defined the economic conditions for many people. The lack of national state capacity to widely improve economic conditions for everyone and to appropriately deal with local conflicts has allowed local conflict to proliferate and grow in recent years (Yusuf, 2019).

Ethiopia's main agricultural exports are flowers, oil seeds, and coffee, but the production of cereals (e.g. Teff, Sorghum, Maize, Wheat, and Barley) comprises of nearly 75% of all agricultural land (Dorosh et al., 2018). Geographically, the cultivation of cereals is spread throughout most of the country, excepting desert areas such as the Somali Region, where dry conditions make the cultivation of any crops impossible (Chamberlin and Schmidt, 2013).

In contrast to a number of other African countries, the new Federal Democratic Republic of Ethiopia government has not engaged in setting cereal prices or holding large buffer stocks for price stabilization (Rashid et al., 2018). Yet, price volatility in domestic Ethiopian cereal markets is similar to its East African neighbors (Dorosh et al., 2018).

General inflation and natural disasters are the greatest drivers of cereal price volatility in Ethiopia (Dorosh et al., 2018). Pertaining to the latter, Ethiopia has always had high levels of climate variation and has been susceptible to famines and food crises, which of course have devastating price effects (Conway and Schipper, 2011). In 2013, the Ethiopian government made reforms to the Ethiopian Strategic Food Reserves Agency (ESFRA) to play a more active role through four key mechanisms: establishing national preparedness for both man-made and natural disaster relief, stimulating grain production, distributing grain in times of high market volatility and inflation, and exporting grain to earn foreign reserves (Dorosh et al., 2018). The newer, broader mandate signifies a move away from the liberalization policies that characterized cereal policy in the 1990s and 2000s.

Finally, the government influences cereal markets through trade policy. In the wake of the 2007-8 global food prices crisis, many African governments imposed export bans on staple crops. Ethiopia has imposed export bans on cereal crops, particularly maize and teff, to keep food prices low and bolster food security (Aragie et al., 2016). The export ban on Maize was briefly lifted in 2010-11, but was quickly reimposed after another rise in global food prices (Yami et al., 2020). Imports are still largely controlled by the Ethiopian Grain Trade Enterprise and the government (Dorosh et al., 2018).

5.3 Data and Measurement

5.3.1 Data Sources and Variable Definitions

Local prices are derived from a primary retail market price data set from the Ethiopian Central Statistics Agency (CSA). The data set has monthly retail market prices for a variety of goods from 2007 until September 2018. The survey covers 120 Ethiopian markets and serves as the basis for the calculation of the National Consumer Price Index (CPI). Enumerators visit each market in the first two weeks of the month and record three different prices points for each good. The monthly price for each of these goods is the average of the three enumerator price points in the dataset.

From the 120 markets observations in the original dataset, 96 markets are used in the final analysis. Addis Ababa has 12 market observations, but the market observations do not have different GPS coordinates. The 12 markets are combined to one by averaging the prices across markets and using the midpoint of Addis Ababa as the location for these markets. There are six cases where the wereda (the third administrative level in Ethiopia) contains two markets. We combine these cases through simple price averaging to obtain one market observation for the weredas. Finally, 10 markets are dropped because they lack sufficient data for analysis.

We construct a producer's price index (PPI) based on the five major cereal crops in Ethiopia: maize, wheat, teff, sorghum, and barley. A producer's price index is chosen because sub-national data on the composition of cereals in local diets is not available, but administration data on cereal production is available. Since most cereal production is consumed domestically, it is likely that consumption shares of each market roughly correspond to the production shares in each market.

The index is composed of price series for each of the five major cereal crops, and the prices are weighted by the average proportion of the crop grown in a particular market's corresponding zone from 2007 to 2015. Mathematically, the index is given by:

$$\mathrm{PPI}_{it} = \sum_{c=1}^{5} \omega_{ic} * p_{ict} \tag{5.1}$$

where ω_{ic} is the crop weight for crop c in market i and p_{ict} is the price for crop c in market i and time t. We index the PPI using the base month of January 2010. All prices are deflated using the ETB to USD exchange rate, which steadily increases during the study period. Prices are deflated using the exchange rate instead of the CPI because cereal prices make up a significant portion of the CPI.

In Section 5.4, we note that month-to-month percent changes are used as independent variables. Month-to-month percent changes in prices ensure that the price series are stationary (see Appendix 5.B) and the independent variables have intuitive interpretations. The variable used in the estimations is mathematically defined as:

$$\Delta p_{it} = \frac{\mathrm{PPI}_{it} - \mathrm{PPI}_{it-1}}{\mathrm{PPI}_{it-1}} \tag{5.2}$$

International market prices are measured using the FAO Cereal Price Index. The cereal index is based on price data from the International Grain Council (IGC) and is composed of maize, barley, sorghum, wheat, and rice prices. Each cereal is given a weight based on the fixed international trade shares of each crop between 2014 and 2016 (FAO, 2013). This index has been used used in numerous studies, such as McGuirk and Burke (2020).

Other studies have used international price indices based on local production or consumption weights, rather than a general cereal index like the FAO price index. We do not follow this approach because Teff is one of the primary cereals in Ethiopia, and Teff is not traded internationally on large scales (because Teff is primarily grown in Ethiopia and the Ethiopian government has imposed export bans on Teff) (Aragie et al., 2016). The creation of a specific international index would therefore be challenging. Since there is sufficient price transmission of prices between cereal crops in Ethiopia, a general international price index is appropriate (Rashid, 2011).

As with the domestic prices, we use the percent change in international prices because level prices are non-stationary (see Appendix 5.B) and the percent change in prices provides intuitive interpretations. The international price variable, p_t^w (where the superscript w denotes world prices), used in the reduced form models and the first stage of the 2SLS models is given by:

$$\Delta p_t^w = \frac{\text{FAO Index}_t - \text{FAO Index}_{t-1}}{\text{FAO Index}_{t-1}} \tag{5.3}$$

Data on conflict and unrest are taken from two sources: The Armed Conflict Location Event Dataset (ACLED) (Raleigh et al., 2010) and Uppsala Conflict Data Program (UCDP) (Sundberg and Melander, 2013). We draw radii of 25km around each market and count the number of conflict events occurring within these radii each month.

The Armed Conflict Location Event Dataset (ACLED) is used as the data source for protests and riots, conflict involving ethnic militia, conflict involving political militia, and conflict involving rebel groups. ACLED is a non-profit organization with the goal of documenting dates, actors, types of violence, locations, and fatalities associated with political violence and protests across the globe. ACLED agglomerates reports of violent events from official publications, media reports, civil society (e.g. NGOs, humanitarian agencies, etc.), local staff, or other sources (e.g. Lloyds Casualty Report). Each event is geo-referenced using GPS points. These points are used to link each event to a market. Several studies in the literature rely on ACLED data (Raleigh et al. 2015; De Winne and Peersman 2019; McGuirk and Burke 2020).

The Uppsala Conflict Data Program (UCDP), compiled by the Uppsala University Department of Peace and Conflict Research, is used as the data source for large-scale battles (Sundberg and Melander, 2013). The unit of analysis in the database is an event, defined as 'The incidence of the use of armed force by an organized actor against another organized actor, or against civilians, resulting in at least 1 direct death in either the best, low or high estimate categories at a specific location and for a specific temporal duration' (Sundberg and Melander, 2013). About 80% of the events in the database are included using international and local media sources, while 20% draw on non-media sources such as NGO reports (e.g. Human Rights Watch), international organizations (e.g. UN), and other local sources (e.g. Oromo Liberation Front publications or 'Ogaden Online'). Events are geo-referenced using GPS points, which allows us to link them to individual markets. McGuirk and Burke (2020) and De Winne and Peersman (2019) use UCDP conflict data in their analysis.

In contrast to McGuirk and Burke (2020) and De Winne and Peersman (2019), we do not use all of the events specified in the UCDP database to define large-scale battles (or 'factor conflict' in the case of McGuirk and Burke (2020) and De Winne and Peersman (2019)). Entries to the database detail the actors involved in each event with a pair of actors, termed a ‘dyad’. One of the most common dyads is the Ethiopian government and civilians. These events typically consist of government violence against civilians and/or violent responses to protests. Since these events are not battles in the sense of two organized actors being involved in an armed clash, we exclude them from our definition of large-scale battles, and include only events where both actors in a dyad are organized actors. Table 5.1 provides descriptions and examples of these events.

Table 5.1: Conflict Definitions and Examples

Category	Scope	Scale	Data Source	Event Example
Protests and Riots	National and Local	Unrest	ACLED	‘Students protested at a school in Nekemte and were met by violent response from police forces.’ (2015-12-31)
Ethnic Militia Conflict	Local	Primarily Battles	ACLED	‘Continuing clashes between Afar Tribesmen and Oromo tribal militias have left 2 dead and 7 wounded.’ (2017-04-02)
Rebel Group Conflict	National	Primarily Battles	ACLED	‘ONLF claim victory against Ethiopian military in battle. Rebel group claims to have killed over 600 Ethiopian soldiers in offensive which began on 10 November’ (2009-11-13)
Political Militia Conflict	National and Local	Primarily Attacks Against Civilians and Bombings	ACLED	‘A bomb exploded near a court in the west of Ethiopia’s capital Addis Ababa on Thursday, wounding two people.’ (2011-03-24)
Large-Scale Battles	National and Local	Battles	UCDP	‘BBC Monitoring Africa: Ethiopian rebel group claims killing 33 soldiers in east’ (2016-02-04)

As control variables, we use travel time to the nearest population center of 50,000 people, market ELF index, the agricultural area under cereal cultivation, and measures for rainfall.

Market connectivity may play a role in price transmission from international to domestic markets and may influence price effects on conflict and unrest. Market connectivity is difficult to measure, so we proxy it with travel time to the nearest city of 50,000 inhabitants. The travel times are calculated by combining infrastructure (road), biophysical (land cover, water, river), and topography (slope) data. The description of this data can be found in Schmidt et al. (2018).

In Section 5.A.7, we report the differences between markets with sufficiently strong instruments and those with weak instruments. Ethnic diversity is included in this comparison, but not included as a control in the empirical specifications (because it is captured by market fixed effects). Ethnic diversity is measured by the Ethno-Linguistic Fractionalization (ELF) Index, discussed above (Posner, 2004). The ELF index is calculated from the Integrated Public Use Microdata Series-International (IPUMS-International), which uses data from The 2007 Housing and Population Census of Ethiopia (CSA, 2007). The microdata consists of a random sample of every 10th household in the original dataset, giving a total of 7,434,086 observations. A random subset of 20% of the total observations was asked about their mother tongue. We use this variable as an indicator for ethnicity. We note that this question is not explicitly about ethnicity, but that there is a near perfect correlation between ethnic group and mother tongue as different

Ethiopian ethnic groups do not speak the same language. We are using the term ethnic group interchangeably with ethno-linguistic group.

Agricultural production data is taken from the Ethiopian Central Statistics Agency (CSA), which keeps annual accounts on the production levels and area under cultivation for various crops at the zone level. The data is only available from 2007 to 2015. Two measures are derived from the cereal cultivation data: the average area under cereal cultivation used in the heterogeneity analysis described in Section 5.4.2 and the production weights used in the construction of the local PPI. Each measure is based on only the five main cereals in Ethiopia - Teff, Barley, Wheat, Sorghum, and Maize.

The measure for average total cereal area is a simple yearly average of the sum of agricultural land (measured in hectares) within each year from 2007 to 2015:

$$\text{cereal area}_i = \frac{\sum_{t=2007}^{2015} \sum_{c=1}^{5} \text{area}_{ict}}{2015 - 2007} \tag{5.4}$$

The production weights for the calculation of the PPI are defined as:

$$\omega_{ic} = \frac{\sum_{t=2007}^{2015} \frac{\text{cereal area}_{it}}{\text{area}_{it}}}{2015 - 2007} \tag{5.5}$$

Precipitation data is derived from the Climate Hazards Center InfraRed Precipitation with Station (CHIRPS) data, which uses a combination of satellite-based rainfall estimates and ground stations to create rainfall estimates for 0.5 degree by 0.5 degree (about 5.5km by 5.5km at the equator) raster grids (Funk et al., 2015). The CHIRPS data is linked to the markets by simply linking the GPS coordinates of the market with the nearest raster cell. Including climate statistics is important given rainfall's effect on conflict (Mach et al., 2019) and droughts working directly through prices to affect conflict (Maystadt and Ecker, 2014).

We calculate the long-run average of precipitation levels (in mm/month) and the standard deviation of rainfall over the study period for each market location. Then, for each month we calculate how many standard deviations (positive or negative) the observed month is from the monthly mean. A variable for positive standard deviations is included as a control in each regression model (and is equal to zero if the deviation is negative). An analogous measure of negative deviations is included as well. This approach follows Raleigh et al. (2015).

Finally oil prices are calculated using the month-to-month percent change in international oil price (not seasonally adjusted) per barrel (in USD), measured by the crude oil index for the West Texas Intermediate in Cushing, Oklahoma (U.S. Energy Information Administration, 2020).

5.3.2 Descriptive Statistics

International and local cereal prices varied substantially during the study period, as seen in Figure 5.2. A plot of the international and local price indices shows that local prices follow a similar pattern to international prices, but lag by several months. Both indices peaked in 2008 during the international food price crisis. After 2012 prices were relatively stable with a flat trend for local prices and a downward trend in international prices. Despite the small divergence in price trends, spikes in international prices were still correlated with spikes in local prices.

Conflict was present in virtually every month during the study period. Figure 5.3, shows that that conflict incidence involving ethnic militia (conflict with local aims) and political militia (small-scale conflict) peaked in early 2008 and in the recent wave of conflict beginning in November 2015. However, conflict involving rebel groups (conflict with national aims)

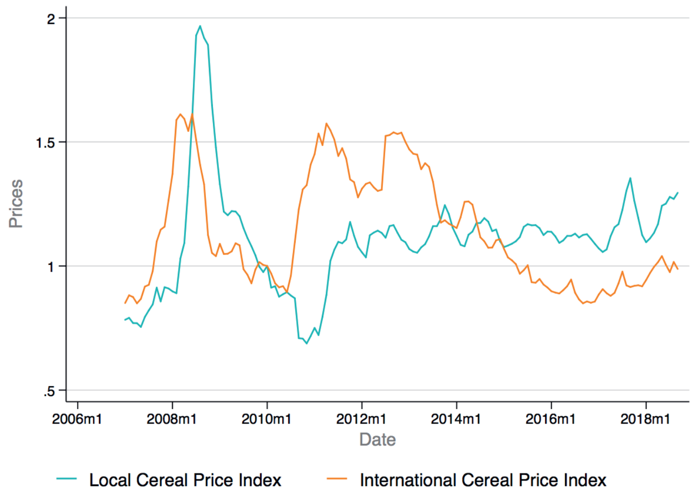

Figure 5.2: Domestic and International Cereal Prices: January 2007 - November 2018

and large-scale battles reached its peak at the end of 2015, but reached several smaller peaks throughout the study period. The discussion in Section 5.2 gives a more qualitative treatment of these trends.

Protests and riots - the main proxy for unrest - follow a different pattern. The incidence of protests and riots is relatively low before November 2015, but has risen dramatically since. After 2016, the number of protests and riots reduced, but still remained higher than pre-2015 levels.

Table 5.2 displays the descriptive statistics for the variables used in the econometric analysis. Over the course of the period, the average market was 107 minutes away from the nearest population center of 50k or more inhabitants. However, this average was 128 minutes in 2007 and reduced to 82 minutes by 2015, likely reflecting infrastructure developments and/or population growth during the period. 23% of markets are classified as urban. The average market has 31% of agricultural land devoted to cereal production, with the market with the least cereal production devoting only 3% of its agricultural land to cereal cultivation and the one with the most, devoting 94%. Markets range from ethnically homogeneous (ELF score of 0.01) to extremely diverse (ELF score of 0.79), reflecting the variation in ethnic diversity across markets in Ethiopia. On average, markets receive 96mm of rainfall per month, but there are both relatively dry markets and markets receiving large amounts of rainfall. Finally, the incidence of conflict and unrest is fairly low in all markets, where on average, markets experience less than 0.10 events per month for any type of event within 25km of the market. Protests and riots are more common than other types of events.

5.4 Methodology

Our methodology draws upon the empirical frameworks used in previous studies on quantifying the effects of global food prices on conflict and unrest (Smith 2014; Hendrix and Haggard 2015; McGuirk and Burke 2020). We use an instrumental variable approach similar to Dube

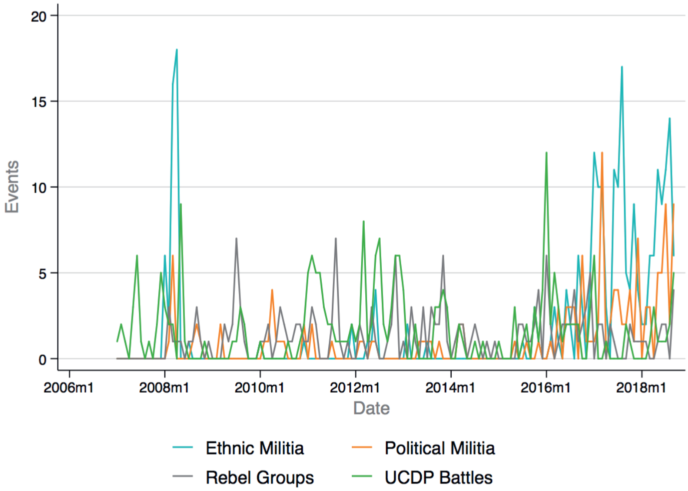

Figure 5.3: Conflict Events 2007 - 2019

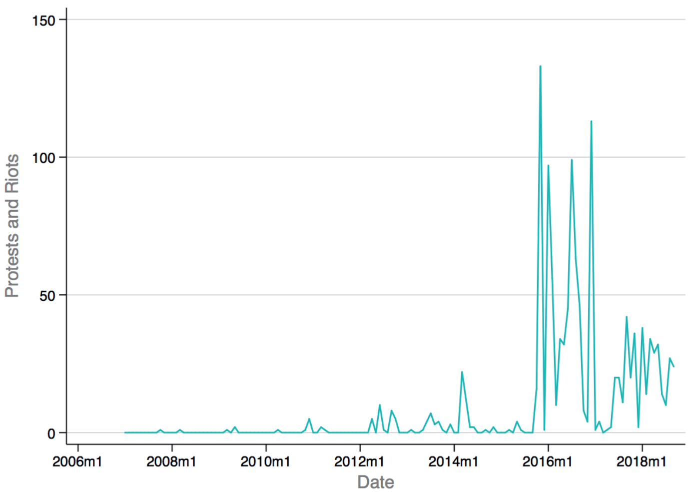

Figure 5.4: Protests and Riots 2007 - 2019

Table 5.2: Descriptive Statistics

	Mean	Standard Deviation	Median	Minimum	Maximum
Travel Time to Pop. Center of 50k (avg.)	107.25	98.32	81.31	0.00	543.30
Travel Time to Pop. Center of 50k (2007)	128.70	114.60	101.00	0.00	625.00
Travel Time to Pop. Center of 50k (2010)	112.75	108.69	88.00	0.00	625.00
Travel Time to Pop. Center of 50k (2015)	82.55	89.37	57.50	0.00	369.00
Urban Indicator	0.23	0.42	0.00	0.00	1.00
Cereal Area Percentage	0.31	0.17	0.26	0.03	0.94
ELF Index	0.29	0.25	0.22	0.01	0.79
Average Monthly Rainfall	95.26	35.19	96.69	13.18	167.63
Conflict Events Involving Ethnic Actors (10km)	0.01	0.02	0.00	0.00	0.10
Conflict Events Involving Ethnic Actors (25km)	0.02	0.04	0.00	0.00	0.19
Conflict Events Involving Political Actors (10km)	0.01	0.02	0.00	0.00	0.14
Conflict Events Involving Political Actors (25km)	0.01	0.02	0.00	0.00	0.16
Conflict Events Involving Rebel Groups (10km)	0.01	0.02	0.00	0.00	0.11
Conflict Events Involving Rebel Groups (25km)	0.02	0.05	0.00	0.00	0.33
Protests and Riot Events (10km)	0.04	0.07	0.01	0.00	0.40
Protests and Riot Events (25km)	0.09	0.17	0.02	0.00	1.12
UCDP Conflict Events (25km)	0.01	0.02	0.00	0.00	0.13
UCDP Conflict Events (25km)	0.02	0.04	0.00	0.00	0.23
Observations	96				

and Vargas (2013) in that we instrument domestic prices with international prices. But, our approach differs in that we use local price series from multiple markets rather than an index constructed through one national price point and production weights for local markets (Dube and Vargas, 2013). There are two types of main outcome variables: an indicator variable for whether a specific type of conflict and unrest event has occurred within a given market and month, and a count of how many events occurred in a given market and month. Models with the former outcome variables use a linear probability model (LPM) to estimate the effect of cereal prices on the probability of conflict and unrest, and models with the count variables as outcomes estimate the effect of cereal prices on the number of conflict and unrest events occurring. Our methodology is able to show the implications of estimating international prices (a reduced form model) versus local prices (a 2SLS model). The difference in these effects is determined by the pass-through rates of international prices to local prices - a commonly overlooked issue in this literature. The outcome variables are based on the distinctions in different types of conflict established in Section 5.3.

The methodology is extended to analyze the mechanisms through which food prices influence conflict and unrest. By introducing an interaction term between food prices and the area devoted to cereal production, we are able to test whether the opportunity cost or predation effect predominates. This approach follows Dube and Vargas (2013). Finally, we test for temporal variation by introducing an interaction term between prices and an indicator variable for whether a period occurs before or after November 2015. This last specification sheds light on price effects during the recent wave of conflict, unrest, and rising ethnic tensions.

5.4.1 The Instrumental Variable Approach: Setup and Validity

Local price effects can be consistently estimated using a Two Stage Least Squares (or Instrumental Variable) approach. Since we have local market price series, we implement a 2SLS model where local prices are instrumented with international prices in the first stage:

$$p_{it} = \beta_0 + \beta_1 p^w_{t-l} + v_{it},\ l\ \in [1, 6] \tag{5.6}$$

where p_{it} is the month-to-month percent change in local prices in market i and time t, and p^w_{t-l} is the world price in time period $t - l$, where $l \in [1, 6]$. v_{it} is the disturbance term. No control variables are included. For each market, the first stage is estimated for each value of the lag operator from one to six. The lag operator which yields the highest F-Statistic is used as the instrument for the second stage estimation for each market. This approach allows for heterogeneity in price transmission from world prices to local price and does not assume an arbitrary lag operator *a priori*. Imposing an arbitrary lag operator (e.g. 2 months) results in few markets having sufficiently strong instruments for unbiased estimations in the second stage. The decision to allow a lag operator up to six months follows from evidence that price transmission from international to domestic markets can take months to fully materialize (Cachia, 2017). It also follows from visual inspection in Figure 5.2. Further, several markets in the study are located in relatively remote areas of the country, meaning transmission could plausibly take months.

While allowing the lag operator to vary between one and six months reduces the number of markets with weak instruments, it also introduces a potential source of endogeneity into the model. The speed of price transmission and therefore, the optimal lag, could be affected by conflict, introducing simultaneity bias into the model. To relieve this concern, we run a series of robustness checks for the second stage estimations using lag operators of three, four, five, and six months for every market in the sample. However, in each of these robustness checks, a portion of the markets have weak instruments because the specified lag operator is not necessarily the optimal lag operator for each market. The results of these checks are shown in Appendix 5.F, and indicate that letting the lag operator vary for each market is not introducing endogeneity into the model.

The second stage of the 2SLS model is given by:

$$\text{event}_{it} = \beta_0 + \beta_1 \text{event}_{i,t-1} + \beta_2 \hat{p}_{t-l} + \beta_3 t + \text{market}_i + \beta_4 t \times \text{market}_i + \text{month}_t + \alpha X + \epsilon_{it} \quad (5.7)$$

where the β terms are coefficients, event_{it-1} is the one month lag of the measure for events in market i, $\hat{p}_{t-l}$ is the estimated lagged month-to-month percent change in local prices from Equation 5.6, t gives a linear time trend, market_i is the market fixed effect, $t \times \text{market}_i$ is the market-specific time trend, month_t is the monthly fixed effect (which controls for seasonality), X is a matrix of control variables, α is the vector of coefficients corresponding to X, and ϵ_{it} is the disturbance term. β_2 in Equation 5.6 gives an unbiased estimate estimate of the effect of food prices on conflict if and only if the relevance condition and the exclusion restriction are met (Angrist et al., 1996). By consequence, if the exclusion restriction is met, then Equation 5.7 will also provide consistent results for the effect of international prices on local output and factor conflict.

The relevance condition states that the instrument has a causal effect on the endogenous regressor - i.e. international prices must have a causal effect on local prices. The relevance condition can be tested empirically by analyzing if the F-Statistic in the first stage of the 2SLS regression is sufficiently large - i.e. above 10 (Stock and Yogo, 2002). Failure to meet this condition leads to the weak instrument problem whereby estimates are biased towards the OLS estimate. In our case, since the first stage is run for each market, we must assess whether the instrument is sufficiently strong for each market. We show the results of the first stage in Section 5.5.1.

The instrument meets the relevance condition in about 50% of the markets, reflecting low pass-through rates of world prices to African markets (Minot, 2011). The 2SLS estimates are biased towards the OLS estimate for the markets that do not meet the relevance condition. We solve this issue by dropping markets with F-Statistics less than 10 (the cutoff for strong instruments (Stock and Yogo, 2002)) from the analysis. As a result, we trade-off consistency for representativeness. In Section 5.5.1, we test for differences among included and excluded markets to asses how (un)representative our sample is. The failure to account for heterogeneity in pass-through rates can lead to misleading estimates. For the markets which international prices are strong enough instrument, we are able to provide estimates that are not biased by price transmission rates.

The exclusion restriction states that the instrument (p_t^w) can only have causal effect on the outcome variable (conflict_{it}) through its correlation with the endogenous variable (p_{it}) and cannot be correlated with the error term (ϵ_{it}) in the model (i.e. the instrument is exogenous). Unlike the relevance condition, the exclusion restriction cannot be shown to hold quantitatively, so we make a qualitative argument for why the exclusion restriction is met.

The first part of the exclusion restriction is met because international prices are unlikely to affect domestic conflict through a means other than the local market prices. The major threat to this assumption is the change in tariff revenue that results from changes in international prices. When international prices are high (low) government revenue from tariffs increases (decreases), and the state should have more capacity to engage in and/or mitigate conflict. However, this effect is unlikely to occur in a matter of months, as the mobilization of resources and development of new strategies related to conflict and unrest is a relatively slow process. Further, cereals contribute to a small portion of national trade, so even if the government could quickly adjust to changes in tariff revenues to deal with conflict, the changes would be fairly minimal.

The second part of the exclusion restriction maintains that the instrument's effect on conflict is the result of a simultaneous relationship or a confounding factor. First, international prices are exogenous to Ethiopian domestic prices. In terms of trade, Ethiopia is a small economy without influence over global cereal prices. Ethiopia imposed an export ban on many cereals for most of the study period (Porteous, 2017), and the world share of exports of Ethiopian cereals was close to 0 on average from 2007 to 2018. While Ethiopia is a net importer of cereal, its global importance as an importer is quite low - very few of the world's cereal imports went to Ethiopia. The vast majority of Ethiopian cereal consumption is from domestic production (Abate et al., 2015). Neither Ethiopian exports nor Ethiopian imports are likely to have any influence on the world market price, eliminating concerns over reverse causality between domestic and international prices.

Another threat to the exogeneity of international prices is the potential for domestic conflict to affect world prices. Domestic conflict could lead to greater instability in the region, which could affect international prices. However, Ethiopia's neighbors - Sudan, Eritrea, Somalia, South Sudan, and Kenya - make up a tiny fraction of global imports of cereals, making it unlikely that regional instability directly influenced global prices through supply or demand effects. Undoubtedly, conflict in Ethiopia affects its neighbors, contributing to their instability.[9] Instability in such a large region could influence global stability, but all of these countries (with the exception of Kenya) are seen as chronically unstable and make up some of the poorest countries in the world (Kessels et al., 2016). In the international context, changes in political and economic (in)stability in the region likely have no bearing on global attitudes in food markets because of the region's relatively small role in global politics, thus ruling out reverse causality through indirect means.

A more plausible threat to the exclusion restriction is that a third factor may influence both local conflict and international food prices. De Winne and Peersman (2019) argues that areas which are systematically more exposed to global markets may also be more exposed to common shocks, thus biasing the estimates. Common factors may affect trade flows, remittances, and oil price shocks - all of which can impact conflict. Trade flows are largely determined at the national level and while some regions may be more exposed than others, we attempt to capture this through including market fixed effects, market-specific trends, and several control variables. For example, markets with greater transportation connectivity could be more exposed to common global shocks. So, we control for travel time to the nearest population center. With these controls and market fixed effects, a general time trend, and a market-specific time trend variable, we control for at least most of the endogeneity, if not all.

Further, we note that following the approach of De Winne and Peersman (2019) by using completely exogenous harvest shocks may be attractive, it also has a drawback that our approach does not suffer from. De Winne and Peersman (2019) looks at the effect of international prices, rather than local prices and reports a sufficiently high first-stage F-Statistic (where the first stage is international prices on exogenous harvest shocks). However, given that international prices do not pass through perfectly to local prices (see Section 5.5.1 and Minot (2011)), it is unlikely that these harvest shocks would be sufficiently strong as an instrument for local market prices in Ethiopia. As a result, such a specification would suffer from weak instrument bias, and the estimates would be biased towards OLS estimates.

Following Dube and Vargas (2013) who uses international commodity prices to instrument

[9]For example, the 2006 Ethiopian invasion of Somalia, the 20-year border war with Eritrea, spillover in conflict to Kenya, conflict-related migration issues with Sudan, and meddling in Sudanese peace process (Mosley, 2020)

for local commodity prices, and Fjelde (2015), Hendrix and Haggard (2015), and McGuirk and Burke (2020) who use international food prices as exogenous regressors, we maintain that international prices are a valid instrument for local prices.

5.4.2 Heterogeneity Analysis

Testing Producer Mechanisms

To identify the mechanisms through which cereal prices are influencing various types of conflict and unrest, we interact month-to-month percent changes in prices with the average area under cereal cultivation from 2007 to 2015 in each market's zone (second administration level in Ethiopia).[10] Markets with higher cereal production are comprised of more producers and markets with less area devoted to cereal production have fewer producers. Specifically, we add an interaction term to the model in Equation 5.7. The second stage of the 2SLS model is expressed as:

$$\begin{aligned} \text{event}_{it} = \beta_0 + \beta_1 \text{event}_{i,t-1} + \beta_2 \hat{p}_{t-l} + \beta_3 \text{cereal area}_i + \beta_4 \hat{p}_{t-l} \times \text{cereal area}_i + \beta_5 t \\ + \text{market}_i + \beta_6 t \ \times \ \text{market}_i + \text{month}_t + \alpha X + \epsilon_{it} \end{aligned} \tag{5.8}$$

where the definitions correspond to those in Equation 5.7, and cereal area$_i$ is the area under cereal cultivation in a given market's zone (second administrative level). In Equation 5.8, the coefficient of interest is β_4, which corresponds to the additional effect of a 1% change in prices on conflict and unrest of having one more hectare under cereal cultivation (and the total price effect is given by $\beta_2 + \beta_4$).

β_4 gives us insights into whether the predation or opportunity cost mechanism predominates. If $\beta_4 < 0$, then the effect of prices on conflict and unrest is lower (or more negative) in markets with more cereal production, and the opportunity cost effect is playing a role, and producers are less willing to engage in conflict when prices increase. Conversely, if $\beta_4 > 0$, then the effect of prices on conflict and unrest is higher (more positive) in markets with more cereal production, and the predation effect is at play, and the potential spoils of conflict are attracting actors in cereal producing areas to engage in conflict.

Testing Heterogeneity Over Time

The final econometric specification tests whether price effects have been different in a recent wave of conflict and unrest, starting in November 2015 and continuing through the end of the study period in September 2018. November 2015 was a distinct turning point in Ethiopian national stability, as seen in Figures 5.3 and 5.4. Theoretically, differences in the effect of food prices on conflict before November 2015 and after can come about for two reasons. First, unrelated frustrations can spillover into political action (Carvalho and Viana, 2017). As Section 5.2 describes, the post-November 2015 unrest was not directly about food, and it is plausible that in this time of increased unrest, economic actors became more sensitive to food prices. Whereas in relatively calm times, actors may not use violent means in response to food prices, in times of unrest, changes in food prices may be the straw that breaks the camel's back. Second, heightened tensions can affect the state's capacity to deal with conflict, as resources are spread thin. This could reduce the perceived costs of non-government actors engaging in violent actions.

[10] 2007-2015 are the only years that have data on cereal production at the zone level, and therefore we must use an average measure rather than a time-varying measure.

From policy standpoint, these models can help policymakers understand price effects in the context of the recent wave of conflict and unrest. From a theoretical perspective, nation-wide instability may change the economic costs of engaging in conflict and unrest for both households and organized actors. We exploit this abrupt turning point in instability to test whether price changes impact conflict and unrest differently in periods of relative stability compared to periods of instability. The first stage of the 2SLS estimation remains the same, but the second stage of the 2SLS estimation becomes:

$$\begin{aligned}\text{event}_{it} = \beta_0 + \beta_1 \text{event}_{i,t-1} + \beta_2 \hat{p}_{t-l} + \beta_3 \text{post 2015}_t + \beta_4 \hat{p}_{t-l} \times \text{post 2015}_t + \beta_5 t \\ + \text{market}_i + \beta_6 t \ \times \ \text{market}_i + \text{month}_t + \alpha X + \epsilon_{it}\end{aligned} \tag{5.9}$$

post 2015 is an indicator variable equal to one if t is November 2015 or later and zero if t is before November 2015. The other variable definitions correspond to those in Equation 5.7. The coefficients of interest in the model are β_2 and β_4. β_2 represents the price effects before November 2015 and $\beta_2 + \beta_4$ represents the price effects after November 2015. If β_4 is positive, then the price effects are more positive after the wave of unrest and conflict began in 2015. A negative β_4 suggests that price effects are more negative after 2015.

5.5 Results

Before conducting any econometric analysis, we check for the stationarity of each of our series. Dicky-Fuller tests show that all types of conflict are level-stationary, I(0), series. However, neither local nor international prices is level stationary. So, we use the percent change from month to month of both local and international prices in all specifications. Each percent change series is stationary. The results of the Dicky-Fuller tests are presenting in Appendix 5.B. In all models, we use stationary series to ensure that the models are detecting causal effects and not spurious trends.

5.5.1 First Stage Results

The first-stage analyzes the effect of international prices on local prices - described in Equation 5.6. The results are shown in Appendix 5.C. Only 47% of markets pass the Stock-Yogo weak instrument criterion of a minimum F-Statistic of ten in the first stage. Of these markets, the median optimal lag is four - meaning that the strongest relationship between local and international prices occurs with a four month delay.[11] In fact, about 55% of the markets that pass the Stock-Yogo weak instrument criterion have an optimal lag of three or four months, indicating that pass-through of international prices takes some time to materialize. We will use the 47% of markets that pass the first stage as the sample for our analysis. Of course, this sample is not representative of Ethiopia as a whole, but including markets with weak instruments would bias the results towards OLS as described in Section 5.4.1.

To demonstrate some of the concerns about the lack of representatives of these markets, we compare the markets in which international prices provide a sufficiently strong instrument (the 'Included Sample') to those where international prices are a weak instrument (the 'Excluded Sample'). We compare the samples along the dependent and control variables. Appendix 5.D indicates that the only significant differences between the included and excluded samples along

[11] Other studies that study price transmission also conclude that it can take months for prices to pass through from international to domestic markets (Cachia, 2017).

independent variables are travel times to the nearest population center for fifty thousand people in 2007, 2010, 2015, and on average across the three years. This is unsurprising given that travel time is a proxy for connectivity and pass-through of international prices to local market prices is largely determined by connectivity.

Among dependent variables, each type of conflict - except for conflict involving rebel groups - is significantly higher in the included markets compared to excluded markets at 10km or 25km radii. This suggests that conflict tends to occur in more connected markets, which are included in our samples. Bazzi and Blattman (2014) brings up the concern that conflict may be occurring in more remote areas and less connected areas. Isolated areas have been shown to have more security concerns than more connected areas (Fafchamps and Minten, 2009). Therefore international price effects in the literature may be attenuated. However, we can see that less connected markets do not experience conflict more - more connected markets have more conflict and unrest events on average (See Table 5.A.7). This difference could be caused by several factors. First, mobilizing groups for conflict may be easier in more connected areas because populations are higher and communication infrastructure is better. Secondly, conflict may be more prone to occur in more connected areas because these areas are more integrated into national politics and therefore have more to lose/gain from involvement in larger violent struggles. Finally, the difference may be an issue of reporting. Violent events are less likely to be reported in more remote areas. Whatever the reason for the difference may be, the sample is *not* representative of all of Ethiopia. The results shown are economically unbiased for the sample, but only give results for markets sufficiently integrated into the world cereal market.

5.5.2 Main Results

Tables 5.3 and 5.4 display the results of the main model specified in Equation 5.7 using the probability and incidence of events, respectively. Both tables indicate that cereal prices have a significant and positive effect on the probability and incidence of locally-driven conflict (conflict involving ethnic militia) and small-scale conflict (conflict involving political militia). A 1% increase in the cereal price index leads to a 0.19% increase in the probability of conflict involving political militia and a 0.13% increase in the probability of conflict involving ethnic militia in a given month. These results are robust to including control variables. In terms of incidence, Table 5.4 shows that a 1% increase in cereal prices leads to an increase of 0.005 and 0.003 for conflict involving ethnic and political militia, respectively. These represent increases of 25% and 26% and of the mean values of the incidence of conflict involving ethnic and political militia. These findings are within the range of values found by Dube and Vargas (2013) regarding the effects of prices on factor conflict.

Cereal prices do not have a significant relationship with conflict with national aims (conflict involving rebel groups) in any specification. The probability of protests and riots appears to be increased by 0.2% in Column 9 of Table 5.3 when cereal prices rise by 1%, but this relationship is not robust to including controls and is not significant when using conflict incidence as an outcome variable in Table 5.4. While the probability of large-scale battles does not appear to be affected by changes in cereal prices, Table 5.4 indicates that the incidence of large-scale battles increases by 0.002 with a 1% increase in the cereal price index. This is an increase equal to 11% of the mean incidence of large-scale battles.

These results indicate that increases in cereal prices cause more local and small-scale conflict, but do not affect national conflict and riots and protests. There is some evidence that large-scale battles are affected, but this relationship is not robust. The similarity in the coefficients between the models with and without controls suggests that the instrument is a valid exogenous regressor. Appendix 5.F shows these results using lag structures of 3, 4, 5, and 6 lags for each market as a robustness check. Further robustness checks using a radius of 10km are shown in Appendix 5.E. The robustness checks confirm the results shown in Table 5.3 and Table 5.4.

Table 5.3: Effects of Cereal Prices on Probability of Unrest and Conflict

	(1) Conflict Involving Ethnic Actors (25km)	(2) Conflict Involving Ethnic Actors (25km)	(3) Conflict Involving Rebel Groups (25km)	(4) Conflict Involving Rebel Groups (25km)	(5) Conflict Involving Political Actors (25km)	(6) Conflict Involving Political Actors (25km)	(7) Large-Scale Battles (25km)	(8) Large-Scale Battles (25km)	(9) Protests and Riots (25km)	(10) Protests and Riots (25km)
Pct. Change Local Cereal Prices	0.00193***	0.00197***	0.000602	0.000369	0.00132***	0.00132***	0.000149	0.000148	0.00206**	0.00130
	(0.000504)	(0.000514)	(0.000620)	(0.000626)	(0.000472)	(0.000473)	(0.000270)	(0.000331)	(0.000833)	(0.000837)
L.Lag Dep. Var.	0.204***	0.203***	0.0570	0.0566	0.00937	0.00906	0.135*	0.134*	0.171***	0.171***
	(0.0549)	(0.0548)	(0.0419)	(0.0419)	(0.0299)	(0.0297)	(0.0730)	(0.0731)	(0.0538)	(0.0542)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market Fixed Effects × Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5966	5964	5966	5964	5966	5964	5841	5839	5966	5964

Optimal lags for each market are used. Standard errors in parentheses. Standard errors clustered by market and date following (McGuirk and Burke, 2020). Estimates are found by estimation Equation 5.7
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5.4: Effects of Cereal Prices on Incidence of Unrest and Conflict

	(1) Conflict Events Involving Ethnic Actors (25km)	(2) Conflict Events Involving Ethnic Actors (25km)	(3) Conflict Events Involving Rebel Groups (25km)	(4) Conflict Events Involving Rebel Groups (25km)	(5) Conflict Events Involving Political Actors (25km)	(6) Conflict Events Involving Political Actors (25km)	(7) UCDP Conflict Events (25km)	(8) UCDP Conflict Events (25km)	(9) Protests and Riot Events (25km)	(10) Protests and Riot Events (25km)
Pct. Change Local Cereal Prices	0.00506***	0.00515***	0.00108	0.000799	0.00249***	0.00258***	0.00201*	0.00223**	0.00203	-0.00155
	(0.00169)	(0.00173)	(0.000699)	(0.000736)	(0.000932)	(0.000908)	(0.00104)	(0.00113)	(0.00225)	(0.00316)
L.Lag Dep. Var.	0.0353	0.0340	0.0188	0.0178	-0.00257	-0.00240	0.101*	0.100*	0.111	0.110
	(0.0397)	(0.0402)	(0.0356)	(0.0357)	(0.0305)	(0.0301)	(0.0574)	(0.0572)	(0.0743)	(0.0735)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market Fixed Effects × Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5966	5964	5966	5964	5966	5964	5966	5964	5966	5964

Optimal lags for each market are used. Standard errors in parentheses. Standard errors clustered by market and date following (McGuirk and Burke, 2020).
Estimates are found by estimation Equation 5.7
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.5.3 Heterogeneity: Testing predation vs. Opportunity Cost Mechanisms

The results in the previous sections indicate that increases in cereal prices increase conflict involving battles with local aims and small-scale conflict. However, these results do not indicate which mechanisms are at play. This section shows the estimates of the models proposed in Equation 5.8 to test whether the predation effect or opportunity cost mechanism predominates for producers. For unrest, the predation effect is not at play (because it does not strictly involve capturing territory and gaining political power). However, the specification serves as a logical check for the main results. The coefficients of interest in each of these models are for the interactions between average cereal area under cultivation and international prices (for reduced form) and local prices (for 2SLS). These coefficients correspond to β_4 in Equation 5.8 and can be interpreted as the additional effect of a 1% increase in prices due to having 1 more hectare of land under cereal cultivation in a market's respective zone ($\beta_2 + \beta_4$ gives the total effect). Negative coefficients for the interaction terms indicate that price effects are smaller due to having more area devoted to cereal cultivation, and positive coefficients indicate that price effects are larger in areas with more cereal cultivation. In general, we find that most interaction terms have negative coefficients, which means that cereal producers less likely to engage in conflict than non-cereal producers as a result of higher prices. This result suggests that the opportunity cost effect is stronger than the predation effect across all types of conflict. However, this result is only statistically significant for conflict involving rebel groups and protests and riots.

The results in Table 5.5 show that for having 10,000 more hectares under cereal cultivation reduces the probability of a 1% increase in cereal prices leading to conflict involving ethnic militia within 25km of a market by .00819% (Column 4). Column 8 indicates that 10,000 more hectares of cereal cultivation reduces the probability of riots and protests by .00745%; however, this relationship is only significant at the 10% confidence level. Analogous interpretations hold for the other columns in Table 5.5.

Table 5.6 displays the results using the incidence of conflict as the outcome measure. As above, having 10,000 more acres under cereal cultivation reduces the incidence of conflict resulting from a 1% increase in cereal prices by .00957 events. This represents a 53% decrease relative to the mean number of events involving rebel groups. Relative to the base effect of .00179, the interaction effect shows that the effect of cereal prices is reversed in large cereal producing areas. Interaction effects for other types of conflict and unrest are not statistically significant in the incidence models.

The interaction between cereal price changes and area under cultivation point towards the opportunity cost effect holding for producers. These results are consistent with McGuirk and Burke (2020), Fjelde (2015), and De Winne and Peersman (2019). However, the results are only statistically significant and robust for conflict with national aims (i.e. conflict involving rebel groups), and are actually positive for protests and riots (albeit insignificant). Surprisingly, the interaction term is negative for conflict involving ethnic militia - the type of conflict most associated with territorial gains.

Table 5.5: Effects of Cereal Prices on Probability of Unrest and Conflict - Interactions with Cereal Area

	(1) Conflict Involving Ethnic Actors (25km)	(2) Conflict Involving Ethnic Actors (25km)	(3) Conflict Involving Rebel Groups (25km)	(4) Conflict Involving Rebel Groups (25km)	(5) Conflict Involving Political Actors (25km)	(6) Conflict Involving Political Actors (25km)	(7) Large-Scale Battles (25km)	(8) Large-Scale Battles (25km)	(9) Protests and Riots (25km)	(10) Protests and Riots (25km)
Avg. Area Under Cereal Cultivation	0.0000556	0.0000538	-0.0000363	-0.0000394	-0.0000562	-0.0000579	0.0000146	0.0000144	0.000384***	0.000390***
	(0.0000589)	(0.0000593)	(0.0000556)	(0.0000556)	(0.0000365)	(0.0000365)	(0.0000232)	(0.0000233)	(0.0000845)	(0.0000868)
Pct. Change Local Cereal Prices	0.00236***	0.00242***	0.00202*	0.00179*	0.00160*	0.00160*	0.000247	0.000243	0.00342***	0.00259**
	(0.000895)	(0.000910)	(0.00106)	(0.00106)	(0.000863)	(0.000875)	(0.000500)	(0.000565)	(0.00131)	(0.00128)
Pct. Change Local Cereal Prices × Avg. Area Under Cereal Cultivation	-2.50e-09	-2.63e-09	-8.26e-09**	-8.19e-09**	-1.63e-09	-1.61e-09	-5.69e-10	-5.48e-10	-7.86e-09*	-7.45e-09*
	(2.92e-09)	(2.94e-09)	(3.25e-09)	(3.20e-09)	(3.10e-09)	(3.12e-09)	(1.50e-09)	(1.55e-09)	(4.42e-09)	(4.28e-09)
L.Lag Dep. Var.	0.204***	0.203***	0.0561	0.0556	0.00951	0.00921	0.135*	0.135*	0.170***	0.170***
	(0.0549)	(0.0548)	(0.0418)	(0.0418)	(0.0299)	(0.0298)	(0.0730)	(0.0731)	(0.0537)	(0.0541)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market Fixed Effects × Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5966	5964	5966	5964	5966	5964	5841	5839	5966	5964

Optimal lags for each market are used. Standard errors in parentheses. Standard errors clustered by market and date following (McGuirk and Burke, 2020).
Estimates are found by estimation Equation 5.8
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5.6: Effects of Cereal Prices on Incidence of Unrest and Conflict - Interactions with Cereal Area

	(1) Conflict Events Involving Ethnic Actors (25km)	(2) Conflict Events Involving Ethnic Actors (25km)	(3) Conflict Events Involving Rebel Groups (25km)	(4) Conflict Events Involving Rebel Groups (25km)	(5) Conflict Events Involving Political Actors (25km)	(6) Conflict Events Involving Political Actors (25km)	(7) UCDP Conflict Events (25km)	(8) UCDP Conflict Events (25km)	(9) Protests and Riot Events (25km)	(10) Protests and Riot Events (25km)
Avg. Area Under Cereal Cultivation	0.0000938	0.0000797	-0.0000389	-0.0000436	-0.0000770	-0.0000767	-0.0000448	-0.0000492	0.000836***	0.000867***
	(0.0000870)	(0.0000882)	(0.0000564)	(0.0000563)	(0.0000477)	(0.0000486)	(0.0000583)	(0.0000587)	(0.000236)	(0.000244)
Pct. Change Local Cereal Prices	0.00454**	0.00465**	0.00273**	0.00246**	0.00284*	0.00294*	0.00272*	0.00298*	0.00166	-0.00222
	(0.00199)	(0.00202)	(0.00121)	(0.00124)	(0.00156)	(0.00161)	(0.00144)	(0.00154)	(0.00336)	(0.00419)
Pct. Change Local Cereal Prices × Avg. Area Under Cereal Cultivation	3.00e-09	2.88e-09	-9.57e-09***	-9.57e-09***	-2.08e-09	-2.12e-09	-4.15e-09	-4.31e-09	2.11e-09	3.86e-09
	(1.13e-08)	(1.13e-08)	(3.64e-09)	(3.62e-09)	(6.30e-09)	(6.39e-09)	(3.99e-09)	(4.04e-09)	(1.11e-08)	(1.08e-08)
L.Lag Dep. Var.	0.0353	0.0340	0.0181	0.0172	-0.00248	-0.00230	0.101*	0.100*	0.111	0.110
	(0.0397)	(0.0402)	(0.0356)	(0.0357)	(0.0305)	(0.0302)	(0.0574)	(0.0571)	(0.0743)	(0.0735)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market Fixed Effects × Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5966	5964	5966	5964	5966	5964	5966	5964	5966	5964

Optimal lags for each market are used. Standard errors in parentheses. Standard errors clustered by market and date following (McGuirk and Burke, 2020). Estimates are found by estimation Equation 5.8.
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.5.4 Heterogeneity Analysis: Understanding Recent Conflict and Unrest

The final set of results presents the estimated differences in price effects before and after November 2015. These specifications are given by Equation 5.9. The results indicate that since 2015, the price effects on conflict involving ethnic militia have increased in magnitude, while the price effects on large-scale battles have become negative. Meanwhile, no significant differences in price effects are found for protests and riots, conflict involving rebel groups, and conflict involving political militia.

Column 2 in Table 5.7 indicates that a 1% increase in cereal prices after November 2015 causes a 0.038% increase in the probability of conflict involving ethnic actors - an effect nearly 60 times as high as the pre-2015 effect of 0.0006. Column 5 indicates that cereal prices significantly affected conflict involving political militia before November, 2015, but these effects were not exacerbated during the recent wave of conflict.

Table 5.8 shows similar results for local conflict - a 1% increase in cereal prices causes a 0.087% increase in the incidence of conflict involving ethnic actors after 2015 - a .084 percentage point increase over pre-2015 effects (which are 0.003). This means that price effects after 2015 are 29 times higher than price effects before 2015. As before, cereal prices have a significant effect on small-scale conflict (i.e. conflict involving political actors) before November 2015, but this effect does not change afterwards.

Interestingly, the pre-November 2015 effect on the incidence of large scale battles is positive with 1% increase in cereal prices causing an increase of 0.003 large-scale battles within 25km of a market. However, the effect after November-2015 is negative with an effect of -.0101 (Column 8). This result suggests that the predation effect held before November 2015, but the opportunity cost mechanism has dominated in the recent wave of conflict and unrest. This relationship needs further exploration in order to understand why there is a change in the dominant mechanism. A similar relationship holds for conflict involving rebel groups, but this is not statistically significant. However, these results are not robust to using the probability of conflict outcome measure in Table 5.7.

Finally, before November 2015, increases in cereal prices decreased the incidence of protests and riots. The interaction term is also negative, but is insignificant. This relationship gives credence to the opportunity cost mechanism, but should be interpreted with caution as the results are not reflected in Table 5.7.

Table 5.7: Effects of Cereal Prices on Probability of Unrest and Conflict - Interactions with Post 2015

	(1) Conflict Involving Ethnic Actors (25km)	(2) Conflict Involving Ethnic Actors (25km)	(3) Conflict Involving Rebel Groups (25km)	(4) Conflict Involving Rebel Groups (25km)	(5) Conflict Involving Political Actors (25km)	(6) Conflict Involving Political Actors (25km)	(7) Large-Scale Battles (25km)	(8) Large-Scale Battles (25km)	(9) Protests and Riots (25km)	(10) Protests and Riots (25km)
Post 2015	0.0228***	0.0217***	0.0119	0.0113	0.0208***	0.0209***	-0.00338	-0.00293	0.148***	0.144***
	(0.00736)	(0.00777)	(0.00729)	(0.00729)	(0.00587)	(0.00619)	(0.00394)	(0.00446)	(0.0219)	(0.0218)
Pct. Change Local Cereal Prices	0.000857**	0.000643*	0.000702	0.000611	0.000733*	0.000668*	0.000360	0.000422	-0.000324	-0.000927
	(0.000355)	(0.000346)	(0.000668)	(0.000712)	(0.000392)	(0.000393)	(0.000345)	(0.000460)	(0.000513)	(0.000671)
Post 2015=1 × Pct. Change Local Cereal Prices	0.0168**	0.0173**	-0.00561	-0.00569	0.00694	0.00703	-0.00382	-0.00398	0.0106	0.0119
	(0.00810)	(0.00843)	(0.00547)	(0.00566)	(0.00465)	(0.00486)	(0.00391)	(0.00409)	(0.0113)	(0.0118)
L.Lag Dep. Var.	0.207***	0.206***	0.0549	0.0543	0.00265	0.00208	0.134*	0.134*	0.125**	0.127**
	(0.0589)	(0.0589)	(0.0421)	(0.0421)	(0.0305)	(0.0304)	(0.0725)	(0.0727)	(0.0532)	(0.0531)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market Fixed Effects × Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5966	5964	5966	5964	5966	5964	5841	5839	5966	5964

Optimal lags for each market are used. Standard errors in parentheses. Standard errors clustered by market and date following (McGuirk and Burke, 2020). Estimates are found by estimation Equation 5.9.
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5.8: Effects of Cereal Prices on Incidence of Unrest and Conflict - Interactions with Post 2015

	(1) Conflict Events Involving Ethnic Actors (25km)	(2) Conflict Events Involving Ethnic Actors (25km)	(3) Conflict Events Involving Rebel Groups (25km)	(4) Conflict Events Involving Rebel Groups (25km)	(5) Conflict Events Involving Political Actors (25km)	(6) Conflict Events Involving Political Actors (25km)	(7) UCDP Conflict Events (25km)	(8) UCDP Conflict Events (25km)	(9) Protests and Riot Events (25km)	(10) Protests and Riot Events (25km)
Post 2015	0.0603***	0.0632***	0.0246*	0.0238*	0.0346***	0.0329***	-0.000143	0.00425	0.488***	0.472***
	(0.0148)	(0.0159)	(0.0129)	(0.0132)	(0.0115)	(0.0106)	(0.0133)	(0.0145)	(0.0934)	(0.0919)
Pct. Change Local Cereal Prices	0.00317**	0.00300**	0.000933	0.000792	0.00163**	0.00166**	0.00262**	0.00310**	-0.00232**	-0.00380**
	(0.00148)	(0.00152)	(0.000701)	(0.000772)	(0.000809)	(0.000843)	(0.00108)	(0.00128)	(0.00110)	(0.00158)
Post 2015=1 × Pct. Change Local Cereal Prices	0.0241*	0.0238*	-0.00377	-0.00380	0.00892	0.00914	-0.0133*	-0.0143*	-0.0466	-0.0436
	(0.0126)	(0.0128)	(0.00791)	(0.00814)	(0.00891)	(0.00905)	(0.00793)	(0.00833)	(0.0472)	(0.0474)
L.Lag Dep. Var.	0.0315	0.0299	0.0163	0.0154	-0.00598	-0.00580	0.0990*	0.0977*	0.0625	0.0639
	(0.0394)	(0.0398)	(0.0365)	(0.0366)	(0.0297)	(0.0296)	(0.0588)	(0.0584)	(0.0766)	(0.0767)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market Fixed Effects × Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5966	5964	5966	5964	5966	5964	5966	5964	5966	5964

Optimal lags for each market are used. Standard errors in parentheses. Standard errors clustered by market and date following (McGuirk and Burke, 2020). Estimates are found by estimation Equation 5.9.
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.6 Conclusion

Conflicts and violence are increasing in a large number of often poorer countries, leading to an increasing number of internally displaced persons and refugees. However, the causes of these conflicts are often not well understood. In this paper, we look at the impact of changing food prices on conflict and unrest. Food prices are important for the purchasing power and well-being of poorer consumers, income of farmers (often making up a large share of the population in such economies), and organizational effectiveness.

Previous literature has used cross-country studies to understand the effects of food prices on conflict and unrest. Recent literature has categorized conflict into output and factor conflict to understand which mechanisms are driving price effects on conflict (McGuirk and Burke 2020; De Winne and Peersman 2019). This paper extends the literature by performing a within-country analysis of the effects of cereal prices on conflict and unrest in Ethiopia. We further categorize conflict into five categories to understand how cereal prices are affecting unrest, conflict waged by actors with local or national aims, and conflict waged with small-scale violent events or large-scale battles. We explore how price effects are different in cereal producing regions compared to non-cereal producing regions to identify which producer mechanisms predominate (the opportunity costs mechanism vs. the predation mechanism). We then estimate how price effects differ in the recent wave of conflict and unrest, starting in November 2015, compared to price effects in the relatively stable period before November 2015.

The results indicate that price effects can be heterogeneous with respect to the type of conflict and unrest, market cereal production levels, and time. In general price increases tend to increase conflict with local ambitions and small-scale violent events (such as bombings and attacks on civilians). However, cereal price increases do not appear to affect large-scale conflict or conflict with national aims. In areas producing more cereals, the price effects on large-scale conflict and conflict with national aims are negative. Interestingly, price effects differ between the period from January 2007 and November 2015. The price effects on conflict involving ethnic militia (conflict with local aims) were exacerbated after November 2015. The price effects for conflict involving rebel groups and large-scale battles were positive before the recent wave of conflict and unrest began, but negative afterwards. The results indicate that price effects are not homogeneous, even within a single country across different times and locations. For example, while the opportunity cost mechanism is shown to predominate for producers in general, the predation effect appears to be predominating in the recent wave of unrest and conflict. These dynamics cannot be detected using cross-country analyses. Therefore, relying on cross-country studies to understand how food prices affect conflict can lead to misinformed and dangerous policy conclusions.

This study is evidence that more within-country studies should be conducted to obtain actionable insights for policymakers, an argument made by O'Brochta (2019) and Blair et al. (2020). Each situation has its own set of governance structures, cultural dynamics, and actors. For example, ethnic federalism is a unique governance structure that appears to be influencing local conflict in Ethiopia, and the peace treaties (and their preceding processes) signed between the federal government and OLF and ONLF in 2018, appear to be dampening and even reversing the price effects on large-scale conflict. While these issues are unique to Ethiopia, other countries with high degrees of ethnic fractionalization and persistent conflict (e.g. Nigeria) may experience similar dynamics.

Further research should continue to explore case studies for particular crops and specific countries. Cross-country results miss important dynamics that can be highly dependent on context. While there are many studies related to the effects of commodity prices on conflict, relatively few of these studies focus on food prices, despite food cultivation being the most prominent source of livelihoods in SSA. Further research should look into food policy measures' (e.g. export bans, price floors) effects on conflict to give governments a more thorough understanding of food prices and conflict. Our methodology and results can inform Ethiopian policymakers to make conflict-sensitive food policy, but can also provide a framework for future country-specific studies.

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Appendix 5

5.A Ethnic Composition

Table 5.A.1: Ethnicity in Regions of Ethiopia

Region	Largest Ethnic Group	Share of Largest Ethnic Group	ELF	Share of Total Population
Tigray	Tigrigna	95.06%	0.10	5.89%
Affar	Affarigna	89.37%	0.20	1.90%
Amhara	Amarigna	92.93%	0.14	23.38%
Oromia	Oromigna	86.87%	0.25	36.55%
Somali	Somaligna	96.83%	0.06	6.04%
Benishangul-Gumuz	Bertagna	25.53%	0.93	1.06%
SNNPR	Sidamigna	19.63%	0.96	20.20%
Gambela	Nuwerigna	46.01%	0.79	0.41%
Harari	Oromigna	57.55%	0.67	0.24%
Addis Ababa	Amarigna	70.64%	0.50	3.74%
Dire Dawa	Oromigna	49.23%	0.76	0.45%
Special Region	Somaligna	73.56%	0.46	0.13%

5.B Dicky-Fuller Tests

5.B.1 Local Prices

Table 5.A.2: Dicky-Fuller: Local Level Prices, I(0)

Market Name	Z-Score	P-Value	N
Adaba	−2.58	0.10	140.00
Addis Ababa	−1.94	0.31	140.00
Adigrat	−2.69	0.08	138.00
Adwa	−2.49	0.12	138.00
Agaro	−2.44	0.13	140.00
Alaba Kulito	−2.70	0.07	138.00
Amaya	−3.11	0.03	138.00
Ambo	−3.40	0.01	140.00

Table 5.A.2: Dicky-Fuller: Local Level Prices, I(0)

Market Name	Z-Score	P-Value	N
Amdework	−2.24	0.19	140.00
Arba Minch	−3.02	0.03	140.00
Assebe Teferi	−2.51	0.11	140.00
Assela	−2.62	0.09	140.00
Assosa	−2.41	0.14	140.00
Awash 7 Kilo	−2.68	0.08	140.00
Awassa	−2.04	0.27	139.00
Aysaita	−2.71	0.07	140.00
Bahir Dar	−2.50	0.11	140.00
Batti	−2.47	0.12	140.00
Bedele	−2.86	0.05	140.00
Bedessa	−3.21	0.02	140.00
Bestechire	−3.38	0.01	140.00
Bonga	−2.27	0.18	140.00
Boroda	−2.90	0.05	140.00
Butajira	−3.03	0.03	140.00
Chagni	−2.74	0.07	140.00
Chana	−3.77	0.00	140.00
Chuahit	−2.68	0.08	140.00
Dangla	−2.97	0.04	140.00
Debre Birhan	−2.37	0.15	140.00
Debre Markos	−3.28	0.02	140.00
Debre Tabor	−2.87	0.05	140.00
Dembecha	−0.92	0.78	119.00
Dembi Dolo	−2.93	0.04	140.00
Dilla	−1.40	0.58	140.00
Dimeka	−2.48	0.12	140.00
Dire Dawa 1	−3.47	0.01	127.00
Dire Dawa 2	−2.82	0.06	140.00
Dixis	−3.22	0.02	137.00
Dollo	−3.20	0.02	140.00
Doyogena	−3.55	0.01	140.00
Dubti	−1.99	0.29	140.00
Ejire	−4.08	0.00	126.00
Endaselassie	−2.37	0.15	127.00
Erer	−4.06	0.00	140.00
Este/Mekane Yesus	−3.60	0.01	140.00
Gambella	−2.24	0.19	140.00
Gidole	−3.85	0.00	140.00
Gimbi	−2.00	0.29	140.00
Gondar	−2.56	0.10	140.00
Hagere selam	−2.56	0.10	140.00
Hagere Mariam	−3.40	0.01	127.00
Harar	−2.52	0.11	140.00

Table 5.A.2: Dicky-Fuller: Local Level Prices, I(0)

Market Name	Z-Score	P-Value	N
Hartishek	−2.96	0.04	140.00
Hosaena	−3.31	0.01	140.00
Inda Aba Guna	−2.44	0.13	140.00
Jigjiga	−2.64	0.09	138.00
Jimma	−3.94	0.00	140.00
Jinka	−3.49	0.01	138.00
Karat	−2.80	0.06	139.00
Kele	−2.55	0.10	140.00
Kemashi	−2.39	0.14	127.00
Ketema	−4.05	0.00	140.00
Kobo	−2.88	0.05	140.00
Kombolcha	−3.27	0.02	140.00
Laska	−2.49	0.12	140.00
Maichwe	−2.99	0.04	140.00
Mambuk	−3.23	0.02	140.00
Masha	−2.06	0.26	140.00
Mekelle	−2.26	0.19	140.00
Melka werer	−3.05	0.03	138.00
Metu	−3.55	0.01	139.00
Mizan Teferi	−2.88	0.05	140.00
Mota	−2.67	0.08	140.00
Moyalle	−2.58	0.10	140.00
Nazareth	−2.57	0.10	138.00
Negele	−3.62	0.01	140.00
Nekemt	−2.45	0.13	140.00
Robe	−2.44	0.13	140.00
Sawla	−2.72	0.07	140.00
Sekota	−4.39	0.00	140.00
Shambu	−3.08	0.03	140.00
Shashemene	−2.58	0.10	140.00
Shebo Kire	−2.43	0.13	140.00
Shewa Benchi	−3.55	0.01	140.00
Shewa Robit	−2.24	0.19	127.00
Shone	−3.12	0.03	116.00
Soyama	−2.39	0.14	127.00
Teppi	−2.57	0.10	140.00
Tercha	−3.44	0.01	138.00
Wolayita Sodo	−2.39	0.14	140.00
Woldia	−2.28	0.18	138.00
Woliso	−3.31	0.01	138.00
Wolkite	−4.00	0.00	140.00
Wukro	−2.07	0.25	140.00
Yem Liyu	−3.94	0.00	138.00
Yirga chefe	−3.04	0.03	140.00

Table 5.A.3: Dicky-Fuller: Percent Change in Local Prices

Market Name	Z-Score	P-Value	N
Adaba	-11.42	6.96×10^{-21}	138.00
Addis Ababa	-6.98	8.06×10^{-10}	138.00
Adigrat	-12.01	3.26×10^{-22}	136.00
Adwa	-15.12	7.39×10^{-28}	134.00
Agaro	-11.55	3.41×10^{-21}	138.00
Alaba Kulito	-10.95	8.63×10^{-20}	134.00
Amaya	-11.02	6.03×10^{-20}	134.00
Ambo	-14.86	1.71×10^{-27}	138.00
Amdework	-13.12	1.58×10^{-24}	138.00
Arba Minch	-10.30	3.33×10^{-18}	138.00
Assebe Teferi	-9.85	4.49×10^{-17}	138.00
Assela	-12.79	7.10×10^{-24}	138.00
Assosa	-8.98	7.35×10^{-15}	138.00
Awash 7 Kilo	-10.96	8.52×10^{-20}	138.00
Awassa	-8.91	1.14×10^{-14}	137.00
Axum	-14.27	1.38×10^{-26}	123.00
Aysaita	-12.51	2.70×10^{-23}	138.00
Bahir Dar	-12.85	5.39×10^{-24}	138.00
Batti	-12.14	1.69×10^{-22}	138.00
Bedele	-11.89	5.84×10^{-22}	138.00
Bedessa	-9.95	2.50×10^{-17}	138.00
Bestechire	-19.21	0.00	138.00
Bonga	-11.45	5.97×10^{-21}	138.00
Boroda	-10.80	1.99×10^{-19}	138.00
Butajira	-10.69	3.66×10^{-19}	138.00
Chagni	-12.82	6.31×10^{-24}	138.00
Chana	-37.89	0.00	138.00
Chuahit	-11.64	2.14×10^{-21}	138.00
Dangla	-13.44	3.83×10^{-25}	138.00
Debre Birhan	-10.75	2.65×10^{-19}	138.00
Debre Markos	-12.77	7.69×10^{-24}	138.00
Debre Tabor	-16.18	4.23×10^{-29}	138.00
Dembecha	-11.83	7.88×10^{-22}	117.00
Dembi Dolo	-10.40	1.88×10^{-18}	138.00
Dilla	-9.15	2.70×10^{-15}	138.00
Dimeka	-13.99	4.07×10^{-26}	138.00
Dire Dawa 1	-10.14	8.39×10^{-18}	123.00
Dire Dawa 2	-12.04	2.70×10^{-22}	138.00
Dixis	-14.16	2.05×10^{-26}	133.00
Dollo	-17.18	6.65×10^{-30}	138.00
Doyogena	-15.56	2.08×10^{-28}	138.00
Dubti	-12.34	6.20×10^{-23}	138.00
Erer	-11.62	2.44×10^{-21}	135.00
Este/Mekane Yesus	-10.37	2.24×10^{-18}	138.00

Table 5.A.3: Dicky-Fuller: Percent Change in Local Prices

Market Name	Z-Score	P-Value	N
Fiche	-26.05	0.00	122.00
Gambella	-11.10	3.79×10^{-20}	138.00
Gidole	-11.62	2.41×10^{-21}	138.00
Gimbi	-9.30	1.11×10^{-15}	138.00
Gondar	-10.84	1.63×10^{-19}	138.00
Hagere selam	-10.87	1.39×10^{-19}	138.00
Hagere Mariam	-9.45	4.63×10^{-16}	123.00
Harar	-11.95	4.34×10^{-22}	138.00
Hartishek	-10.87	1.35×10^{-19}	138.00
Hosaena	-14.17	2.01×10^{-26}	138.00
Inda Aba Guna	-12.97	3.07×10^{-24}	138.00
Jigjiga	-9.92	2.98×10^{-17}	134.00
Jimma	-21.33	0.00	138.00
Jinka	-12.50	2.88×10^{-23}	134.00
Karat	-11.83	8.10×10^{-22}	137.00
Kele	-11.75	1.22×10^{-21}	138.00
Kemashi	-10.82	1.80×10^{-19}	123.00
Ketema	-11.75	1.20×10^{-21}	138.00
Kobo	-12.37	5.24×10^{-23}	138.00
Kombolcha	-11.49	4.88×10^{-21}	138.00
Laska	-11.71	1.49×10^{-21}	138.00
Maichwe	-16.02	6.21×10^{-29}	138.00
Mambuk	-11.22	1.99×10^{-20}	138.00
Masha	-9.84	4.73×10^{-17}	138.00
Mekelle	-9.36	8.05×10^{-16}	138.00
Melka werer	-19.95	0.00	133.00
Metu	-14.54	5.14×10^{-27}	137.00
Mizan Teferi	-11.78	1.01×10^{-21}	138.00
Mota	-11.61	2.53×10^{-21}	138.00
Moyalle	-11.25	1.71×10^{-20}	138.00
Nazareth	-13.96	4.60×10^{-26}	136.00
Negele	-12.72	9.65×10^{-24}	138.00
Nekemt	-11.85	7.15×10^{-22}	138.00
Robe	-11.49	4.71×10^{-21}	138.00
Sawla	-11.29	1.37×10^{-20}	138.00
Sekota	-11.28	1.50×10^{-20}	135.00
Shambu	-86.02	0.00	137.00
Shashemene	-12.29	7.82×10^{-23}	138.00
Shebo Kire	-15.17	6.41×10^{-28}	138.00
Shewa Benchi	-12.29	7.91×10^{-23}	138.00
Shewa Robit	-10.49	1.19×10^{-18}	123.00
Shone	-13.18	1.19×10^{-24}	112.00
Soyama	-9.77	7.26×10^{-17}	123.00
Teppi	-12.25	9.73×10^{-23}	138.00

Table 5.A.3: Dicky-Fuller: Percent Change in Local Prices

Market Name	Z-Score	P-Value	N
Tercha	-12.56	2.14×10^{-23}	134.00
Wolayita Sodo	-13.63	1.71×10^{-25}	138.00
Woldia	-12.01	3.21×10^{-22}	135.00
Woliso	-11.53	3.93×10^{-21}	134.00
Wolkite	-11.62	2.39×10^{-21}	138.00
Wukro	-14.69	3.08×10^{-27}	138.00
Yem Liyu	-12.19	1.30×10^{-22}	134.00
Yirga chefe	-12.25	9.59×10^{-23}	138.00

5.B.2 International Prices

Table 5.A.4: Dicky-Fuller: International Prices

	Z-Score	P-Value	Observations
Level	-1.613224	.4762836	140
Percent Change	-7.498565	4.31e-11	138

5.B.3 Output and Factor Violence

Table 5.A.5: Dicky-Fuller: Output and Factor Violence

	Z-Score	P-Value	Observations
Ethnic Militia	-4.369018	.0003366	140
Political Militia	-7.001796	7.29e-10	140
Rebel Groups	-9.534296	2.84e-16	140
UCDP Battles	-6.763347	2.76e-09	140
Protests and Riots	-5.374808	3.83e-06	140

5.C First Stage Results

Table 5.A.6: First Stage Results

Market Name	Region	Coefficient	R^2	F-Statistic	Optimal Lag
Adaba	Oromia	0.62	0.09	12.62	5
Addis Ababa	Addis Ababa	0.39	0.14	21.36	5
Adigrat	Tigray	0.40	0.05	7.63	3
Adwa	Tigray	0.36	0.02	2.66	5
Agaro	Oromia	0.48	0.08	11.75	4
Alaba Kulito	SNNPR	0.51	0.10	14.18	5

Table 5.A.6: First Stage Results

Market Name	Region	Coefficient	R^2	F-Statistic	Optimal Lag
Amaya	SNNPR	1.14	0.09	12.63	3
Ambo	Oromia	0.65	0.06	9.03	5
Amdework	Amhara	0.32	0.03	3.59	5
Arba Minch	SNNPR	0.70	0.08	11.01	3
Assebe Teferi	Oromia	0.52	0.14	21.71	4
Assela	Oromia	0.52	0.08	12.34	3
Assosa	Benishangul Gumuz	0.55	0.11	16.07	4
Awash 7 Kilo	Afar	0.52	0.09	13.94	4
Awassa	SNNPR	0.42	0.16	24.95	4
Axum	Tigray	0.56	0.06	7.20	4
Aysaita	Amhara	1.00	0.08	12.27	1
Bahir Dar	Amhara	0.56	0.11	16.55	5
Batti	Amhara	0.47	0.07	9.75	3
Bedele	Oromia	0.58	0.07	10.13	6
Bedessa	Oromia	0.64	0.09	13.49	5
Bestechire	SNNPR	0.64	0.06	8.60	6
Bonga	SNNPR	0.54	0.07	10.56	6
Boroda	Oromia	0.36	0.09	13.99	3
Butajira	SNNPR	0.81	0.14	21.39	3
Chagni	Amhara	0.52	0.09	13.08	4
Chana	SNNPR	0.36	0.07	9.40	4
Chuahit	Amhara	0.44	0.04	5.01	6
Dangla	Amhara	0.62	0.08	11.41	5
Debre Birhan	Amhara	0.70	0.14	21.79	5
Debre Markos	Amhara	0.65	0.08	11.33	6
Debre Tabor	Amhara	0.47	0.05	6.90	3
Dembecha	Amhara	1.38	0.10	13.16	2
Dembi Dolo	Oromia	0.63	0.06	8.19	4
Dilla	SNNPR	0.39	0.04	4.92	3
Dimeka	SNNPR	0.54	0.04	6.01	1
Dire Dawa 1	Dire Dawa	0.65	0.15	20.15	5
Dire Dawa 2	Dire Dawa	0.34	0.09	13.95	3
Dixis	Oromia	0.85	0.09	11.98	3
Dollo	Somali	0.52	0.04	5.41	3
Doyogena	SNNPR	0.64	0.08	11.60	3
Dubti	Afar	0.55	0.06	8.10	5
Erer	Somali	162.57	0.01	1.43	0
Este/Mekane Yesus	Amhara	0.75	0.04	4.98	0
Fiche	Oromia	0.57	0.06	7.29	5
Gambella	Gambella	0.58	0.07	9.56	3
Gidole	SNNPR	0.70	0.06	8.70	3
Gimbi	Oromia	0.49	0.07	10.50	3
Gondar	Amhara	0.39	0.08	11.80	6
Hagere Mariam	SNNPR	0.70	0.06	9.29	1
Hagere selam	Harari	0.36	0.06	7.73	3

Table 5.A.6: First Stage Results

Market Name	Region	Coefficient	R^2	F-Statistic	Optimal Lag
Harar	Somali	0.52	0.05	6.92	4
Hartishek	SNNPR	0.70	0.11	17.19	3
Hosaena	Tigray	0.76	0.05	6.39	4
Inda Aba Guna	Somali	0.34	0.04	5.46	4
Jigjiga	Oromia	0.49	0.10	14.10	4
Jimma	SNNPR	0.70	0.09	12.72	3
Jinka	SNNPR	0.50	0.06	8.09	0
Karat	Benishangul Gumuz	0.53	0.03	3.86	1
Kele	Amhara	0.51	0.06	9.06	4
Kemashi	Amhara	0.56	0.09	11.44	3
Ketema	SNNPR	0.40	0.01	1.77	4
Kobo	Tigray	0.57	0.04	5.92	6
Kombolcha	Benishangul Gumuz	0.62	0.04	5.18	0
Laska	SNNPR	0.52	0.06	8.92	6
Maichwe	Tigray	0.35	0.03	4.35	5
Mambuk	Afar	0.42	0.07	10.16	4
Masha	Oromia	0.47	0.10	14.90	6
Mekelle	SNNPR	0.53	0.11	17.05	5
Melka werer	Amhara	0.54	0.01	1.70	1
Metu	Somali	0.40	0.04	5.07	5
Mizan Teferi	Oromia	0.36	0.04	4.98	5
Mota	Oromia	0.64	0.10	14.19	3
Moyalle	Oromia	0.76	0.14	21.35	3
Nazareth	Oromia	0.99	0.16	24.99	3
Negele	SNNPR	0.66	0.05	6.67	0
Nekemt	Amhara	0.39	0.04	4.91	4
Robe	Oromia	0.69	0.08	11.34	3
Sawla	Oromia	0.70	0.13	20.38	5
Sekota	Gambella	0.37	0.02	2.57	5
Shambu	SNNPR	0.53	0.05	7.00	6
Shashemene	Amhara	0.52	0.09	13.20	4
Shebo Kire	SNNPR	0.53	0.06	8.58	4
Shewa Benchi	SNNPR	0.66	0.05	6.86	3
Shewa Robit	SNNPR	0.78	0.10	11.72	6
Shone	SNNPR	0.54	0.04	4.02	3
Soyama	SNNPR	0.39	0.07	9.01	3
Teppi	Amhara	0.61	0.10	15.21	5
Tercha	Oromia	0.56	0.05	6.44	3
Wolayita Sodo	SNNPR	0.61	0.10	13.90	6
Woldia	Tigray	0.51	0.06	7.55	6
Woliso	SNNPR	1.22	0.04	4.81	1
Wolkite	SNNPR	0.38	0.05	6.26	5
Wukro	Oromia	0.32	0.02	3.21	2
Yem Liyu	SNNPR	0.61	0.07	9.63	3
Yirga chefe	Benishangul Gumuz	0.46	0.03	3.60	2

5.D First Stage T-Tests on Included and Excluded Samples

Table 5.A.7: Comparison of Included and Excluded Markets

Variable	Excluded	Included	Difference
Travel Time to Pop. Center of 50k (avg.)	129.13	82.46	-46.671**
	(0.00)	(0.00)	(0.019)
Travel Time to Pop. Center of 50k (2007)	153.75	100.31	-53.434**
	(0.00)	(0.00)	(0.022)
Travel Time to Pop. Center of 50k (2010)	136.94	85.33	-51.608**
	(0.00)	(0.00)	(0.019)
Travel Time to Pop. Center of 50k (2015)	99.18	63.71	-35.465*
	(0.00)	(0.00)	(0.052)
Urban Indicator	0.23	0.22	-0.013
	(0.00)	(0.00)	(0.888)
Cereal Area Percentage	0.33	0.29	-0.037
	(0.00)	(0.00)	(0.288)
ELF Index	0.29	0.29	0.005
	(0.00)	(0.00)	(0.923)
Average Monthly Rainfall	90.37	100.80	10.430
	(0.00)	(0.00)	(0.148)
Conflict Events Involving Ethnic Actors (10km)	0.01	0.01	0.002
	(0.01)	(0.00)	(0.694)
Conflict Events Involving Ethnic Actors (25km)	0.01	0.03	0.013*
	(0.01)	(0.00)	(0.079)
Conflict Events Involving Political Actors (10km)	0.00	0.01	0.005
	(0.00)	(0.02)	(0.129)
Conflict Events Involving Political Actors (25km)	0.01	0.02	0.009*
	(0.00)	(0.00)	(0.060)
Conflict Events Involving Rebel Groups (10km)	0.00	0.01	0.004
	(0.02)	(0.01)	(0.232)
Conflict Events Involving Rebel Groups (25km)	0.01	0.02	0.011
	(0.06)	(0.00)	(0.258)
Protests and Riot Events (10km)	0.02	0.06	0.045***
	(0.00)	(0.00)	(0.001)
Protests and Riot Events (25km)	0.06	0.13	0.078**
	(0.00)	(0.00)	(0.029)
UCDP Conflict Events (10km)	0.00	0.02	0.015*
	(0.03)	(0.01)	(0.053)
UCDP Conflict Events (25km)	0.02	0.04	0.019
	(0.03)	(0.00)	(0.204)
Observations	51	45	96

[1] Significance levels: $^{*} < 10\%$ $^{**} < 5\%$ $^{***} < 1\%$
[2] P-Values in parentheses

5.E Robustness Checks: 10km Radius

Table 5.A.8: Effects of Cereal Prices on Probability of Unrest and Conflict

	(1) Conflict Involving Ethnic Actors (10km)	(2) Conflict Involving Ethnic Actors (10km)	(3) Conflict Involving Rebel Groups (10km)	(4) Conflict Involving Rebel Groups (10km)	(5) Conflict Involving Political Actors (10km)	(6) Conflict Involving Political Actors (10km)	(7) Large-Scale Battles (10km)	(8) Large-Scale Battles (10km)	(9) Protests and Riots (10km)	(10) Protests and Riots (10km)
Pct. Change Local Cereal Prices	0.000713***	0.000722***	0.0000409	-0.000120	0.000649***	0.000570**	0.00107	0.00118	0.00179**	0.00113
	(0.000246)	(0.000261)	(0.000287)	(0.000300)	(0.000219)	(0.000231)	(0.000723)	(0.000804)	(0.000739)	(0.000707)
L.Lag Dep. Var.	0.190***	0.188***	0.0140	0.0138	0.0103	0.00970	0.159***	0.158***	0.138**	0.138**
	(0.0704)	(0.0702)	(0.0366)	(0.0366)	(0.0489)	(0.0483)	(0.0512)	(0.0511)	(0.0539)	(0.0541)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market Fixed Effects × Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5966	5964	5966	5964	5966	5964	5966	5964	5966	5964

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

Table 5.A.9: Effects of Cereal Prices on Incidence of Unrest and Conflict

	(1) Conflict Events Involving Ethnic Actors (10km)	(2) Conflict Events Involving Ethnic Actors (10km)	(3) Conflict Events Involving Rebel Groups (10km)	(4) Conflict Events Involving Rebel Groups (10km)	(5) Conflict Events Involving Political Actors (10km)	(6) Conflict Events Involving Political Actors (10km)	(7) UCDP Conflict Events (25km)	(8) UCDP Conflict Events (25km)	(9) Protests and Riot Events (10km)	(10) Protests and Riot Events (10km)
Pct. Change Local Cereal Prices	0.000763***	0.000860***	0.000381	0.000204	0.000835**	0.000801***	0.000207	0.000244	0.00362***	0.00186
	(0.000280)	(0.000330)	(0.000378)	(0.000377)	(0.000365)	(0.000308)	(0.000375)	(0.000425)	(0.00137)	(0.00169)
L.Lag Dep. Var.	0.136	0.135	-0.0221	-0.0226	-0.0175	-0.0176	0.0584	0.0584	0.0718	0.0721
	(0.0909)	(0.0907)	(0.0251)	(0.0253)	(0.0363)	(0.0356)	(0.0493)	(0.0494)	(0.0689)	(0.0691)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market Fixed Effects × Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5966	5964	5966	5964	5966	5964	5966	5964	5966	5964

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

Table 5.A.10: Effects of Cereal Prices on Probability of Unrest and Conflict - Interactions with Cereal Area

	(1) Conflict Involving Ethnic Actors (10km)	(2) Conflict Involving Ethnic Actors (10km)	(3) Conflict Involving Rebel Groups (10km)	(4) Conflict Involving Rebel Groups (10km)	(5) Conflict Involving Political Actors (10km)	(6) Conflict Involving Political Actors (10km)	(7) Large-Scale Battles (10km)	(8) Large-Scale Battles (10km)	(9) Protests and Riots (10km)	(10) Protests and Riots (10km)
Avg. Area Under Cereal Cultivation	-0.00000191	-0.00000386	0.0000206	0.0000206	-0.00000114	-0.00000327	-0.0000264	-0.0000305	-0.0000383	-0.0000331
	(0.00000496)	(0.00000548)	(0.0000207)	(0.0000208)	(0.00000265)	(0.00000304)	(0.0000511)	(0.0000510)	(0.0000575)	(0.0000598)
Pct. Change Local Cereal Prices	0.00109***	0.00112**	0.000281	0.000109	0.000563*	0.000462	0.00158	0.00170	0.00201**	0.00128
	(0.000421)	(0.000440)	(0.000378)	(0.000399)	(0.000308)	(0.000321)	(0.00104)	(0.00112)	(0.000951)	(0.000893)
Pct. Change Local Cereal Prices × Avg. Area Under Cereal Cultivation	-2.19e-09*	-2.27e-09*	-1.40e-09	-1.32e-09	5.00e-10	6.22e-10	-2.97e-09	-2.99e-09	-1.29e-09	-8.84e-10
	(1.24e-09)	(1.25e-09)	(1.22e-09)	(1.19e-09)	(1.41e-09)	(1.43e-09)	(3.39e-09)	(3.43e-09)	(3.44e-09)	(3.26e-09)
L.Lag Dep. Var.	0.190***	0.188***	0.0140	0.0137	0.0103	0.00963	0.159***	0.158***	0.138**	0.138**
	(0.0705)	(0.0702)	(0.0365)	(0.0365)	(0.0489)	(0.0484)	(0.0514)	(0.0512)	(0.0540)	(0.0541)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market Fixed Effects × Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5966	5964	5966	5964	5966	5964	5966	5964	5966	5964

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

Table 5.A.11: Effects of Cereal Prices on Incidence of Unrest and Conflict - Interactions with Cereal Area

	(1) Conflict Events Involving Ethnic Actors (10km)	(2) Conflict Events Involving Ethnic Actors (10km)	(3) Conflict Events Involving Rebel Groups (10km)	(4) Conflict Events Involving Rebel Groups (10km)	(5) Conflict Events Involving Political Actors (10km)	(6) Conflict Events Involving Political Actors (10km)	(7) UCDP Conflict Events (25km)	(8) UCDP Conflict Events (25km)	(9) Protests and Riot Events (10km)	(10) Protests and Riot Events (10km)
Avg. Area Under Cereal Cultivation	-0.00000247	-0.00000339	0.0000206	0.0000198	-0.000000773	-0.00000126	0.0000156	0.0000157	-0.000103	-0.0000953
	(0.00000590)	(0.00000730)	(0.0000207)	(0.0000208)	(0.00000245)	(0.00000680)	(0.0000222)	(0.0000224)	(0.000117)	(0.000124)
Pct. Change Local Cereal Prices	0.00128***	0.00141***	0.000693	0.000503	0.000491	0.000436	0.000148	0.000188	0.00388**	0.00192
	(0.000487)	(0.000547)	(0.000550)	(0.000565)	(0.000343)	(0.000426)	(0.000601)	(0.000660)	(0.00173)	(0.00195)
Pct. Change Local Cereal Prices × Avg. Area Under Cereal Cultivation	-2.99e-09**	-3.20e-09**	-1.81e-09	-1.73e-09	2.00e-09	2.11e-09	3.40e-10	3.24e-10	-1.52e-09	-3.82e-10
	(1.51e-09)	(1.57e-09)	(1.66e-09)	(1.66e-09)	(2.54e-09)	(2.69e-09)	(1.59e-09)	(1.64e-09)	(6.66e-09)	(6.22e-09)
L.Lag Dep. Var.	0.136	0.135	-0.0221	-0.0226	-0.0175	-0.0176	0.0584	0.0584	0.0718	0.0720
	(0.0909)	(0.0908)	(0.0250)	(0.0253)	(0.0363)	(0.0356)	(0.0493)	(0.0494)	(0.0690)	(0.0691)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market Fixed Effects × Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5966	5964	5966	5964	5966	5964	5966	5964	5966	5964

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

Table 5.A.12: Effects of Cereal Prices on Probability of Unrest and Conflict - Interactions with Post 2015

	(1) Conflict Involving Ethnic Actors (10km)	(2) Conflict Involving Ethnic Actors (10km)	(3) Conflict Involving Rebel Groups (10km)	(4) Conflict Involving Rebel Groups (10km)	(5) Conflict Involving Political Actors (10km)	(6) Conflict Involving Political Actors (10km)	(7) Large-Scale Battles (10km)	(8) Large-Scale Battles (10km)	(9) Protests and Riots (10km)	(10) Protests and Riots (10km)
Post Nov. 2015=1	0.0134***	0.0132***	0.0109**	0.0103**	0.0175***	0.0174***	-0.00893	-0.00562	0.104***	0.0996***
	(0.00405)	(0.00415)	(0.00457)	(0.00451)	(0.00471)	(0.00492)	(0.00855)	(0.00915)	(0.0188)	(0.0184)
Pct. Change Local Cereal Prices	0.000137	0.0000263	0.0000675	0.00000458	0.000188**	0.0000646	0.00168**	0.00197**	-0.000203	-0.000883*
	(0.0000866)	(0.000101)	(0.000298)	(0.000343)	(0.0000818)	(0.000119)	(0.000810)	(0.000984)	(0.000382)	(0.000514)
Post Nov. 2015=1 × Pct. Change Local Cereal Prices	0.00862*	0.00882*	-0.00370	-0.00366	0.00510	0.00517	-0.0107*	-0.0115*	0.0143	0.0157
	(0.00499)	(0.00513)	(0.00398)	(0.00412)	(0.00364)	(0.00379)	(0.00567)	(0.00590)	(0.0110)	(0.0116)
L.Lag Dep. Var.	0.202***	0.200***	0.0103	0.0102	0.00238	0.00169	0.156***	0.155***	0.108**	0.111**
	(0.0726)	(0.0722)	(0.0379)	(0.0378)	(0.0497)	(0.0491)	(0.0523)	(0.0522)	(0.0527)	(0.0525)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market Fixed Effects × Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5966	5964	5966	5964	5966	5964	5966	5964	5966	5964

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

Table 5.A.13: Effects of Cereal Prices on Incidence of Unrest and Conflict - Interactions with Post 2015

	(1) Conflict Events Involving Ethnic Actors (10km)	(2) Conflict Events Involving Ethnic Actors (10km)	(3) Conflict Events Involving Rebel Groups (10km)	(4) Conflict Events Involving Rebel Groups (10km)	(5) Conflict Events Involving Political Actors (10km)	(6) Conflict Events Involving Political Actors (10km)	(7) UCDP Conflict Events (25km)	(8) UCDP Conflict Events (25km)	(9) Protests and Riot Events (10km)	(10) Protests and Riot Events (10km)
Post Nov. 2015=1	0.0199***	0.0198***	0.0200*	0.0199*	0.0291***	0.0274***	-0.000647	0.000163	0.229***	0.219***
	(0.00611)	(0.00624)	(0.0103)	(0.0109)	(0.00975)	(0.00894)	(0.00686)	(0.00777)	(0.0552)	(0.0539)
Pct. Change Local Cereal Prices	0.000164	0.000182	0.000185	0.0000848	0.000238**	0.000209	0.000512	0.000669	-0.000205	-0.00173*
	(0.000113)	(0.000185)	(0.000314)	(0.000339)	(0.000111)	(0.000291)	(0.000399)	(0.000554)	(0.000575)	(0.000934)
Post Nov. 2015=1 × Pct. Change Local Cereal Prices	0.00734	0.00746	-0.00141	-0.00138	0.00476	0.00488	-0.00647	-0.00675	0.0179	0.0207
	(0.00550)	(0.00566)	(0.00560)	(0.00576)	(0.00734)	(0.00744)	(0.00749)	(0.00782)	(0.0259)	(0.0263)
L.Lag Dep. Var.	0.138	0.137	-0.0243	-0.0247	-0.0206	-0.0205	0.0582	0.0578	0.0553	0.0583
	(0.0928)	(0.0927)	(0.0271)	(0.0274)	(0.0356)	(0.0351)	(0.0487)	(0.0490)	(0.0772)	(0.0776)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market Fixed Effects × Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5966	5964	5966	5964	5966	5964	5966	5964	5966	5964

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

5.F Robustness Checks: Lag Operators

Table 5.A.14: Effects of Cereal Prices on Probability and Incidence of Protests and Riots - Lag Operator Robustness Checks

Lag Operator	Model Type	(1) Probability (10km)	(2) Probability (25km)	(3) Incidence (10km)	(4) Incidence (25km)	Observations
Lag 3	Reduced Form	0.00156***	0.00184**	0.00240*	0.0026	6020
		(0.000549)	(0.000712)	(0.00124)	(0.00188)	
	IV	0.00341**	0.00402**	0.00523*	0.00566	6020
		(0.00143)	(0.00179)	(0.00288)	(0.00421)	
Lag 4	Reduced Form	-0.000458	-0.00119	-0.00227	-0.00767**	5969
		(0.000725)	(0.000904)	(0.00205)	(0.00375)	
	IV	-0.00133	-0.00345	-0.00659	-0.0223*	5969
		(0.00213)	(0.00270)	(0.00616)	(0.0119)	
Lag 5	Reduced Form	-0.000432	-0.000311	-0.00061	-0.00116	5921
		(0.000622)	(0.000776)	(0.00166)	(0.00277)	
	IV	-0.0011	-0.000792	-0.00155	-0.00295	5921
		(0.00157)	(0.00194)	(0.00418)	(0.00693)	
Lag 6	Reduced Form	-0.0000138	0.000279	0.000796	0.00152	5874
		(0.000487)	(0.000703)	(0.0011)	(0.00207)	
	IV	-0.0000386	0.000782	0.00223	0.00425	5874
		(0.00135)	(0.00197)	(0.00314)	(0.00583)	
Controls		Yes	Yes	Yes	Yes	
Time Trend		Yes	Yes	Yes	Yes	
Market Fixed Effects		Yes	Yes	Yes	Yes	
Market Fixed Effects × Time Trend		Yes	Yes	Yes	Yes	
Month Fixed Effects		Yes	Yes	Yes	Yes	

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Each coefficient reported in this table represents a coefficient for a different model based on the lag operator in the leftmost column. The outcome variables in each model are given by the numbered column titles. Reduced form models estimate the effect of a change in international prices on the outcome variables, and IV models estimate the effect of a change in local prices on the outcome variables using international prices as an instrument. The coefficients for price changes are reported. IV Estimates are found by first estimating Equation 5.6 using the lag operator specified in the leftmost column and then estimating Equation 5.7.

Table 5.A.15: Effects of Cereal Prices on Probability and Incidence of Conflict Involving Ethnic Militia - Lag Operator Robustness Checks

Lag Operator	Model Type	(1) Probability (10km)	(2) Probability (25km)	(3) Incidence (10km)	(4) Incidence (25km)	Observations
Lag 3	Reduced Form	0.000506***	0.00124***	0.000753***	0.00347**	6020
		(0.000156)	(0.000289)	(0.000283)	(0.00132)	
	IV	0.00110***	0.00270***	0.00164**	0.00759***	6020
		(0.000386)	(0.000739)	(0.000663)	(0.00293)	
Lag 4	Reduced Form	.000247**	0.000806***	0.000241	0.00212***	5969
		(0.000120)	(0.000276)	(0.000155)	(0.000578)	
	IV	0.000716**	0.00234***	0.000700	0.00620***	5969
		(0.000340)	(0.000712)	(0.000434)	(0.00175)	
Lag 5	Reduced Form	0.000173	0.000559**	0.000184	0.00262**	5921
		(0.000176)	(0.000264)	(0.000232)	(0.00116)	
	IV	0.000439	0.00142**	0.000468	0.00669**	5921
		(0.000432)	(0.000649)	(0.000572)	(0.00305)	
Lag 6	Reduced Form	0.000331**	0.000882***	0.000393*	0.00372**	5874
		(0.000138)	(0.000327)	(0.000208)	(0.00157)	
	IV	0.000929**	0.00247***	0.00110*	0.0105**	5874
		(0.000389)	(0.000837)	(0.000581)	(0.00423)	

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Each coefficient reported in this table represents a coefficient for a different model based on the lag operator in the leftmost column. The outcome variables in each model are given by the numbered column titles. Reduced form models estimate the effect of a change in international prices on the outcome variables, and IV models estimate the effect of a change in local prices on the outcome variables using international prices as an instrument. The coefficients for price changes are reported. IV Estimates are found by first estimating Equation 5.6 using the lag operator specified in the leftmost column and then estimating Equation 5.7.

Table 5.A.16: Effects of Cereal Prices on Probability and Incidence of Conflict Involving Rebel Groups - Lag Operator Robustness Checks

Lag Operator	Model Type	(1) Probability (10km)	(2) Probability (25km)	(3) Incidence (10km)	(4) Incidence (25km)	Observations
Lag 3	Reduced Form	0.000348	0.000788	0.000571	0.00117	6020
		(0.000288)	(0.000646)	(0.000389)	(0.000766)	
	IV	0.00076	0.00172	0.00125	0.00256	6020
		(0.000665)	(0.00150)	(0.000889)	(0.00180)	
Lag 4	Reduced Form	-0.000157	-0.000985**	0.000147	-0.000484	5969
		(0.000145)	(0.000396)	(0.000275)	(0.000664)	
	IV	-0.000457	-0.00286**	0.000427	-0.00141	5969
		(0.000400)	(0.00119)	(0.000796)	(0.00192)	
Lag 5	Reduced Form	0.0000639	0.000496	0.000309	0.000904*	5921
		(0.000235)	(0.000443)	(0.000313)	(0.000543)	
	IV	0.000163	0.00126	0.000786	0.0023	5921
		(0.000596)	(0.00115)	(0.000809)	(0.00142)	
Lag 6	Reduced Form	-0.000212	0.00000321	-0.000082	0.000277	5874
		(0.000169)	(0.000394)	(0.000192)	(0.000468)	
	IV	-0.000593	0.00000901	-0.00023	0.000775	5874
		(0.000494)	(0.00109)	(0.000539)	(0.00127)	

Standard errors in parentheses

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

Each coefficient reported in this table represents a coefficient for a different model based on the lag operator in the leftmost column. The outcome variables in each model are given by the numbered column titles. Reduced form models estimate the effect of a change in international prices on the outcome variables, and IV models estimate the effect of a change in local prices on the outcome variables using international prices as an instrument. The coefficients for price changes are reported. IV Estimates are found by first estimating Equation 5.6 using the lag operator specified in the leftmost column and then estimating Equation 5.7.

Table 5.A.17: Effects of Cereal Prices on Probability and Incidence of Conflict Involving Political Militia - Lag Operator Robustness Checks

Lag Operator	Model Type	(1) Probability (10km)	(2) Probability (25km)	(3) Incidence (10km)	(4) Incidence (25km)	Observations
Lag 3	Reduced Form	0.000329*	0.000406	0.00033	0.000735	6020
		(0.000182)	(0.000257)	(0.000318)	(0.000461)	
	IV	0.000717*	0.000885	0.00072	0.0016	6020
		(0.000375)	(0.000552)	(0.000663)	(0.000992)	
Lag 4	Reduced Form	0.000347**	0.000684***	0.000771***	0.00146***	5969
		(0.000141)	(0.000218)	(0.000282)	(0.000388)	
	IV	0.00101***	0.00199***	0.00225***	0.00425***	5969
		(0.000374)	(0.000625)	(0.000852)	(0.00127)	
Lag 5	Reduced Form	0.000283*	0.000766***	0.00042	0.00144**	5921
		(0.000148)	(0.000288)	(0.000276)	(0.000579)	
	IV	0.000720*	0.00195**	0.00107	0.00367**	5921
		(0.000398)	(0.000816)	(0.000717)	(0.00160)	
Lag 6	Reduced Form	0.0000962	0.000509**	0.000148	0.000854**	5874
		(0.000102)	(0.000246)	(0.000169)	(0.000361)	
	IV	0.000270	0.00143**	0.000415	0.00239**	5874
		(0.000284)	(0.000707)	(0.000469)	(0.00107)	

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Each coefficient reported in this table represents a coefficient for a different model based on the lag operator in the leftmost column. The outcome variables in each model are given by the numbered column titles. Reduced form models estimate the effect of a change in international prices on the outcome variables, and IV models estimate the effect of a change in local prices on the outcome variables using international prices as an instrument. The coefficients for price changes are reported. IV Estimates are found by first estimating Equation 5.6 using the lag operator specified in the leftmost column and then estimating Equation 5.7.

Table 5.A.18: Effects of Cereal Prices on Probability and Incidence of Large Scale Battles - Lag Operator Robustness Checks

Lag Operator	Model Type	(1) Probability (10km)	(2) Probability (25km)	(3) Incidence (10km)	(4) Incidence (25km)	Observations
Lag 3	Reduced Form	0.00106*	0.000418*	0.000621*	0.00175*	6020
		(0.000561)	(0.000234)	(0.000322)	(0.000977)	
	IV	0.00232*	0.000903*	0.00136*	0.00383*	6020
		(0.00131)	(0.000533)	(0.000745)	(0.00231)	
Lag 4	Reduced Form	0.00119*	0.000578	0.000683	0.00153*	5969
		(0.000686)	(0.000498)	(0.000492)	(0.000811)	
	IV	0.00348	0.00168	0.00199	0.00447*	5969
		(0.00217)	(0.00154)	(0.00154)	(0.00254)	
Lag 5	Reduced Form	0.00028	-0.000232	-0.000107	0.000799	5921
		(0.000573)	(0.000250)	(0.000281)	(0.000724)	
	IV	0.000712	-0.000584	-0.000274	0.00204	5921
		(0.00148)	(0.000604)	(0.000698)	(0.00195)	
Lag 6	Reduced Form	-0.000108	0.00009	0.000299	0.000371	5874
		(0.000414)	(0.000212)	(0.000270)	(0.000657)	
	IV	-0.000304	0.000251	0.000839	0.00104	5874
		(0.00115)	(0.000588)	(0.000751)	(0.0018)	

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Each coefficient reported in this table represents a coefficient for a different model based on the lag operator in the leftmost column. The outcome variables in each model are given by the numbered column titles. Reduced form models estimate the effect of a change in international prices on the outcome variables, and IV models estimate the effect of a change in local prices on the outcome variables using international prices as an instrument. The coefficients for price changes are reported. IV Estimates are found by first estimating Equation 5.6 using the lag operator specified in the leftmost column and then estimating Equation 5.7.

Chapter 6

Synthesis

6.1 Overview

Scholars across millennia have been interested in the role of uncertainty in the human condition. The ancient Roman philosopher, Cicero asserts 'It is not in the power even of God himself to know what event is going to happen accidentally and by chance' (1923: p. 391). In this world of uncertainty, for those playing an active role in society, as economic actors do, Cicero argues, 'before undertaking any enterprise, careful preparation must be made.' (2014: p. 75). Classical philosophy was concerned with whether the world is uncertain and if so, whether humans should prepare themselves for such uncertainty. Economic inquiry takes these propositions as given and explores how economic actors manage uncertainty both normatively and descriptively. The economic study of risk management has become the source of great debate in economic circles for centuries and is only intensifying with the rise of behavioral economics.

From the practical viewpoint of economic development, understanding risk in agriculture is more important than ever as climate change makes smallholder production more volatile (Raza et al., 2019). Further, understanding decision-making under risk in the context of markets is imperative as development programs are increasingly leveraging market-based approaches (Kubzansky et al., 2011). For example, the private sector is expected to cover 70% of the annual 2.5 trillion USD funding gap to reach the SDGs, and private sector involvement can only come through well-functioning markets (World Bank, 2019). Without research to give evidence to how and why economic actors behave in the presence of risk, market-based development programs are unlikely to have 'careful preparation', resulting in initiatives with ineffective or even averse effects on development outcomes.

The four studies in this thesis show that risk can influence economic actors' interactions with markets in various ways. Chapter 2 develops a non-separable household model and uses non-causal empirical analysis to show that risk induces production diversification, which can reduce income and consequently dietary diversity for households with high market participation. Chapter 2 proposes that production risk may explain why the empirical literature often finds low correlations between production diversity and dietary diversity. Chapter 3 uses a lab-in-the-field experiment to show that the assumption that women are more risk averse than men is not valid in all situations, and that join decision-making between spouses can overcome some of the inefficiencies of individual decision-making and lead to better on-farm household investment decisions. Chapter 4 shows that exposure to shocks and risk preferences are correlated with side-selling behavior among specialty coffee cooperative members in Peru. The chapter highlights that households may be using marketing strategies to manage their risk. Finally, Chapter 5 shows that changes in cereal prices in Ethiopia can affect the incidence of conflict and unrest, and the direction of this effect depends on the actors involved and scope of conflict. These findings underscore the fact that food market risk may have far-reaching consequences, perhaps even leading to national instability.

This thesis builds upon the age-old scholarly interest in decision-making under risk by examining the context of smallholder farmers and agrarian markets in low-income countries. Each chapter presents a distinct study relating to various countries, levels of economic actors, and topics. However, taken together, the chapters reveal three important crosscutting themes: the importance of heterogeneity for economic inquiry and development policy, the scholarly and practical relevance of economic theory, and the need to rethink assumptions on markets. Within the context of each overarching theme, the rest of this section discusses this thesis's lessons learned, contributions to economic thought, policy recommendations, and areas of future research.

6.2 Heterogeneity: One Size Fit All Policies for Diverse Actors?

Development practitioners and researchers often fall victim to the idea that there is a 'silver bullet' to end poverty. Microfinance, cash transfers, and now digital solutions have all been the subject of such hype (Jayati Ghosh, 2011; Morduch, 1999; Shepherd et al., 2020). Yet, after the hype fizzles away and the field moves onto the 'next big thing', each solution gets relegated to its rightful place – an appropriate solution for solving some problems, in some contexts, and for some actors. In the ideal case, well designed and targeted polices that address specific problems in specific contexts for specific actors can accelerate progress towards development goals (Ruben and Pender, 2004). However, in reality, even good solutions can fall short of being effective because policymakers and economists alike are often uninterested in the details of policy design (Duflo, 2017). Such details are crucial for policy effectiveness, and for economists to play a positive role in society, they must be like a 'plumber' – tinkering and evaluating policy design to discover what solutions and delivery methods are most effective (Duflo, 2017). An increased focus on policy targeting and heterogeneity is one way in which economists can play the role of the plumber.

A comprehensive development approach requires policy targeting, and this thesis helps explain why policy targeting is crucial. Each chapter underscores heterogeneity in responses to economic factors. Given that there are 570 million smallholders worldwide, it should come as no surprise that actors operate under diverse circumstances and respond to diverse economic conditions differently (Lowder et al., 2016). *Chapter 2* shows that within Tanzania, whether on-farm diversification drives household dietary diversity depends on the household's reason for diversification. The reasons for diversification can come from various sources (risk mitigation, productivity gains, and lack of market access), and households' decisions to diversify are dependent on exogenous factors. Even in smaller, sub-national geographic areas, *Chapter 4* shows that households respond differently to shocks and these responses are based on various household economic conditions, such as farm size and off-farm labor income. The heterogeneity is not just at the household level as *Chapter 3* shows that individuals within households respond to risk differently. This makes not only household-level policy targeting important, but also intra-household-level policy targeting. Finally, *Chapter 5* shows that changes in cereal market prices change the incentives across entire food systems and can have diverse and complex effects on conflict and unrest. Taken together, the chapters show that economic actors' responses to risk can vary widely and depend on numerous external characteristics. Such heterogeneity is present in across all levels of economic systems.

The policy recommendations are clear – agricultural and food policies cannot be one size fit all; they must address the differing needs of heterogeneous smallholders and of various actors in economic systems. While there is a growing emphasis on coordinating policy internationally and a long history of national initiatives to transform agriculture, such approaches are unlikely to address the needs of all actors across food systems (Mansuri and Vijayendra, 2013). Policies must be flexible and local such that they can work in different communities and work for all actors within those communities.

From a research standpoint, future work should focus on understanding and highlighting heterogeneity to aid policymakers in designing flexible policy. Precise estimates of mean effects are useful, but understanding heterogeneous effects is important for both policy design and external validity. For example, assume a hypothetical original study precisely estimates average effects in a given setting, but fails to analyze heterogeneity in policy effects. If the studied policy is to be applied to another setting where the average beneficiary is different from that of the original study, then the results of the original study are unlikely to be informative in the new setting. However, if the original study analyzes heterogeneity, then the policy designers in the new setting can potentially assess how the policy would affect the beneficiaries of interest.

Further, in cases when researchers help design programs, preliminary needs assessments should be undertaken within communities of interest so that development programs address heterogeneous community needs, rather than researchers' and even donors' agendas. Such assessments can be done in the form of qualitative interviews or field group discussions with intended beneficiaries. For example, for a hypothetical program distributing improved seeds, *Chapter 2* suggests that farmers with high market access would prefer improved cash crop seeds and those with low market access would prefer improved food crop seeds. A needs-assessment could directly test if this is the case even through informal, low-budget fieldwork. If services provided through development programs are not in demand, then the programs have little chance at success. Whether grassroots approaches to development based on observed community needs are beneficial should be a topic for future research as well. While this thesis provides suggestive evidence that participatory approaches may be beneficial, further research is needed to directly assess the merits of such approaches.

6.3 The Lasting Relevance of Economic Theory

In the last three decades there has been a major shift in economic research from theoretical to empirical inquiry (Hamermesh, 2013). Long before this shift, Noble Prize wining economist Tjalling Koopmans, was concerned with economic inquiry straying away from theory: 'The decision not to use theories of man's economic behavior, even hypothetically, limits the value to economic science and to the maker of policies, of the results obtained or obtainable by the [empirical] methods developed.' (1947: p. 172). Despite the movement towards empirical work, complementary theory is still needed to give frameworks for empirical analysis and increase external validity of economic studies focused on particular contexts (Card et al., 2011; Garcia and Wantchekon, 2010).

This thesis shows how economic theory can complement empirical work by guiding empirical analysis and building external validity. The literature studying the links between production diversity, market access, and dietary diversity is highly empirical (Jones, 2017; Nandi et al., 2021; Sibhatu and Qaim, 2018a). *Chapter 2* presents a theoretical model to explain the findings in this literature in an expected utility framework. Aside from contributing a stylized framework that makes the results of many studies easier to digest, the theoretical framework uncovers a key mechanism previously unstudied in the literature – market access's mediating effect on the influence of production diversity on dietary diversity. Empirical analysis in *Chapter 2* suggests that this mechanism is likely to be at play. Similarly, *Chapter 5* reveals economic theory's role in guiding empirical analysis. While *Chapter 5* does not present a new theory, the analysis is heavily influenced by the theoretical framework in McGuirk and Burke (2020). Based off the theoretical mechanisms identified in McGuirk and Burke (2020), the empirical analysis explores heterogeneity in price effects for more granular types of conflict than previously analyzed. In both chapters, empirical insights based on economic theory are key topical contributions to the respective strands of literatures.

Chapter 4 presents an extension of the theoretical framework in Woldie (2010) and Wollni and Fischer (2015). While the theory helps inform the empirical analysis, it also gives external validity to empirical results from a highly specific context (organic coffee cooperative members in two Peruvian districts). The model shows why households choose to side-sell based on assumptions of price premiums, payment delays, fixed costs to marketing, and price risk. To explain behavior of coffee farmers in other settings (e.g. when private traders offer premiums), only the model's assumptions need to be adjusted. Without theory, future empirical analysis may find seemingly contradictory results, but in reality actors operate through the same mechanisms under a different set of market conditions. In other words, the theory allows for other researchers to understand the mechanisms and behavior influencing outcomes and assess which conditions are likely to hold in a different setting.

Much of funding for development research is directed towards practical, empirical, and policy-relevant research. Economic theory is often overlooked as belonging to academics sitting in ivory towers. However, this thesis shows that economic theory can be both practical and policy-relevant while also enhancing empirical research. It can help policy makers understand what policy mechanisms are important and for which actors they are likely to matter most. Future research should further develop rigorous, mathematical theory to understand human behavior, especially in new areas of research. Mathematical theory is particularly important because it can reveal relationships between variables that qualitative conceptual frameworks may miss, and it translates relatively easily into econometric models. By developing theoretical frameworks, researchers can also help policy-makers target key mechanisms to improve livelihoods and provide guidelines for future programs. However, researchers should be cautious not to overemphasize such models, as they are often normative, and actors' behavior can deviate greatly from model predictions. The importance of economic theory does not take away from the importance of empirical studies, but rather theory complements empirical work.

6.4 Rethinking Assumptions on Markets

In the decades following independence, most Sub-Saharan African countries implemented agricultural marketing boards – state controlled entities tasked with buying and selling agricultural goods. While models of marketing boards differed, most often they were monopsonistic such that producers could only sell their output through the marketing boards (Barrett and Mutambatsere, 2008). 20^{th} century agricultural economists' interests reflected these realities and often focused on how governments should implement price controls in agricultural markets (Singh et al., 1986). However, governments began to liberalize agricultural markets in the late 20^{th} century, allowing for private buyers and sellers to operate and relinquishing control over prices (Barrett and Mutambatsere, 2008). These changes not only transformed agricultural value chains, but also approaches towards development, which have become increasingly market-based (Kubzansky et al., 2011).

While economic inquiry has reflected liberalization trends and is more focused on markets and how economic actors interact with markets, this thesis brings up several shortcomings in economic research related to markets. Many studies of markets make assumptions or simplifications that are inappropriate in the low-income country context. Throughout the thesis, some of the pitfalls in the analysis of markets and actors' interaction with markets are addressed. Specifically, the thesis either directly or indirectly addresses the theoretical assumption of perfect markets, deficiencies in the measurement of market access, and the implicit assumption of well-integrated markets.

Chapter 2 shows that the theoretical assumption of perfect markets can lead to predictions that are not realistic for all farmers. Specifically, under perfect markets and no risk, the model suggests that farmers specialize their production. However, most smallholders engage in at least some production diversification – once the assumption of perfect markets is relaxed, the model predicts diversification based on consumption preferences. Economists have adjusted to this reality in some cases through non-separable models (de Janvry et al., 1991; Fafchamps, 1992; Finkelshtain and Chalfant, 1990; Omamo, 1998). However, not all theoretical models include imperfect markets. For example, models for marketing decisions of cooperative members typically assume perfect markets (Woldie, 2010; Wollni and Fischer, 2015). The theoretical model in *Chapter 4* builds on Woldie (2010) and Wollni and Fischer (2015) by adding fixed costs to marketing for the private channel, but the cooperative channel is assumed not to have transaction costs. This assumption, while unrealistic, is somewhat appropriate because coffee is a cash crop and households are unlikely to consume more than a nominal amount of coffee at home. Further, these models take market participation as given. Therefore, transaction costs can be deducted from market prices, but they will not induce households to consume coffee at home. However, if the model were to be applied to cooperatives dealing in food crops, then this assumption would be inappropriate and a non-separable model with imperfect markets would be needed. Future economic models should carefully consider the assumption of perfect markets and whether it reflects reality.

Following the theoretical importance of market access, this thesis underscores a major concern in the empirical assessment of market access. Theoretically, market access is measured through transaction costs, but empirical measurement is much more difficult because transaction costs are not always monetary, vary over time, and are not well recorded (Chamberlin and Jayne, 2013). Further, the theoretical model in *Chapter 2* assumes that transaction costs are the same for all goods for simplicity. This assumption has little basis in reality, as each agricultural value chain operates differently and has different levels of transaction costs. While the assumption can easily be relaxed in the theoretical model, empirically it is much more difficult to do so because obtaining crop disaggregated data on transaction costs is challenging. The literature on dietary diversity and market access typically relies on physical distance to market to proxy for market access for all crops (Nandi et al., 2021; Sibhatu and Qaim, 2018b). As previously documented, this measure is woefully inadequate (Chamberlin and Jayne, 2013). For example, *Chapter 2* shows that there is only a weak correlation between distance to market and market participation. This surprising result comes about because many farmers sell their produce at the farm-gate and physical access to markets is only one of many dimensions of market access (Chamberlin and Jayne, 2013). However, few studies give second thought to using the distance to market measure and are doomed to find biased results when linking any outcome to incorrectly specified market access proxies. A solution to this problem is beyond the scope of this thesis, but this thesis reinforces the issues proposed in Chamberlin and Jayne (2013) and reiterates the need to develop better market access measures.

While neglect of local marketing structures can lead to poor market access measures, disregarding local market integration with international markets can lead to questionable results when analyzing price effects. In much of the literature relating conflict to food prices, studies use international prices as a source of exogenous variation to identify causal effects. Studies using only international prices implicitly assume that these prices pass through to domestic prices. However, price pass through rates to African markets are far from perfect (Dillon and Barrett, 2016). In *Chapter 5*, international prices are not significantly correlated with retail market prices in about half of the markets considered. When using an IV estimator, this means nearly half of the instruments are prone to weak instrument bias if no adjustments are made. In the reduced form, which previous studies use, weak pass through rates suggest that overall international price effects are consistently identified, but for markets which are actually integrated to international markets, the effects are underestimated. Econometrically speaking, these studies cannot identify local average treatment effects. Intuitively, without domestic price data, the integrated markets cannot be identified and there is no way to estimate true price effects for relevant markets. *Chapter 5* overcomes these issues by using domestic price data. When using international prices as an exogenous regressor, future economic studies should consider pass through rates and ideally incorporate local market data. Since national governments do not have control over international prices, the effect of domestic prices on conflict is of greater interest in any case.

Taken together, these concerns show that there is a need to re-assess assumptions concerning markets. Careful analysis of market structures, how farmers access markets, and how markets behave is needed in studies related to markets. Policies should also reflect these factors to complement existing market structures.

6.5 Implications for Future Research and Policy

This thesis gives important lessons for future research and policymaking. Future research can build off the studies in this thesis in a number of ways, and four key ways are highlighted in this section. First, the non-separable household model in Chapter 2 can be extended to understand how off-farm labor, livestock, different incentives for diversification (such as differing factor returns or economies of scope), gendered decision-making, dynamic decision-making, and finance can affect household production diversification and dietary diversity. A range of other issues can be added to the model, but there is a clear need for a nutrition-sensitive non-separable model to fully understand smallholder decision-making. Further, the empirics assessing market access, production diversity, and dietary diversity should extend into causal analysis. For causal analysis of production diversity, this can mean assessing nutrition outcomes in RCTs that promote the production of new crops. For market access, experimental interventions are more difficult, but digital technologies may make market access interventions cheaper, and more feasible for researchers. Second, more research is needed on gender and labor-intensive investment decision-making. This research should focus on new settings and try to apply field experiments to understand gender dynamics in investment decision-making so that decisions can be analyzed in a real-word setting, rather than in a controlled, lab-in-the-field setting. Third, future research should assess causal impacts of the determinants of side-selling. Casaburi and Macchiavello (2015) is an example of one study that has done so, but more studies are needed in a literature largely devoid of causal evidence. Such evidence would help cooperatives to implement more effective policies aimed at reducing side-selling. Finally, there is a growing need leverage domestic price datasets to uncover causal price effects on conflict and unrest in low-income countries. Chapter 5 is one of the only within country studies on the topic, and cross-country studies do not give practical or localized advice to policymakers. As a result, much of this literature is bound to remain in the academic sphere and not influence policy. Within country studies that take into account local dynamics and context can improve the practical implications of this literature.

From a policy standpoint, each chapter provides a practical policy implication. Chapter 2 suggests that nutrition-sensitive policies targeting smallholders for crop adoption should be targeted based on market access. Since farmers have different needs, people-centered policies rather than intervention-centered policies are needed. The results in Chapter 3 suggest that targeting female farmers is not optimal for improving household investment, and programs should target both spouses to achieve the most efficient investment outcomes. This does not mean that programs should not be gender-sensitive – gender sensitization trainings are likely needed to encourage joint decision-making within households and reduce men's shirking in labor tasks. However, only targeting women is not likely to address these issues. From Chapter 4, cooperatives should think twice about alleviating liquidity constraints to reduce side-selling (especially during widespread production shocks) – doing so may encourage farmers to use their cash to cover private marketing costs and increase side-selling. Rather, cooperatives should focus on reducing payment times and implementing structures that reduce the cost of marketing to the cooperative, particularly for medium-sized farmers who are the most likely culprits to side-sell. Finally, Chapter 5 shows that government's may be able to reduce conflict and unrest through food policy. However, such policy should be targeted based on local characteristics. If governments use food-pricing policy (for example, via buffer stocks, subsidies, or trade policy) to increase prices when they are low in net-producing areas and decrease prices when they are high in net-consuming areas, then conflict and unrest can be reduced. This is especially true in times of heightened instability. Improving institutional quality would also go a long way in reducing food-related conflict and unrest – a task easier said than done.

6.6 Conclusions

This thesis investigates how humans make decisions under risk and how markets can influence such decisions. It uses various methodologies, studies different levels of economic actors, and uses evidence from a diversity of contexts. The thesis finds that households' production diversification strategies (a form of *ex ante* risk management) depend on market access levels and food preferences. *Ex post*, households engage in different marketing strategies to respond to production shocks, but these strategies depend on their level of outside income and risk preferences. Further, within households, risk management strategies differ between men and women. At meso-economic levels, violent responses to changes in food prices depend on local market characteristics and actors' economic and political motivations. Taken as a whole, the thesis suggests that the relationship between risk management and markets is complex and varies widely based on economic actors' characteristics and local contexts. A combination of theory and various empirical methodologies is needed to understand these relationships, and future research and policy should focus on understanding the nuances of economic decision-making under risk to accelerate progress towards development goals.

From the outset, the goal of this thesis has been to understand how economic actors manage risk *ex ante* and *ex post*, and how markets influence these decisions. In the first regard, each chapter assesses decision-making under risk in certain contexts and comes to a wide range of conclusions for different economic actors across several contexts. However, the thesis is limited in the second aim. None of the chapters is able to empirically address how introducing markets or enhancing market structures causes changes in risk management decisions. Rather, each chapter analyzes the decision-making in the context of certain market structures, and can give some insights into the influence of markets on decision-making, but not rigorous, causal evidence. Future research should focus on causal evidence of decreasing market transaction costs or introducing markets on risk management decisions. Finally, The findings of this thesis are also limited in the policy recommendations it makes. None of the recommendations is based on analysis of specific policies. Future research should identify policies related to market access and understand how these policies affect behavior related to risk.

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Summary

This thesis explores how markets influence economic actors' *ex ante* and *ex post* risk management strategies in Tanzania, Peru, and Ethiopia. It makes both theoretical and empirical contributions to various strands of literature with analysis across different levels of economic actors – individuals within households, households, and markets. The thesis highlights the importance of understanding actors' heterogeneity in risk management practices and the need for a wide range of methodologies to analyze various actors and contexts. Chapter 1 provides a brief discussion on previous economic inquiry pertaining to risk management, places this thesis within the context of previous research, presents an overview of the methodologies used, and highlights the main research questions in this thesis.

Chapter 2 presents a theoretical household model for nutrition sensitive agriculture under risk. The model describes how production diversity and market access are related to dietary diversity, and empirical evidence is obtained using cross-sectional nationally representative data from Tanzania. The theoretical predictions and empirical results suggest that market access mediates the influence of production diversity on dietary diversity. These results help explain why the empirical literature has found that increased on-farm production diversity does not always translate into increased dietary diversity. From a policy standpoint, Chapter 2 implies that nutrition-sensitive agriculture interventions should target participants based on their level of market access.

Chapter 3 examines whether intra-household decision-making regimes and labor allocations affect household investment strategies and labor productivity among spouses. Using a randomized lab-in-the-field experiment, Chapter 3 tests for differences in labor-intensive investment decision-making between men alone, women alone, and both spouses together as well as labor productivity differences between men and women. The results show that when spouses make decisions together, they can overcome some inefficiencies observed from solo decision-makers. Further, the results suggests that men put forth less effort than women in the experiment's real-effort task, which hinders the chances of successful investment. Chapter 3 argues that future agricultural programs should take intra-household gender dynamics into account and include gender sensitization training in their implementation strategies.

Chapter 4 analyzes how marketing decisions change when households are affected by production shocks. It empirically and theoretically studies the relationship between Coffee Leaf Rust (CLR) incidence on Peruvian specialty coffee cooperative members' farms and their propensity to sell coffee outside the cooperative. The empirical analysis uses panel data methods and shows that CLR is associated with higher rates of marketing to non-cooperative channels. Households' risk tolerance and extent of non-coffee income amplify this relationship. These findings underscore the need for heterogeneous institutional responses to production shocks – even within cooperatives in a small area, household responses to shocks can vary widely.

Chapter 5 studies the effect of market prices on internal conflict from a mesoeconomic perspective. The chapter tests whether changes in cereal prices in domestic retail markets across Ethiopia increase or decrease the incidence of nearby violence across different types of violent events. Using an instrumental variables empirical specification that takes advantage of exogenous international prices, the results show that increases in cereal prices raise the incidence of nearby protests and riots, conflict with local aims, and small-scale violent events. However, conflict with national aims and large-scale battles are not affected by changes in cereal prices, and there is significant heterogeneity in the results across cereal producing and non-cereal producing areas. These results suggest that different theoretical mechanisms are at play simultaneously, and food-pricing policies should take into account heterogeneity of domestic markets to promote internal stability.

Chapter 6 discusses the chapters and presents a synthesis of crosscutting themes throughout the thesis. First, there is need for economic research to identify and assess heterogeneity in economic actors' responses to risk for future policies to maximize welfare and ensure marginalized actors are not left behind. Further, such policies should be based on research that takes into account theoretical mechanisms so that policy designers can assess whether previous empirical findings are likely to hold in the context at hand. Finally, economic researchers should be careful in the assumptions they make concerning markets in low-income countries. In many settings, assumptions on well-functioning markets, farmers' market access, and price integration are untested and unfit, leading to research with faulty outcomes and misguided policy recommendations.

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Name of the learning activity	Department/Institute	Year	ECTS*
A) Project related competences			
A1 Managing a research project			
WASS Introduction Course	WASS	2018	1
Writing PhD proposal	WASS	2018	3
"Ethnicity, Violence, and Maize Prices: An Analysis of Ethiopian Markets"	WUR Section Economics 'EconMonday' Seminar, Wageningen	2019	0.5
"Modelling the Relationship Between Production Diversity, Transaction Costs, and Household Nutrition"	WUR Section Economics Special Seminar, Wageningen	2019	0.5
"Rethinking the Link between Production Diversity and Dietary Diversity: Theory and Evidence"	Wageningen Economic Research Brown Bag Seminar, Virtual	2021	0.5
"How (NOT) to Improve coffee data quality: lessons in human and artificial intelligence"	Laterite Lunch Seminar, Virtual	2021	0.5
"Investment and Household Bargaining in Small-scale Farming Households"	KVS New Paper Sessions (Leiden University/Virtual)	2021	1
"Rethinking the Link between Production Diversity and Dietary Diversity: Theory and Evidence"	31st International Conference for Agricultural Economists (Virtual)	2021	1
"Investment and Household Bargaining in Small-scale Farming Households"	Symposium on Economic Experiments in Developing Countries (SEEDEC) (Virtual)	2021	1
A2 Integrating research in the corresponding discipline			
Impact Assessment Of Policy and Programmes, DEC32806	WUR	2018	6
Advanced Microeconomics, ECH-51806	WUR	2018	6
Advanced Microeconometrics	Tinbergen Institute	2018	3
B) General research related competences			
B1 Placing research in a broader scientific context			
Risk Analysis and Risk Management in Agriculture: Updates on Modeling and Applications	WASS	2018	3
The Foundations of Info-Metrics. Information-Theoretic Methods of inference	WASS	2019	3

B2 Placing research in a societal context			
Making an Impact	WGS	2020	1
C) Career related competences/personal development			
C1 Employing transferable skills in different domains/careers			
Career Assessment	WGS	2020	0.3
Total			**31.3**

*One credit according to ECTS is on average equivalent to 28 hours of study load

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PROPOSITIONS

1. There are hundreds of millions of small farmers from a myriad of backgrounds and cultures, so the pursuit to understand the representative smallholder is futile.
(this thesis)

2. The shift in economic inquiry from the theoretical to the empirical risks creating knowledge devoid of understanding.
(this thesis)

3. Creative ideas and important research questions are more likely to come from experience, observation, and conversation than reading academic papers.

4. Adherence to schools of thought stifles the creation of knowledge and runs contrary to scientific ideals.

5. Success is more a function of environment and chance than of individual contributions – fortunately, so is failure.

6. If policymakers listened to their constituents more than they listened to experts, then improvements in the human condition would be accelerated.

Propositions belonging to the thesis entitled

Risk, Shocks, and Markets: Theory and Evidence from Economic Actors in Low and Middle Income Countries

Michael Robert Keenan

Wageningen, 16 May 2022