Three essays on development economics:
rural labor markets, trade liberalization and crime

DOCTORAL THESIS

Presented to the Faculty of Management, Economics and Social Sciences of the University of Fribourg, Switzerland

by

Christian Camilo ARCINIEGAS ACOSTA
from Colombia

in fulfillment of the requirements for the degree of
Doctor of Philosophy (Ph.D.) in Economics

Accepted by the Faculty of Management, Economics and Social Sciences
on May 5th, 2025 at the proposal of

Prof. Dr. Christelle Dumas (*University of Fribourg*), thesis supervisor
Prof. Dr. Günther Fink (*University of Basel*), first referee
Prof. Dr. Kai Gehring (*University of Bern*), second referee
Prof. Dr. Martin Huber (*University of Fribourg*), president of the jury

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Acknowledgments

Back in 2012, when I finished my undergraduate studies in Bogotá, I told myself: "Christian, get a job and make some money. Get some experience and do a Master's in a few years, but never a PhD." And here I am, writing these lines more than 10 years later, about to become a *philosophiae doctor* in Economics.

The past five years have been quite a journey. A pandemic arrived just a few months after I started the PhD. I visited Africa for the first time thanks to one of the projects described later in this thesis, and I ended up writing parts of one of the chapters in a library in Warsaw during a self-imposed writing "workation." I happened to discuss my research with my supervisor in French and write and present it in English, but after five years I still haven't adapted to Swiss working hours or the early lunch at 11:30. Some examples of my PhD life.

None of this would have been possible without the intellectual, emotional, and friendly support of many people I met along the way. I want to thank all of them for supporting me in every possible way. Special thanks to my supervisor, Christelle Dumas. Thank you for giving me the opportunity to join the Chair and conduct my thesis under your supervision. Thanks for all the time you spent discussing, guiding, and commenting on my work, and for your patience as well. I hope all supervisors dedicate as much time to their supervisees as you do. Asante sana!

Thanks as well to the members of the jury for investing their time in reviewing my work and providing valuable feedback to improve this dissertation. Thanks to the professors, PhD students, and the administrative team at the Department of Economics. The coffee breaks and well-deserved *Fübis* (aka Feierabendbier—I did my best to integrate into Swiss culture) helped a lot in maintaining good mental health and a nice work-life balance (they probably also contributed a bit to my slight delay in handing in the thesis, but I enjoyed them). Listing names might be risky, but I want to mention some of the people at the University who made this a pleasant experience: Ximena J., Patricia S., Yves K., Christian Z., Leander K., Johannes S., Andreas S., Bénédicte D., Yannick S., Ellen M., Elsa G., Xavi R., Alexandre L. & D., and all the fifth-floor crew. Sorry if I forgot someone. Nicole Papaux and Ruth Neuhaus made the administrative burden non-existent. Merci.

Finally, I want to thank Clémence for her love, patience, and support, and the Dumoncel family for hosting me every Christmas in Champéry and becoming my *de facto* family. To my family and friends in Colombia... despite the long distance and the few times I went back to *die Heimat* during these five years, your remote support made this journey much easier. Esto es por y para ustedes. Gracias.

Lastly, a note of thanks to myself for taking on this adventure. A PhD is far more than an intellectual challenge—it is a personal one. Writing this thesis was as much a journey of personal discovery as it was an academic endeavour, and I'm grateful for both. Enjoy the reading.

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Introduction

The likelihood of achieving the Sustainable Development Goal (SDG) of ending poverty by 2030 is, unfortunately, low. If current trends persist, nearly 600 million people are projected to still live in extreme poverty by the end of the decade (United Nations, 2024).[1] More starkly, it is expected that 80% of the world's poor will reside in Africa in 2030 (The Economist, 2025), predominantly in rural areas. In essence, 21st-century poverty is largely a rural African phenomenon (Beegle and Christiaensen, 2019; Lee et al., 2021).

This thesis does not claim to offer solutions to these pressing global challenges. However, it aims to expand our knowledge and understanding of critical issues related to them. Specifically, the chapters in the next pages explore two topics deeply related to development issues affecting countries in the Global South: (i) the functioning of rural labor markets, including the persistence of agrarian non-market labor institutions; and (ii) the effects of trade liberalization and export commodities on crime and violence. Agriculture serves as the unifying topic between these themes, reflecting its relevance in shaping both rural livelihoods and broader societal outcomes.

Agriculture, and more broadly the agrarian economy, are widely related to the achievement of the SDGs. For example, for the period 1993-2002, it is estimated that around 80% of the worldwide reduction in rural poverty is directly linked to improved economic conditions in rural areas (Byerlee et al., 2009). Indeed, Barrett et al. (2017) note that "agricultural transformation based on productivity growth, improved market functioning and growth in the rural non-farm economy, remains essential to achieve the goal of inclusive growth and prosperity in Sub-Saharan Africa" (p. i17). Agriculture is therefore central to at least four of the SDGs: no poverty (SDG 1), zero hunger (SDG 2), decent work and economic growth (SDG 8), and life on land (SDG 15). This is largely relevant in Africa, where the agricultural sector contributes approximately to 20% of the continent's GDP and employs half of the labor force (FAO, 2022).

The significant role of agriculture for economic development has motivated development economists to conduct extensive research on a wide range of topics. These include,

[1] The UN reports that only 23 of the 135 SDG targets with available trend data are on track to be achieved within the next five years or have already been met, meaning a low 17% success rate.

among many others, the role of informal institutions in helping farmers overcome market imperfections and the debate over whether natural resources are a curse or a blessing for an economy. Building on these topics, this thesis consists of three chapters —two single-authored and one co-authored— that address related questions. Specifically, I examine in this thesis the role of labor exchange -a non-market institution- in the agrarian economy in countries of Sub-Saharan Africa (SSA), and how the Mexican avocado production and export boom affected patterns of violence across the country.

The export of high-value crops has been widely recognized for its potential to reduce poverty and stimulate economic growth (Crost and Felter, 2020). More broadly, export-oriented agriculture has been promoted as a driver of development, particularly in fragile states (World Economic Forum, 2014). Over the past two decades, exports of agricultural commodities have increased fivefold, creating a global market now valued at USD 1.5 trillion.[2] Smith (2015) revisits the concept of resource curse and shows that resource-rich developing countries experience positive effects on GDP per capita from resource exploitation that can persist in the long term under certain conditions. However, despite the potential benefits of export-oriented agriculture for economic growth, the context in which the export-oriented sector operates can hinder its potential for development. One significant challenge is the presence of criminal organizations in the region or country where these resources exist.

Although hundreds of studies since the early 2000s have examined the relationship between the value of primary commodities and armed civil conflict (Blair et al., 2021), important gaps persist in the literature. Much of the existing research has focused on illegal commodities and violence linked to civil conflicts or wars, leaving other forms of violence—such as those involving mafia-type organizations and their ties to legal agricultural commodities—relatively understudied. To help address this gap, Chapter 1 (single-authored) investigates how the removal of a long-standing import ban on Mexican avocados in the US affected both lethal and non-lethal violence in avocado-producing municipalities in Mexico. The chapter also explores how these effects vary depending on municipalities' exposure to the export market.

Next, chapters 2 and 3 take the reader to Sub-Saharan Africa (SSA) to study a non-market institution in the agrarian economy relatively understudied by development economists.

Economists have for long recognized the pivotal role of agriculture in economic development (de Janvry and Sadoulet, 2022). The dual-sector model developed by Lewis (1954) is an example of this. The process of structural transformation, with the ultimately goal of transforming low-income agricultural-dependent economies into high-income industrialized ones with a small yet highly productive agricultural sector has been

[2] Own calculations based on data from UNCTAD and WTO.

a long-standing paradigm in economics. However, extensive urban underemployment and small productivity gaps between urban and rural workers suggest that, instead of prioritizing a rapid shift of labor to non-agricultural sectors, economic growth and poverty alleviation can be effectively pursued within rural areas and the agrarian economy, while focusing less on urban-oriented industrialization (Byerlee et al., 2009; de Janvry et al., 2022).

Within the agrarian economy, there exists a non-market institution that is present in the developing world and has been largely documented by researchers in other social sciences: labor exchange (also known as labor-sharing). Chapters 2 and 3 explore this informal institution through the lens of theoretical models, and empirical analysis using novel data collected in the field and the LSMS-ISA surveys.[3]

Traditional models in economics consider only family and hired workers as labor inputs, overlooking the role of labor exchange as an alternative means for farmers to access labor. Data I use in one of the chapters of this thesis show that 55% of rural households across four countries in SSA engage in labor exchange, with as much as 88% in Ethiopia. As noted by de Janvry and Sadoulet (2022) "understanding farm household behavior is key for the design of policy to reduce rural poverty" (p. 10), and a relevant aspect of this behavior seems to be the use of labor exchange as an integral part of farming activities.

In Chapter 2, a joint project with Christelle Dumas (University of Fribourg) and Matthias Fahn (University of Hong Kong), we examine how labor exchange teams in rural Tanzania enhance women's opportunities to obtain paid work in the labor market while reducing monitoring costs for landlords. Beyond its academic contributions, this project provided a unique opportunity to conduct fieldwork, collect novel data, and engage in the entire research process—from conceptualizing the idea to collaborating with experienced researchers, securing funding, and working with partners based in Africa. My primary contributions to this co-authored project include conceptualization, data curation and software, formal analysis and investigation, as well as writing-reviewing, and editing. On a personal level, the most rewarding experience was supervising and conducting fieldwork for data collection in the Kagera region of northwestern Tanzania. Witnessing firsthand how individuals behave in their everyday lives, and understanding how the data we analyze with sophisticated econometric techniques reflect this behavior, is deeply fulfilling for a development economist.

Finally, Chapter 3 extends the analysis to other SSA countries to incorporate labor-sharing into the production function and decision-making process of agrarian households. In this single-authored chapter, I develop a simple theoretical model that formally integrates labor-sharing into the production function and empirically examine how farmers in

[3]Living Standards Measurement Study - Integrated Surveys on Agriculture (LSMS-ISA).

Ethiopia, Malawi, Niger, and Nigeria allocate different types of labor—family, hired, and exchange—when facing rainfall shocks. Rainfed agriculture dominates in Africa, with more than 90% of total cropland dependent on rainfall (Calzadilla et al., 2013; Abrams, 2018), and SSA is home to the majority of countries most vulnerable to climate change (United Nations Economic Commission for Africa, 2023). As one of the most pressing challenges humanity faces—and will continue to face in the years to come—the ability of farmers in SSA to adapt their labor utilization and, more broadly, their livelihoods to climate anomalies remains central to the fight against poverty.

Note to the reader

The three chapters of this thesis are presented as stand-alone essays, each of which can be read independently. The following abstracts provide an overview of the key themes and findings of each chapter.

Chapter 1: The guacamole curse: Avocados, crime, and violence in Mexico

There is extensive evidence of the impact of natural resource windfalls on violence. Nevertheless, most of the literature focuses on civil conflict and civil wars. There is limited evidence concerning the effect of natural resource booms on other forms of violence, or other dimensions of political and social life. In this paper, I study avocado production in Mexico over the past 30 years to shed light on the impact of a legal commodity boom on both lethal and non-lethal violence, as well as various types of crime. I exploit geographic differences in the exogenous suitability of a municipality to produce avocados with movements in the international price of the fruit to estimate the effect of the avocado boom on three different outcomes: homicides, drug cartel-related attacks, and non-lethal crimes. The findings show that, in line with the opportunity cost mechanism highlighted in the literature, municipalities that are more suitable to produce avocados have experienced a reduction in homicides and attacks by drug cartels. This effect is mainly driven by the period following the lifting of an 83-year ban on Mexican avocado imports into the US. However, municipalities that are highly oriented toward the export market did not experience this reduction in violence. Instead, these municipalities have seen an increase in non-lethal crimes, particularly in threats and property crime.

Chapter 2: Informal labor exchange teams and participation on the labor market: Evidence from rural Tanzania (joint with Christelle Dumas and Matthias Fahn)

Development economists have long studied how informal arrangements among community members may substitute for an imperfect and incomplete market. This paper assesses whether informal arrangements may actually promote exchanges in the market. We study rural labor exchange teams, an organization that is found in many different areas but still underdocumented in the economic literature. Our theoretical analysis shows that these teams offer an advantage to employers, who may outsource the monitoring of workers' effort to the team. Team members are incentivized to provide high effort because a deviation would lead to the team dissolution, including for own farm production. Data from north-west Tanzania is consistent with the model's predictions: women who are part of a labor exchange team are more likely to obtain paid farm work, and are more often hired for tasks for which teams have a comparative advantage.

Chapter 3: Rainfall, remoteness, labor exchange, and farm labor allocation in Sub-Saharan Africa

The majority of the world's most climate-vulnerable countries are in Sub-Saharan Africa, where 80% of the global poor are projected to reside by 2030. This chapter examines how rural households in Ethiopia, Malawi, Niger, and Nigeria adjust their use of family labor, hired workers, and labor exchange (a non-market institution) in response to rainfall deviations, with a focus on how these adjustments vary by remoteness. I develop a simple farm optimization model to test predictions on labor utilization at the farm level, using nationally representative data from over 9,500 households across the four countries. The empirical results show that, in response to negative rainfall deviations, farmers close to population centers reduce family person-days by 13.8%, while in more remote locations the adjustment is of a 7% reduction in labor exchange usage. Surprisingly, and contrary to the model's predictions, farmers increase their demand for hired labor during periods of negative rainfall. Additionally, no significant effects of increased rainfall on labor utilization are observed. This chapter contributes to the literature on rural labor markets in Africa by integrating labor exchange into the analysis of labor allocation and providing new insights into how weather anomalies affect agricultural labor markets.

Chapter 1

The guacamole curse: Avocados, crime, and violence in Mexico

1.1 Introduction

Most of the literature on the resource curse focuses exclusively on the effect of commodities' windfalls on civil conflict and civil war (Nillesen and Bulte, 2014). A recent meta-analysis by Blair et al. (2021) reports that more than 350 empirical papers that study the relationship between natural resources and armed civil conflict have been published in the past twenty years. Despite this extensive body of research, there has been a lack of clear evidence on the relationship between *legal* agricultural commodities[1] and conflict (Van der Ploeg, 2011), and the recent evidence about how agriculture export commodities affect conflict and violence is mixed and not yet conclusive (Crost and Felter, 2020; McGuirk and Burke, 2020).

In this chapter, I study avocado production in Mexico over the past thirty years to shed light on the effect of a legal commodity export boom on different types of lethal and non-lethal violence: homicides, drug cartel attacks, and crimes. Mexico is the world's largest producer of avocados and the Mexican avocado export industry is worth more than USD 3 billion nowadays. Following the lifting of an 83-year import ban in the US in 1997, exports of Mexican avocados have increased by over 20 times in the past two decades, and per capita consumption of fresh avocados has increased by more than

Special thanks to Christelle Dumas, Lorenzo Casaburi, Paolo Buonanno, Suana Oh, Oliver Vanden Eynde, and Clément Imbert for their helpful comments and discussions. I also thank participants and discussants at the 3rd Workshop on the Economics of Crime for Junior Scholars WEC-Jr (CEP-LSE), 22nd EUDN PhD Workshop on Development Economics (Paris School of Economics), PhD Conference in Economics and Finance (Imperial College London), 17th RGS Doctoral Conference in Economics (University of Duisburg-Essen), 4th EENR Conference (University of Orléans-Léo), ECWE 2024 (University of Verona), 7th conference of the Development Economics Network Switzerland-DENS (University of Geneva), and the Annual Congress of the Swiss Society of Economics and Statistics SSES 2024. A previous version of this chapter has been disseminated as a working paper (See Arciniegas (2024)). This chapter differs from the working paper only in minor stylistic adjustments.

[1] There is a large strand of literature that focuses on illegal resources (such as marijuana, cocaine, and opium) and civil conflict. See for example Angrist and Kugler (2008); Mejia and Restrepo (2013); Gehring et al. (2023).

400% in the US during the same period (Carman, 2019). At the same time, the homicide rate in Mexico has been constantly rising since the mid-2000s. Pettersson and Öberg (2020) show that, only in 2019, 60% of all non-state conflict deaths worldwide occurred in Mexico. In that year, there were 29.1 violent deaths per 100,000 inhabitants in Mexico while the world average was estimated at 5.8.[2] Data on non-lethal crimes show that, before the COVID pandemic, there were eight times more kidnappings and three times more serial assaults in Mexico than the average in the world.[3]

Several international media outlets claim that the avocado boom is the reason behind the increase in violence in some regions in Mexico, as reported by the New York Times, The Guardian, South China Morning Post, the Deutsche Welle, The Economist and Forbes magazine, among others. According to these reports, avocado-producing municipalities in Mexico have experienced a rise in homicides, extortion cases, and kidnappings due to criminal organizations who seek to extract rents from the lucrative avocado market. If these claims are true, one should expect to empirically find that avocado-producing regions in Mexico have experienced higher levels of crime and violence compared to regions with low levels of avocado production.

The economic analysis of natural resources and violence has identified two main mechanisms that can be at play when a country or region experiences a positive economic shock to a commodity: the opportunity cost mechanism and the rapacity effect mechanism. The former corresponds to situations in which positive economic shocks reduce violence, whereas the latter to cases in which violence increases (Dal Bó and Dal Bó, 2011; Dube and Vargas, 2013).

Which of the two mechanisms prevail depend on the context of each situation. In the case of the avocado sector in Mexico, and according to media reports, the rapacity effect should be prevailing. Based on the framework developed by Schelling (1971) and extended by Gambetta and Reuter (1995), certain characteristics of legal markets make them particularly vulnerable to becoming targets of criminal organizations. These include weak legal institutions, the presence of industries with high and easy observable output and profits, and fragmented production with many small producers. The avocado sector in Mexico share these traits. However, the literature that studies labor-intensive or agricultural commodities —such as avocados— find evidence in favor of the opportunity cost mechanism: higher commodity prices are associated with less conflict (Blair et al., 2021).

To causally test the effect of the Mexican avocado boom on crimes and violence and determine which mechanism prevails, I exploit the fact that climatic and soil conditions determine which municipalities are better suited for avocado production. To do so, I

[2]Own calculations based on data from the United Nations Office on Drugs and Crime (UNODC). Data retrieved from https://dataunodc.un.org/content/data/homicide/

[3]ibid.

construct an exogenous, time-invariant index that measures the biophysical suitability of each Mexican municipality to produce avocados using long-term climate data collected from 1494 weather stations and geo-referenced data of 9549 soil profiles across Mexico.

The empirical strategy exploits geographical variation in the production suitability of each municipality with temporal variation in the international price of avocados. The causal effect of the avocado boom is identified by the differential impact of price shocks on municipalities with distinct pre-determined suitabilities to produce avocados. This approach follows Gehring et al. (2023) and complements those used in previous studies of the effect of agricultural commodities on civil conflict (e.g. Dube and Vargas (2013); Crost and Felter (2020)).

I estimate the effect of the avocado boom on three different outcomes: homicides, drug cartel-related attacks, and crimes. Results on homicides show that municipalities that are more suitable to produce avocados have experienced, between 1990 and 2019, an average reduction of 2.03 homicides per 100'000 population, equivalent to a reduction of 12.1% compared to the mean homicide rate in low-suitable municipalities. This result is robust to a battery of validity and robustness tests that include, among others, alternative measures of the outcome variable, wild cluster bootstrap inference, and random permutations of the suitability index. I also find that the number of attacks committed by drug cartels have decreased in highly suitable municipalities as well, and that non-lethal crimes have not increased.

The finding of a positive effect of avocado production in reducing crime and violence across Mexican municipalities contrasts with the expected hypothesis that the rapacity effect would prevail, as well as with media reports. Nevertheless, these results align with the broader literature on agricultural commodities and violence: higher prices for labor-intensive agricultural goods reduce conflict (Dube and Vargas, 2013; Blair et al., 2021; Ferraz et al., 2022). This literature suggests that the opportunity cost mechanism predominates over the rapacity effect when agricultural commodities experience positive economic shocks.

To further investigate the discrepancy between the expected hypothesis, the results, and the literature, I examine violence patterns in municipalities in the western state of Michoacán, the major producer of avocados in Mexico. The lifting of the US import ban in 1997 was conditioned on strict phytosanitary requirements, and only municipalities certified by both Mexican and US authorities are allowed to export avocados to the US. To better understand the potential link between avocado exports and violence, I analyze homicide and crime patterns in the first 24 municipalities in Michoacán that were granted export authorization in 1997 and compare them to those in the rest of the state.

Contrary to the country-level results, I find no evidence of a reduction in homicides in municipalities that produce avocados for the export market. I find that, indeed, these municipalities seem to have experienced an increase in property crime and attacks by drug cartels. This result is in line with recent evidence on the effect of agricultural export booms (Crost and Felter, 2020; Estancona and Tiscornia, 2023; Crost et al., 2023) and reflects the claims of newspaper investigations. Although the findings point towards an increase in violence in avocado-producing and export-oriented municipalities in the state of Michoacán, results are not fully robust to some checks, and thus causal interpretation must be cautious.

My results provide evidence of both the opportunity cost mechanism and the rapacity effect, operating within the context of a single commodity in the same country. I observe an overall reduction in lethal violence in municipalities with higher levels of avocado production, consistent with the literature highlighting the opportunity cost mechanism which suggests that improved economic conditions reduce incentives for violence (Dal Bó and Dal Bó, 2011; Dube and Vargas, 2013; Blair et al., 2021). At the same time, in line with recent findings by Crost and Felter (2020) and Estancona and Tiscornia (2023), I find an increase in drug cartel attacks and other crimes, as well as suggestive evidence of a rise in homicide rates, in a small subset of municipalities heavily exposed to the export market. These seemingly "contrasting" results demonstrate how a single commodity can both mitigate and exacerbate violence, stressing the importance of better understanding how attributes of economic activities can determine its effect on violence (Crost et al., 2023).

This chapter contributes as well to the literature that studies the Mexican Drug War. Because of its relevance and the large number of victims, scholars from different disciplines have studied the causes and consequences of the violence that has been ravaging Mexico in the last twenty years. Most of this literature has focused on the institutional and political context (Dell, 2015; Shirk and Wallman, 2015; Trejo and Ley, 2018) or on how changes in the drug-trafficking market are behind the increase in the number of deaths (Kellner and Pipitone, 2010; Castillo et al., 2020). My chapter contributes to this growing literature by pointing out how a boom in the production and export of a legal commodity shapes the economic decisions of criminal organizations and can be a causal explanation for the increase in crime and violence experienced in certain regions of the country.

Finally, the chapter also relates to the literature on the economics of organized crime and its infiltration in the legal economy (Schelling, 1971; Reuter, 1987; Gambetta and Reuter, 1995; Balletta and Lavezzi, 2023; Piemontese, 2023). There is little scholarly evidence on how natural resources affects other forms of violence, such as attacks committed by drug cartels and non-lethal crimes.[4] Even though results for the case of Michoacán are not fully conclusive of a causal increase in crimes and drug cartel attacks due to the avocado boom, they are suggestive of how agricultural booms can shape criminal activity patterns.

The rest of the chapter is organized as follows: Section 1.2 presents the background and related literature close to my paper. Section 1.3 presents the data sources and details the empirical strategy. Section 1.4 presents the main results on homicides, drug cartel attacks, and crimes at the country level. Section 1.5 then discusses the case of export-oriented municipalities in the state of Michoacán. Section 1.6 presents the robustness checks of the main estimations. Finally, Section 1.7 concludes.

1.2 Background and Related Literature

The avocado (*persea americana*) is a perennial tree native to Mesoamerica whose fruit can be harvested all year long. It has been cultivated in central Mexico and northern Guatemala hundreds of years before the arrival of the Spaniards in the 15th century. The name of its fruit (*aguacate* in Spanish) comes from the náhuatl noun "ahuacatl" which means "testicles of the tree". Nowadays there are around 400 different varieties of avocados, with the Hass type being the most commercialized one in the international market.

The tree grows at different altitudes, oscillating between 800 and 2500 meters above sea level. It requires between 1000 and 2000 millimeters of annual rainfall to grow, temperatures ideally between 18°C (62°F) and 24°C (75°F), and requires a pH-neutral or mildly acid soil. The Trans-Mexican Volcanic Belt that goes through western Mexico provides mineral-rich soil ideal for avocado growth. A hectare of avocados usually contains between 120 and 180 trees (depending on the variety of avocado and the topography of the terrain), and a single tree can produce between 800 and 1500 fruits per year in the most productive phase of the life cycle (usually at the eighth or tenth year after cultivation), with the first harvest occurring at the fifth year (SAGARPA, 2011).

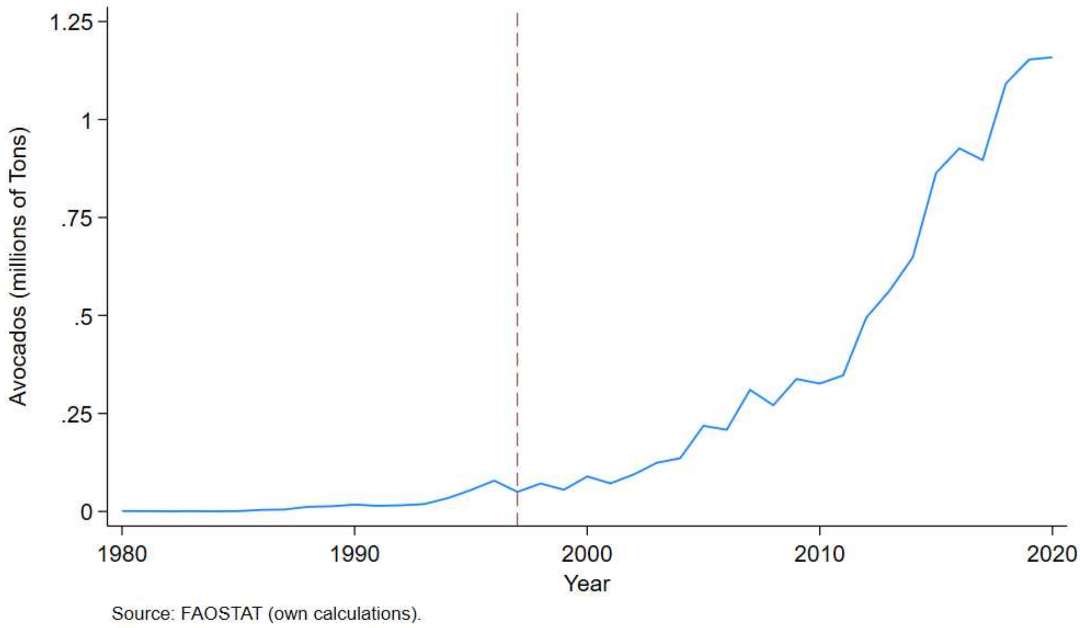
Mexico has been historically one of the largest producers of this fruit. However, in 1914 the United States banned the imports of Mexican avocados alleging phytosanitary

[4] A couple of papers have studied how the activities and apparition of mafia-type organizations are related to natural resources. Buonanno et al. (2015) document that the emergence of the Sicilian mafia in Italy in the 19th century is linked to a positive shock in the demand for Sulphur; while Dimico et al. (2017) trace the origins of this mafia-type organization to locations with high levels of income coming from the production of oranges and lemons for overseas export. Murphy and Rossi (2020) argue that the origins of the Mexican drug cartels can be traced back to the Chinese migrants who settled in Mexico in the early 20th century who brought with them poppy seeds and established a trafficking business with the US that eventually shaped the origins of current Mexican drug cartels. However, these papers link the natural resources to the origins of the organizations but do not explain how the current levels of crime and violence are related to the presence of natural resources today.

reasons to prevent the spread of weevils, invasive pests, and other diseases that could affect US production. Following the NAFTA agreements of the 1990s, the US Department of Agriculture (USDA)'s Animal and Plant Health Inspection Service passed a rule that lifted the ban on Mexican avocados imports after 83 years of prohibition on November 1997.[5]

The opening of the market was gradual and consisted of four phases that progressively extended the geographical distribution and duration of the shipping season. Initial exports were only allowed to 19 northeastern states and the District of Columbia and only during four months in the winter season (November to February). More states were progressively added to the list and the time window was extended, first to six months in 2001 (mid-October to mid-April) and then year-round in 2007.[6] From February 2007 onwards, imports in the US of Mexican avocados were finally authorized all year long to all the fifty states of the country and the market was completely liberalized (Peterson and Orden, 2008). Figure 1.1 plots the evolution of Mexican avocado exports in the past 40 years, highlighting the effect of the lifting of the imports ban in 1997.

Figure 1.1: Evolution of Mexican avocado exports and the US market liberalization in 1997



[5]Amendment of Title 7 of the Code of Federal Regulations (CFR) 319.56-2ff, governing the importation of fresh Hass avocados from Mexico to the United States. Mexican producers willing to export their fruits to the US must comply with strict phytosanitary, marking, and shipping requirements and only certified producers -both by American and Mexican authorities- are allowed to export avocados.

[6]In 2004 the list was extended to cover all the rest of the states but three: California, Florida, and Hawaii. These three states were only included in 2007, as they are the largest producers of avocados in the US.

The avocado industry in Mexico has recently received attention from different media outlets and scholars from the social sciences. Various media reports and qualitative literature claim that the number of homicides, extortion cases, and kidnappings in avocado-producing regions have increased as a consequence of the presence of drug cartels who seek to diversify their business and profit from the avocado export bonanza (Fisher and Taub, 2018; Viohl, 2020; Linthicum, 2019; Ornelas, 2018). Homicides are reported to be the consequence of the fight of cartels while they try to gain control and establish their power in a region, and extortion and kidnapping the consequence of cartels trying to gain control over the production of avocado and extract rents out of the legal producers. I test these claims in the next sections and try to establish a causal link between the boom generated by the liberalization of avocado imports in the US and the figures of crime and violence in producing municipalities in Mexico.

The literature on natural resources and conflict have highlighted two key mechanisms that can emerge when a country or region experiences a positive economic shock from a commodity: the opportunity cost mechanism and the rapacity effect one. The opportunity cost mechanism suggests that such shocks can decrease violence, while the rapacity effect mechanism points to situations where violence escalates (Dal Bó and Dal Bó, 2011; Dube and Vargas, 2013).

The main idea of the opportunity cost mechanism is that, when a commodity or sector experiences a positive shock that increases salaries, rents, or welfare in general, individuals have less incentives to engage in violent activities as they have more to lose when economic conditions improve. That is, the opportunity cost of violence is higher and it becomes less attractive. On the other hand, the rapacity effect channel posits that positive shocks will increase the incentive to incur in criminal activities as the potential gains from them are larger than their costs, thereby increasing the incentive to use violence to secure those rents. This is particularly accrue when resources are easily lootable and stakes are large.

As Ferraz et al. (2022) point out, the empirical evidence on how economic shocks impact violence is largely ambiguous. Which mechanism prevails depend on the specificities of each context. However, at least three elements can help in determining which mechanism will dominate: (i) whether the shock operates in an illegal or legal sector; (ii) the lootability of the resource; and (iii) institutional strenght and economic conditions, such as the rule of law and the degree of inequality.

Earlier literature and cross-country studies have found mixed evidence on the relationship between natural resource windfalls and violent conflicts (Besley and Persson, 2008; Brückner and Ciccone, 2010; Bazzi and Blattman, 2014). However, there appear to be some stylized patterns based on the type of resource. Studies examining the impact of oil, minerals, and other capital-intensive commodities generally find a positive relationship with violence: the extraction of minerals or oil in a country increases the risk and intensity of civil conflict. For labor-intensive or agricultural commodities —such as avocados— the evidence suggests a negative relationship: higher commodity prices are associated with less conflict (Blair et al., 2021).

For legal agricultural commodities and crops there is still mixed evidence about the effect of positive economic shocks on violence. On the one hand, Dube and Vargas (2013) find that an increase in the price of coffee reduces the number of attacks of rebel groups in coffee-producing regions in Colombia; and Dube et al. (2016) show that negative shocks in the international price of maize contribute to higher levels of violence in Mexico when farmers switched to the production of marihuana and drug cartels fight for its control. These results are in line with cross-country evidence of a negative correlation between export revenues and the incidence, intensity, and onset of conflicts in Africa (Berman and Couttenier, 2015; Fjelde, 2015). On the other hand, Crost and Felter (2020) find that a positive shock to banana prices increases conflict in banana-export-producing regions in the Philippines when insurgent groups seek to extract rents by extorting big producers and export companies; while Kenny et al. (2020) report a similar effect in the case of palm oil in Indonesia.

The works of Yoo (2022), Estancona and Tiscornia (2023), De Haro-Lopez (2023), Erickson and Owen (2024), and De Haro-Lopez (2024) are close to mine and investigate the effects of avocado production in Mexico on lethal violence. These studies rely on different identification strategies, cover different (and shorter) periods, and only a specific group of states or municipalities. Furthermore, they find divergent results. While Estancona and Tiscornia (2023) find that "large increases in the municipality's share of avocado export value are associated with a large number of homicides" between 2004 and 2010, Yoo (2022) and Erickson and Owen (2024) find a negative effect of the avocado boom on homicides, either at the state-level in five states of Mexico between 2010 and 2017 (Yoo, 2022), or at the municipality-level in the states of Michoacán and Jalisco between 2011 and 2019 (Erickson and Owen, 2024).

De Haro-Lopez (2024) analyzes how the U.S. opioid crisis affects violence in avocado-growing municipalities in Mexico between 2011 and 2019. She finds that a decrease in heroin demand in the U.S. (due to increases in Fentanyl availability) increased murders of agricultural workers in avocado-growing municipalities in Mexico, while it reduced violence in poppy-growing municipalities. On the contrary, in De Haro-Lopez (2023) she finds that, between 1990-2006, avocado-growing municipalities experienced a reduction of up to 25% in homicide rate after the U.S. opened its market for Mexican avocados. These opposed results could be the consequence of the different time spans these authors use for their analysis, and/or the subset of states and municipalities they study.

I complement these studies by exploiting a strategy that allows me to analyze all municipalities in Mexico over more than thirty years, and where identification comes from variation in the differential impact of price shocks on municipalities with distinct predetermined suitabilities to produce avocados. Among others, my empirical estimation includes a state-level time trend to capture state-specific shocks potentially correlated to violence outcomes. None of the aforementioned studies control for state-specific effects, which in the context of Mexican violence is relevant and necessary to avoid biased estimates.[7]

I am also able to examine medium- and long-term effects by analyzing the impact of the avocado boom on thirty years of homicide data (1990–2019) and twenty years of drug cartel-related attacks (2000–2018). Additionally, I extend those studies to include other forms of violence by measuring non-lethal crimes at the municipality level, while also investigating the effect on homicides. Regarding homicides, which are the primary outcome analyzed in the other articles, Yoo (2022), Estancona and Tiscornia (2023), and Erickson and Owen (2024) exploit the lifting of the U.S. import ban but do not discuss nor address violence levels prior to 1997. With the data I collected on homicides from 1990 onwards, I can analyze the period preceding the lifting of the avocado ban to strengthen the causal interpretation of my results.[8]

1.3 Data and Empirical Strategy

1.3.1 Data

I use data from administrative and academic sources covering the period between 1990 to 2022 to causally test if the avocado boom has caused an increase in crimes and violence across Mexican municipalities. Specifically, I study the effect of avocado production on three main outcomes: homicides, attacks attributed to drug cartels, and crimes in each municipality-year.

Homicides are widely used in the literature to measure the incidence of crime (Dix-Carneiro et al., 2018) and, as noted by Soares (2004), data on homicides are a low-biased measure of the incidence of crime and violence in the context of developing countries, where underreporting is prevalent and non-random. The main data on homicides come from INEGI, Mexico's National Institute of Statistics and Geography. INEGI records

[7]Military operations against drug cartels during the *Mexican Drug War* took place in states where drug cartels were mostly present. For example, only ten days after taking office, President Felipe Calderón declared a crackdown against drug cartels in the state of Michoacán. Between 2008-2012, the "Joint Operation Nuevo León-Tamaulipas" took place in Northeastern states in Mexico. Accounting for those state-specific policies is therefore necessary.

[8]De Haro-Lopez (2023) is an exception. She examines violence in avocado-growing municipalities before and after NAFTA, covering the period 1990–2006. De Haro-Lopez (2024) further expands the analysis to include non-lethal crimes such as extortion and theft.

all deaths caused by homicides in each Mexican municipality since 1990.[9] Although my identification strategy does not explicitly rely on the lifting of the US import ban in 1997, the homicide data allow me to check the robustness of my results by comparing homicide trends across municipalities with different production suitabilities before the avocado export boom took off.

To measure the impact of avocado production on drug cartel activities, I use data from the "Organized Crime Violence Event Data" (OCVED) project (Osorio and Beltran, 2020). OCVED uses web-scraping techniques combined with Machine Learning and supervised Natural Language Processing algorithms to extract information from more than 70 Mexican newspapers to identify and geolocalize violent events committed by drug cartels across Mexico between 2000-2018. The data contain both lethal and non-lethal attacks where the author(s) were identified as members of drug cartels. Although these data do not allow me to separate homicides from other types of crimes, it is a good proxy for the violence committed by drug cartels.

Finally, I use data from SESNSP (Mexico's Executive Secretariat of the National System of Security) for the period 2011 - 2022 to categorize crimes by type.[10] Although SESNSP data is only available at the municipality level since 2011, it breaks down crimes in different categories, according to whether the crime was intentional or not, and the type of arm used to commit the crime. Some of the crimes collected by SESNSP include extortion cases, threats, kidnappings, and theft, among others. This allows me to measure the impact of the avocado boom on other forms of crime and non-lethal violence, outcomes that have been less studied in the literature of the resource curse.

I leverage the fact that biophysical geographic conditions determine which municipalities are better suited to produce avocados. I gather data from 1494 weather stations in Mexico (resolution 8" x 8") over the period 1902-2011 to estimate the mean annual temperature (°C), the mean minimum temperature of the coldest month (°C), the mean annual precipitation (mm), and the mean relative humidity (%) for each municipality. Additionally, I use maps of 9,549 soil profiles (scale 1:250,000) collected by INEGI across Mexico between 1985 - 2000, before the lifting of the imports ban and at the onset of the export boom. The soil profiles contain information on the soil's pH, texture, depth, salinity (ECe), organic matter, and cation exchange capacity (meq/100 g). I combine these data to create an exogenous time-invariant avocado suitability following Grüter et al. (2022) which I use to identify the causal effect of the avocado boom on violence. See details in section 1.3.2.

I also collect data on avocado production from SIAP (*Servicio de Información Agroalimentaria y Pesquera*), an attached organ to the Mexican Secretariat of Agriculture and

[9]https://www.inegi.org.mx/sistemas/olap/proyectos/bd/continuas/mortalidad/defuncioneshom.asp?s=est
[10]https://www.gob.mx/sesnsp/acciones-y-programas/incidencia-delictiva-299891?state=published

Rural Development -SAGARPA- that collects geographical and statistical data on agriculture and fishery.[11] SIAP reports the annual number of hectares planted with avocado, the production (in tons), the yield per hectare, and the value of production, both at the state level (since 1980) and at the municipal level (since 2003).

I use data from FAOSTAT and the US Department of Agriculture (USDA) Economic Research Service's Fruit and Tree Nuts Yearbook Tables to collect data on various measures of the international price of avocados. FAOSTAT collects data on each country's export and import prices, and USDA presents over 20 years of time-series data for U.S. avocado prices. As the main measure of price for my empirical estimation, I construct an "international import price" for each year since 1990 using the import price in each country (excluding Mexico) to estimate an average global import price. I then standardize this price to have a mean zero and standard deviation of one.[12]

Finally, I use administrative data from Mexico's National Council for the Evaluation of Social Development Policy (CONEVAL) and Mexico's National Population Council (CONAPO) to gather different socio-economic indicators at the municipality level such as poverty, inequality, literacy, and population size.[13] I also retrieved different measures of wholesale and retail cocaine prices in the US and Western Europe from the United Nations Office on Drugs and Crime (UNODC). Table 1.1 summarizes the different data sources used in this chapter.

Table 1.1: Data sources

Data	**Source**	**Period**	**Level**
Homicides	INEGI	1990 - 2019	municipality
Drug Cartel attacks	OCVED	2000 - 2018	municipality
Non-lethal crimes	SESNSP	2011 - 2022	municipality
Climate	INEGI	1902 - 2011	raster (8" x 8")
Soil profiles	INEGI	1985 - 2000	vector (1:250,000)
Avocado production	SIAP	2003 - 2020	municipality
Avocados prices	FAOSTAT	1980 - 2020	country (world)
Socio-economic controls	CONEVAL & CONAPO	1990 - 2020	municipality
Other	UNODC, USDA		

Descriptive statistics in Table 1.A.1 compare high- and low-suitability municipalities across geographic and socioeconomic dimensions, as well as levels of violence. A raw mean comparison confirms that municipalities differ significantly in geographic features,

[11] The data is available on -line or remotely through the SIACON database

[12] See Figure 1.C.1 in the Appendix for a detail on the price measures and their evolution in the period of analysis.

[13] In some cases it was necessary to extrapolate data points to complete and balance the panel, since not all indicators have available data for every municipality-year.

as predicted by the index, but also in socioeconomic characteristics. However, no statistically significant differences are observed in violence patterns, whether measured by homicides or drug cartel attacks. The empirical strategy described in the next section seeks to identify a causal relationship between suitability to produce avocados and levels of lethal and non-lethal violence across municipalities in Mexico.

1.3.2 Empirical strategy

To estimate whether the avocado boom has increased violence in producing municipalities, my empirical strategy combines geographical variation in the suitability of each municipality to produce avocados with temporal variation in the international price of the fruit. I construct a suitability index following Grüter et al. (2022) that mimics the FAO's land evaluation approach using geo-referenced data on long-term climate patterns and soil features across the Mexican territory. Each climatic and soil feature is categorized into four suitability classes -high, moderate, marginal, or unsuitable- depending on the requirements for avocado production (see Table 1.B.1 in the Appendix). I then aggregate all features to create an aggregated average suitability index that takes on values between 0 and 3, where zero indicates complete unsuitability and three corresponds to the case where all the municipality's biophysical characteristics are optimal for avocado production.[14] Figure 1.2 shows the avocado suitability index map of Mexico at the municipality level.[15]

To check whether the suitability index is a good predictor of real avocado production, I evaluate if municipalities that have the highest suitability index are the ones that plant and produce more avocados. Figure 1.B.2 in the Appendix shows that the average production of avocados in highly suitable municipalities is between 5 and 8 times larger than in moderately and marginally suitable ones. Moreover, Figure 1.B.3 shows that in highly suitable municipalities the amount of land dedicated to avocado growing has been

[14]In cases where soil data is not available at the municipality level, the index considers the climate requirements to assess the suitability of the municipality. As Grüter et al. (2022) note, climate requirements are more important limiting factors than land and soil requirements when assessing the suitability to grow different types of crops, including avocados. Nevertheless, I use both climate and soil features when available to reinforce the index. In the robustness checks presented in section 1.6, I estimate the main estimation using the climatic component of the suitability index only.

[15]I use existent municipalities in Mexico's administrative census of 1995 to construct the suitability index and estimate the empirical results in the next section. This corresponds to the most recent administrative census before the lift of the US import ban in 1997 and allows me to mitigate potential endogeneity concerns coming from changes in violence levels in municipalities more exposed to the export market after the lift of the ban. The 1995 administrative division of Mexico should not be correlated with endogenous avocado production capacities and violence incidence at the municipality level during the period of analysis. As such, results are estimated for 2428 out of the 2459 current municipalities in the country. Figure 1.B.1 in the Appendix presents the suitability index map and the map of avocado production in Mexico.

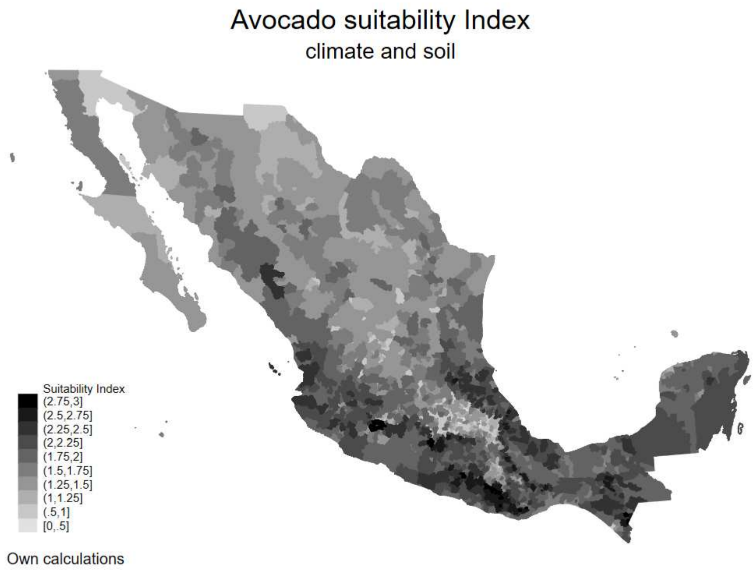


Figure 1.2: Constructed avocado suitability index at the municipality level

continuously increasing since 2003.[16] Tables 1.B.2 and 1.B.3 confirm that the suitability index correctly predicts avocado production and the number of hectares planted with avocados in the municipality. Municipalities that are classified in the index as highly suitable for avocado production cultivate and produce more avocados than the rest of the municipalities. Columns 1 and 2 in both Tables show that the estimated coefficient for highly suitable municipalities is positive -expected sign- and statistically significant after controlling for the municipality area and year fixed effects. This result is robust as well to the interaction of the suitability index with the international price of avocados. Column 5 shows that increases in the avocado price in $t-1$ increase the area (ha) and the production of avocados in highly suitable municipalities, compared to the rest of municipalities.

In what follows, I classify municipalities as either high- or low-suitable for avocado production, where highly suitable municipalities are the ones with an index between 2.5 and 3.0. I interact this dummy indicator with the international price of avocados in year $t-1$ to identify the effect of price shocks across Mexican municipalities with different levels of production suitability. I estimate the following equation in reduced form:

$$Y_{m,s,t} = \beta_0 + \beta_1 Suitability_m \times Price_{t-1} + \overrightarrow{X_{m,t}}\beta + \mu_m + \lambda_t + \gamma_s \cdot t + \epsilon_{m,t} \qquad (1.1)$$

where $Suitability_m$ equals one if the municipality m is highly suitable for avocado production, $Price_{t-1}$ is the standardized lagged value of the international import price of avocados, $\overrightarrow{X_{m,t}}$ is a set of socio-economic controls that include the population size, the

[16] Figures show data starting in 2003 since this is the year for which there is available data on avocado production at the municipal level.

Gini index and standardized values of the poverty and illiteracy rates in the municipality, and μ_m and λ_t are municipality- and year fixed effects. Since Mexico is the largest producer of avocados in the world, endogenous supply changes in production areas can affect the international price. As Gehring et al. (2023) note, the year fixed effects absorb shocks and changes in the country's avocado supply. Moreover, my preferred specification employs the world import price to further palliate possible endogeneity issues by capturing exogenous demand shocks in other countries that are presumably not affected by levels of violence in Mexico. I also include a state-specific time trend $\gamma_s \cdot t$ to account for state-level policies that target drug cartels or seek to reduce crime and violence in specific areas. The outcome $Y_{m,s,t}$ corresponds to (i) homicides per 100'000 inhabitants in the municipality m in state s between 1990 and 2019, (ii) number of violent and non-violent attacks per 100'000 inhabitants attributed to drug cartels for the period 2000-2018, and (iii) number of reported crimes after 2011 per 100'000 inhabitants.

1.4 Results

1.4.1 Homicides

I first study the effect of the avocado boom on homicides. INEGI provides data on homicides at the municipal level dating back to 1990, which allows for analysis before and after the U.S. lifted its avocado import ban in 1997. Table 1.2 presents results where the outcome is the number of homicides per 100,000 inhabitants in Mexican municipalities between 1990 and 2019.

Table 1.2: Effect of avocado suitability and world price on homicide rate (per 100,000 pop.)

	Homicide rate in municipality m in year t (1990-2019)				
	(1)	(2)	(3)	(4)	(5)
Suitability Index=1	4.94***	4.95***			
	(1.51)	(1.51)			
Avocado price (lag)	6.13***		5.13***		
	(0.84)		(0.78)		
Suitability Index=1 × Avocado price (lag)	-4.66***	-4.64***	-4.73***	-4.71***	-2.03**
	(1.00)	(1.00)	(1.02)	(1.02)	(0.74)
Observations	68498	68498	68498	68498	68498
Controls	Yes	Yes	Yes	Yes	Yes
Year F.E.		Yes		Yes	Yes
Municipality F.E.			Yes	Yes	Yes
State time trend					Yes
Sample mean of Y	17.4	17.4	17.4	17.4	17.4

Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Two-way clustered standard errors at the municipality and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

The results show that over this 30-year period, increases in the international price of avocados are associated with reductions in violence in municipalities with high suitability for avocado production. This result is robust to estimations that include only municipal or year fixed effects (Cols. 2 and 3), municipal and year fixed effects (Col. 4), and a state time trend (Col. 5). My preferred specification (Col. 5) shows that a one standard deviation increase in the international import price of avocados is associated with a reduction in the homicide rate of 2.03 homicides per 100'000 inhabitants, equivalent to a reduction of 12.1% with respect to the average homicide rate in municipalities with low suitability to produce avocados.

My identification strategy isolates variation due to the differential impact of price shocks on municipalities with distinct pre-determined trends, which are determined by geographic and biophysical conditions. With the homicide data, I can test if there were differences in the number of homicides per 100'000 population between municipalities that are more or less suitable for avocado production before the US lifted the avocado imports ban in 1997. Table 1.3 splits the homicide results before and after the lift of the ban, and presents the results for the homicide rate between 1990 and 1997 (Cols. 1-4), and 1998 to 2019 (Cols. 5-8).

Table 1.3: Effect of avocado suitability and world price on homicide rate (per 100'000 pop.) - before and after 1997

	Homicide rate in municipality m in year t (1990-2019)							
	Before (1990-1997)				After (1998-2019)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Suitability Index=1	15.61***				2.53**			
	(2.74)				(1.17)			
Avocado price (lag)		2.33				4.86***		
		(2.02)				(1.13)		
Suitability Index=1 × Avocado price (lag)	2.67	2.73	2.54	1.04	-3.59***	-3.70***	-3.71***	-1.74**
	(2.29)	(3.87)	(3.93)	(3.88)	(0.80)	(0.84)	(0.83)	(0.63)
Observations	16534	16534	16534	16534	51964	51964	51964	51964
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes		Yes	Yes	Yes		Yes	Yes
Municipality F.E.		Yes	Yes	Yes		Yes	Yes	Yes
State time trend				Yes				Yes
Sample mean of Y	19.9	19.9	19.9	19.9	16.6	16.6	16.6	16.6

Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Two-way clustered standard errors at the municipality and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

As Table 1.3 shows, there were no significant differences in the homicide rate between high- and low-suitable municipalities before 1997. Results in Columns 5-8 indicate that the effect of the increase of international avocado prices in reducing homicides in more suitable municipalities occurred after the US opened its market to Mexican avocados. This result provides evidence in favor of the opportunity cost mechanism discussed in the economics of conflict and resource curse literature (Collier and Hoeffler, 1998; Dube and Vargas, 2013; Ferraz et al., 2022), as opposed to a rapacity effect channel. That is, increases in commodities' prices have a beneficial effect in terms of reducing violence.

To further validate this result, I run a placebo test in the spirit of Crost and Felter (2020) that includes, in the baseline estimation, the interaction of the suitability measure with the international price in year $t+1$. As Table 1.D.1 in the appendix shows, the coefficient for the interaction between the suitability indicator and the international price of avocado in period $t+1$ is non-significant and of smaller magnitude than the main coefficient reported in Table 1.3. This result reassures the evidence in favor of a causal effect of the avocado export boom in reducing the homicide rate in municipalities with higher production capacities.

1.4.2 Attacks by drug cartels and non-lethal crimes

Results on homicides suggest that the violence has decreased in highly-suitable municipalities. Nevertheless, anecdotal evidence from press reports suggests that violence in major avocado-producing regions has increased, particularly due to drug cartels targeting this lucrative industry. These reports claim, in particular, that violence and crime in those regions have increased as a consequence of drug cartels who seek to extract rents from the profitable avocado industry. To examine these claims, I analyze data from the OCVED project and report results in Table 1.4.

Table 1.4: Effect of avocado suitability and world price on drug cartel violent attacks (per 100'000 pop.)

	Attacks rate in municipality m (2000-2018)				
	(1)	(2)	(3)	(4)	(5)
Suitability Index=1	-19.54***	-19.43***			
	(6.71)	(6.65)			
Avocado price (lag)	13.86***		18.70**		
	(3.25)		(7.41)		
Suitability Index=1 × Avocado price (lag)	-10.65**	-10.74**	-11.61**	-11.77**	-3.29*
	(3.95)	(3.83)	(4.61)	(4.67)	(1.72)
Observations	46132	46132	46132	46132	46132
Controls	Yes	Yes	Yes	Yes	Yes
Year F.E.		Yes		Yes	Yes
Municipality F.E.			Yes	Yes	Yes
State time trend					Yes
Sample mean of Y	23.8	23.8	23.8	23.8	23.8

Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Two-way clustered standard errors at the municipality and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

Table 1.4 shows that, as in the case of homicides, municipalities highly suitable for avocado production experienced a reduction in drug cartel attacks per 100,000 population between 2000 and 2018. Column 4 shows that, without accounting for state-specific trends, this reduction is of more than 40% with respect to the mean of attacks in low-suitable municipalities. After controlling for state time trends (Col. 5), the effect is still negative and statistically different from zero, although the magnitude decreases significantly to 3.3 attacks per 100'000 population. This is still a relevant reduction in the number of attacks.

Since not all municipalities experience attacks by drug cartels -as cartels are not necessarily active or present in all municipalities across the country-, the distribution of the number of attacks has an important mass zero. For this, I estimate a Pseudo-Poisson likelihood model to better capture this feature of the drug cartel attacks outcome. Results in Table 1.E.1 in the Appendix show that, when drug cartel attacks are measured as the count of attacks (instead of cases per 100'000 people) in each municipality, municipalities with a high suitability index experienced, on average, a decrease of 21% in lethal and non-lethal attacks carried out by drug cartels.[17]

To measure the potential impact of the avocado boom on other types of crime, I use administrative data available at the municipality level from 2011 onwards. SESNSP data reports and classifies crimes into more than twenty categories, according to the type of crime (e.g. felony or misdemeanours), the kind of weapon used, or whether the crime is against physical integrity or a private or public good, etc.[18] I classify the list of crimes into seven categories as a function of the media reports and potential income-related crimes that are more susceptible to be affected by the avocado boom. The reduced list of crimes I consider in my specification are: extortion, threatening, kidnapping, robbery, theft, injuries, and others. I test the effect separately for each crime, and I also construct a standardized weighted average index of crimes to mitigate potential inference issues related to multiple hypothesis testing (Anderson, 2008; Schwab et al., 2020). Table 1.5 below reports the results of estimating equation 1.1 on the number of non-lethal crimes per 100'000 pop. at the municipality level.[19,20]

Results indicate no statistically significant difference in criminality between highly suitable and non-suitable municipalities from 2011 to 2017. Neither the aggregated index nor individual crime categories show varying levels of crime between these municipalities. If anything, the results in Table 1.5 suggest that highly suitable municipalities did not experience an increase in non-lethal crimes over this seven-year period.

[17]Note that the number of observations is lower compared to the results in Table 1.4 when municipality (and the state time trend) fixed effects are included. This is due to the presence of singletones or separated observations in the data that can prevent the maximum likelihood estimates for the Poisson regression to exist (Correia et al., 2020). As such, they are dropped from the regression for the estimator to converge.

[18]Some examples of the types of crimes recorded by SESNSP include: breaking and entering, crimes committed by public servants, damage to property, domestic violence, dispossession, extortion, forgery, fraud, robbery, and sexual harassment, and others

[19]SESNSP started reporting crimes at the municipality level in 2011. In 2018 there was a change in methodology on how crimes are classified, and some of my categories were affected by this recomposition. Therefore, in Table 1.5 I present the results on crimes between 2011 and 2017, and in Table 1.F.1 in the Appendix, I present the results up to 2022 after an attempt to harmonize the change in methodology before and after 2018.

[20]Compared to the previous tables, Table 1.5 presents only the results of the full estimation (i.e., including controls and all fixed effects, rather than introducing them one by one) to save space.

Table 1.5: Effect of avocado suitability and world price on crimes per 100'000 pop. (by type)

	Crime rate in municipality m in year t (2011-2017)							
	Crime	Category 1			Category 2		Category 3	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Index	Extortion	Threat	Kidnap	Robbery	Theft	Injuries	Other
Suitability Index=1 × Avocado price (lag)	0.05	-0.20	1.97	1.23	14.91	3.39	32.79	7.47
	(0.10)	(0.33)	(2.64)	(2.72)	(16.03)	(8.78)	(24.47)	(6.62)
Observations	12731	12731	12731	12731	12731	12731	12731	12731
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State time trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample mean of Y	.0132	2.54	10.4	22.3	157	155	252	33

Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Two-way clustered standard errors at the municipality and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

Taken together, the findings for homicides, drug cartel attacks, and non-lethal crimes provide evidence supporting the opportunity cost mechanism in the avocado sector across Mexican municipalities. This overall result supports the hypothesis that the expansion of the avocado market has contributed to reducing violence in avocado-growing regions, and largely contradict the newspaper reports of an increase in criminality in the avocado sector. Moreover, these findings align with the literature on how booms in legal agricultural commodities can have a positive effect in decreasing conflict and violence in producing regions (Blair et al., 2021).

1.5 Michoacán and the export market

The previous results show that, across Mexico, municipalities that are highly suitable to produce avocados have experienced a reduction in the homicide rate and in drug cartel attacks per 100'000 population, and that crimes did not increase in those municipalities. Nevertheless, the anecdotal evidence suggests that drug cartels have actually increased their criminal activities in avocado-producing regions, especially in the western state of Michoacán where most of the production of avocados for the export market is concentrated. For instance, Ornelas (2018) and Herrera and Martinez-Alvarez (2022) provide qualitative evidence about how criminal organizations entered the export-agriculture market in Michoacán, where they started to extort avocado farmers as a means of extracting rents from the avocado export boom.

The US Department of Agriculture's (USDA) Amendment that lifted the import ban of fresh Hass avocados from Mexico to the United States in 1997 specifies that only municipalities that satisfy rigorous requirements are authorized to export avocados. Municipalities must comply with strict phytosanitary requirements, field sanitation practices, special packinghouse procedures and shipping requirements, and various other safeguards, to be allowed to export avocados to the US (USDA Animal & Plant Health

Inspection Service, 1997). The list of authorized municipalities to export avocados has evolved over time, but in 1997 only 24 municipalities in Michoacán were allowed to export avocados. In what follows, I focus my analysis on the state of Michoacán and compare these 24 municipalities with the rest of the never-approved municipalities within the state (i.e. excluding the ones who have received the USDA approval after the 24 ever-first municipalities did). Figure 1.3 maps the state of Michoacán and the distribution of municipalities according to their USDA-approval status.[21]

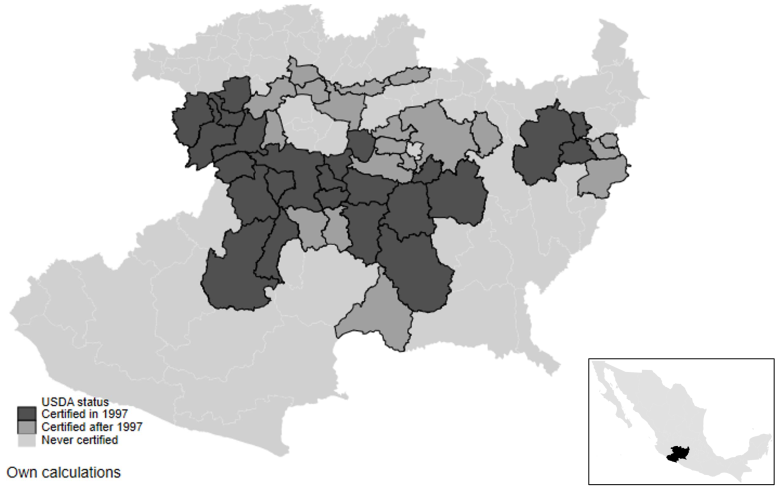


Figure 1.3: Municipalities in the state of Michoacán by USDA approval status

I replicate the baseline equation and include a binary variable for the ever-first authorized municipalities by USDA. Therefore, I estimate the following equation for municipalities in the state of Michoacán[22]:

$$\begin{aligned} Y_{m,t} = {} & \beta_0 + \beta_1 Suitability_m + \beta_2 USDA_m + \beta_3 Price_{t-1} + \beta_4 (Suitability_m \times USDA_m) \\ & + \beta_5 (Suitability_m \times Price_{t-1}) + \beta_6 (USDA_m \times Price_{t-1}) \\ & + \beta_7 (Suitability_m \times Price_{t-1} \times USDA_m) + \vec{X}_{m,t}\beta + \mu_m + \lambda_t + \epsilon_{m,t} \end{aligned} \tag{1.2}$$

If drug cartels have concentrated their criminal activities in avocado-producing municipalities exposed to the export market -where potential profits are higher-, then we should expect to find a positive coefficient for the USDA-authorized municipalities in Michoacán. If this is true, one would expect to find that $\beta_6 + \beta_7 > 0$. Below I present

[21]There are 113 municipalities in Michoacán. Among them, 24 received USDA approval in 1997, 19 have obtained certificates for export after 1997, and 70 have never received approval. Rojas and Schaefer (2024) study the effects on market structure and spillovers in violence of a phytosanitary zone expansion for avocado exports from the state of Jalisco in 2022.

[22]Note that this equation does not include the state time trend as it is only estimated for municipalities in the state of Michoacán. Moreover, the equation is written with all the variables and its interactions, although in the full specification the municipality and year fixed effects will absorb β_1, β_2, β_3, and β_4. The tables that report the results only show β_5, β_6, and β_7 for all specifications (progressively including fixed effects) to simplify the visualization of results.

the results of estimating equation 1.2 for the homicide rate (Tables 1.6 and 1.7), the number of drug cartel-related attacks per 100'000 pop. (Table 1.8), and crimes (Table 1.9) for municipalities in the state of Michoacán.

Table 1.6: Effect of avocado suitability and world price on homicide rate (per 100'000 pop.) - Michoacán

	Homicide rate in municipality m in year t (1990-2019)			
	(1)	(2)	(3)	(4)
Suitability Index=1 × Avocado price (lag)	-2.04	-0.94	-3.27	-1.92
	(4.52)	(3.92)	(5.18)	(4.60)
USDA=1 × Avocado price (lag)	-2.12	-1.60	-2.33	-1.55
	(1.86)	(1.96)	(2.16)	(2.26)
Suitability Index=1 × USDA=1 × Avocado price (lag)	2.63	2.08	2.15	1.65
	(5.49)	(4.97)	(6.24)	(5.78)
Observations	2726	2726	2726	2726
Controls	Yes	Yes	Yes	Yes
Year F.E.		Yes		Yes
Municipality F.E.			Yes	Yes
Sample mean of Y	26.3	26.3	26.3	26.3
Test p-val: $\beta 5 + \beta 7 = 0$	.844	.708	.722	.931
Test p-val: $\beta 6 + \beta 7 = 0$	.926	.926	.976	.985

Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Two-way clustered standard errors at the municipality and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

Contrary to the findings in the previous section, which show a negative relationship between the avocado boom and homicide rates across Mexican municipalities, Table 1.6 indicates that in Michoacán, there was no reduction in homicides in highly suitable municipalities or those USDA-approved for avocado export. The coefficients in Column 4, which account for municipality and year fixed effects, are not statistically significant. Furthermore, Table 1.7 reveals no differences in homicide rates across municipalities before and after the lifting of the import ban in 1997. These results suggest that the reduction in homicides observed across avocado-producing municipalities in Mexico after 1997 is attenuated in Michoacán, particularly in municipalities focused on the export market. That is, the export market seems to offset the opportunity cost effect as the profits are larger and more important in the export market, as profits in this market are larger than in the local market.

Table 1.7: Effect of avocado suitability and world price on homicide rate (per 100'000 pop.) in Michoacán, before and after 1997

	Homicide rate in municipality m in year t (1990-2019)					
	Before (1990-1997)			After (1998-2019)		
	(1)	(2)	(3)	(4)	(5)	(6)
Suitability Index=1 $\times$ Avocado price (lag)	21.61**	26.74	24.20	-2.89	-3.67	-2.63
	(6.83)	(22.20)	(22.45)	(3.46)	(4.02)	(3.53)
USDA=1 $\times$ Avocado price (lag)	-3.79	-3.27	-4.36	-2.04	-2.64	-2.10
	(4.83)	(10.32)	(10.57)	(1.90)	(2.24)	(2.25)
Suitability Index=1 $\times$ USDA=1 $\times$ Avocado price (lag)	-22.62**	-25.06	-23.13	4.83	4.88	4.43
	(7.59)	(22.25)	(22.81)	(4.24)	(4.88)	(4.45)
Observations	658	658	658	2068	2068	2068
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes		Yes	Yes		Yes
Municipality F.E.		Yes	Yes		Yes	Yes
Sample mean of Y	36.4	36.4	36.4	23.1	23.1	23.1
Test p-val: $\beta5 + \beta7 = 0$	.836	.783	.881	.424	.65	.482
Test p-val: $\beta6 + \beta7 = 0$	.059	.267	.286	.534	.645	.617

Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Two-way clustered standard errors at the municipality and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

The results for the drug cartel-related attacks provide further evidence in this direction. Table 1.8 shows that in the period 2000-2018, municipalities that received USDA approval to export avocados to the US experienced an increase in the number of attacks by drug cartels compared to other municipalities in the state of Michoacán. On average, these municipalities suffered an increase of 21.04 attacks per 100'000 population, which corresponds to a 58% increase with respect to the sample mean. The increase in the number of drug cartel attacks in USDA-approved municipalities is statistically and economically relevant: USDA-approved municipalities have experienced more attacks by drug cartels than highly suitable municipalities that were not allowed to export avocados in 1997. These results seem to confirm the qualitative evidence and the media reports that claim an increase in drug cartels attacks and violence in municipalities that produce avocados for the export market. More importantly, Table 1.8 shows that the opportunity cost mechanism reverses with the export market, leaving room for the rapacity effect channel to come at play with its consequential increase in violence in municipalities that produce avocados for exports.

Table 1.8: Effect of avocado suitability and world price on drug cartel violent attacks - Michoacán

	Attacks rate in municipality m in year t (2000-2018)			
	(1)	(2)	(3)	(4)
Suitability Index=1 × Avocado price (lag)	-4.78	-8.01	0.45	-3.71
	(9.90)	(10.11)	(8.19)	(8.63)
USDA=1 × Avocado price (lag)	-9.82	-12.65	-0.43	-4.33
	(8.65)	(8.56)	(8.12)	(7.98)
Suitability Index=1 × USDA=1 × Avocado price (lag)	21.23	24.05*	21.39	25.37*
	(13.35)	(12.72)	(13.45)	(12.72)
Observations	1786	1786	1786	1786
Controls	Yes	Yes	Yes	Yes
Year F.E.		Yes		Yes
Municipality F.E.			Yes	Yes
Sample mean of Y	35.9	35.9	35.9	35.9
Test p-val: $\beta 5 + \beta 7 = 0$	.12	.098	.068	.039
Test p-val: $\beta 6 + \beta 7 = 0$	.372	.332	.11	.073

Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Two-way clustered standard errors at the municipality and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

Results by type of crime in Table 1.9 provide a broader view on the criminality pattern across avocado-producing and exporting municipalities in Michoacán. Press reports claim that drug cartels have particularly increased their non-lethal attacks by threatening, extorting, and even kidnapping avocado producers in these municipalities in order to extract rents from producers.

Column 1 in Table 1.9 presents the overall criminality index results. Although the coefficients are not precisely estimated, they point towards an increase in crimes in export-oriented municipalities, and the test of joint significance of coefficients β_6 and β_7 is virtually significant at the 10%. Disaggregated results by type of crime (Cols. 2-8) show that extortion cases have not increased in export-oriented municipalities, whereas the number of threats in avocado-growing and exporting municipalities have substantially increased compared to non-exporter localities. There is also evidence suggesting that cases of robbery and theft increased in export-oriented municipalities more than 50% compared to the sample mean. This pattern of results are in line with De Haro-Lopez (2024), who finds an increase in violent thefts and truckload thefts, and a reduction in extortion cases in avocado-suitable municipalities, after the fentanyl epidemic in the US shifted drug cartels attention from the heroin to the avocado market.[23]

[23] She also finds an increase in murders in avocado-suitable municipalities, but her results cover the state of Michoacán plus six other states. Moreover, in Table 1.G.43 I report that avocado-growing and export-oriented municipalities in Michoacán experienced an increase in the homicide rate per 100’000 population when I only use the climatic component of the suitability index. Section 1.6 discuss this case as a robustness check.

Table 1.9: Effect of avocado suitability and world price on crime rate (by type) - Michoacán

	Crime rate in municipality m in year t (2011-2017)							
	Crime	Category 1			Category 2		Category 3	
	(1) Index	(2) Extortion	(3) Threat	(4) Kidnap	(5) Robbery	(6) Theft	(7) Injuries	(8) Other
Suitability Index=1 × Avocado price (lag)	-0.23	-0.44	-9.91	-2.43	-29.47**	-44.53**	61.02	6.66
	(0.15)	(0.97)	(7.77)	(9.50)	(11.97)	(15.19)	(33.13)	(4.42)
USDA=1 × Avocado price (lag)	0.12	-1.08	-2.21	14.56**	56.91*	30.18*	12.77	-1.36
	(0.10)	(0.62)	(3.16)	(5.29)	(28.26)	(14.24)	(14.83)	(3.66)
Suitability Index=1 × USDA=1 × Avocado price (lag)	0.17	-0.40	21.80*	-12.40	49.05	51.42*	-119.55**	-7.27
	(0.19)	(0.71)	(9.55)	(12.68)	(44.91)	(22.01)	(46.18)	(4.85)
Observations	658	658	658	658	658	658	658	658
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample mean of Y	.047	2	12.2	37.6	89	104	93.4	11
Test p-val: $\beta5 + \beta7 = 0$	.729	.518	.0468	.108	.667	.753	.0783	.894
Test p-val: $\beta6 + \beta7 = 0$	.106	.146	.0749	.863	.0276	.00758	.0508	.0896

Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Two-way clustered standard errors at the municipality and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

The findings in this section show that homicides did not decrease in export-oriented municipalities in Michoacán, compared to an overall reduction in avocado-suitable localities across Mexico. That is, the beneficial effect of the avocado boom in reducing violence in producing municipalities is weakened by attractiveness of the export market.[24] Second, drug cartels increased their attacks in avocado-growing municipalities that were exposed to the export market since the lift of the imports ban in the US in 1997.[25] Third, citizens in these municipalities have experienced an increase in threats and property crimes.[26] These results point towards a prevalence of the rapacity effect in export-oriented municipalities in Michoacán, as compared to the opportunity cost mechanism that is at play at the country level.

The rapacity effect observed in Michoacán's export-oriented municipalities can be better understood through the lens of established theoretical frameworks on organized crime. As proposed by Schelling (1971) and further developed by Gambetta and Reuter (1995), Lavezzi (2008), and Balletta and Lavezzi (2023), certain characteristics of legal markets make them particularly vulnerable to become targets of criminal organizations who seek to extract rents and monopolize criminal activity under their area of influence. These include weak legal institutions, the presence of industries with high and easy observable output and profits, and fragmented production with many small producers.

[24] It is estimated that the avocado sector in Michoacán generates 310,000 direct jobs and 78,000 indirect jobs. Source: Mexico's Secretariat of Agriculture and Rural Development

[25] For example, farmers in the municipality of Cherán opted to stay out of the avocado market, despite its potential for high revenues and employment. Concerned about the violence and crime associated with the avocado export boom, they decided not only to abstain from production but also to actively prevent avocado farming within the municipality's boundaries. See NZZ's full newspaper report (in German).

[26] For instance, De Haro-Lopez (2024) suggests that drug cartels increased their attacks against civilians in avocado-suitable municipalities, instead of fighting among them for territorial expansion to other municipalities.

The avocado industry in Michoacán exhibits these traits: it operates within a context of institutional fragility (Aguirre and Herrera, 2013; Shirk and Wallman, 2015), and avocado production in Michoacán is concentrated along many micro and small producers.[27] These conditions not only facilitate drug cartels' intrusion into the avocado market but also exacerbate their ability to extract rents and monopolize criminal activity. This highlights how context-specific characteristics of a commodity and its market can shape the interplay between economic development and crime, as suggested in recent studies of agricultural export booms (Crost and Felter, 2020; Estancona and Tiscornia, 2023; Crost et al., 2023).

Importantly, although these results suggest a possibly causal effect of the avocado boom on crime and violence in export-oriented municipalities in Michoacán, it is important to note that crimes are highly underreported in Mexico due to distrust of police (De Haro-Lopez, 2024) or possibly by fear of retaliation. Therefore, these results can be seen as a conservative estimate of the real effect. Additionally, during the period of analysis, farmers in Michoacán organized self-defense militias and vigilante groups to fight drug cartels and other criminal organizations (Alvarez-Rodríguez et al., 2020; Erickson and Owen, 2024), which could have an impact on the violence patterns in the region.

1.6 Robustness Checks

I conduct a series of robustness checks to validate the results of the previous sections. I first validate the robustness of the country-level results of Section 1.4, and then I validate the robustness of results for municipalities in Michoacán and the effect of the USDA export approval of Section 1.5.

1.6.1 Country-level results (Section 1.4)

I conduct eight different robustness checks to validate the results of a reduction in homicides and drug cartel attacks, and no increase of non-lethal crimes, in highly-suitable municipalities for the production of avocados across Mexico.[28] The tests are:

(i) a shorter time window depending on the years covered by the OCVED project (2000-2018) and the SESNSP data for non-lethal crimes (2011-2017);
(ii) measuring the outcome as the log of, and the inverse hyperbolic sine transformation of, the number of homicides in the municipality;

[27] For example, more than 95% of Michoacán's 26,000 registered avocado farmers allowed to export to the US cultivate less than 10 hectares of land. Source: https://www.gob.mx/agricultura/articulos/mexico-y-sus-exportaciones?idiom=es

[28] I do not systematically discuss the robustness checks on crimes, as they are non-significant in the main estimation. Nevertheless, I conduct and present all results for crimes in the Appendix as well.

(iii) excluding one year or one state at a time and then estimating the main regression;
(iv) a more conservative estimation clustering the standard errors at the state level;
(v) wild cluster bootstrap p-values and confidence intervals;
(vi) random permutations of the suitability index;
(vii) alternative definitions of the suitability index (using the continuous measure or a indicator using only climatic factors); and
(viii) State-by-year fixed effects instead of a state-linear time trend.

A discussion of each test, as well as the Tables of results and Figures are presented in the Appendix section 1.G.1. Table 1.10 below summarizes the findings of the robustness checks.

Table 1.10: Summary of robustness checks on the number of homicides and drug cartel attacks per 100'000 population.

Robustness check	Homicides	Drug cartel attacks
1. Same time periods	-	-
2. Alternative measures of the outcome	✓	-
3. Exclusion of years and states	✓	✓
4. Clustering of the std. err.	✓	✓
5. Wild cluster bootstrap	✓	✓
6. Permutation of the suitability index	✓	×
7. Alternative definition of the suitability index	✓	-
8. State-by-year Fixed Effect	✓	-

Note: ✓ indicates robustness, - indicates partial robustness (i.e. non-significance but similar magnitude/sign of the coefficient), and × indicates lack of robustness.

The results for the homicide rate are robust to all the aforementioned tests. The only test where the estimated coefficient is not fully robust is when reducing the period of analysis from 1990-2019 to 2011-2017, which is the period with available data on non-lethal crimes at the municipality level. Overall, this battery of robustness checks reassures the findings of section 1.4 about the reduction of homicides in highly suitable municipalities following the opening of the avocado market in the US in 1997.

Results on drug cartels are robust to clustering the standard errors at the state level and to wild bootstrap inference, but they fail to be statistically significant to: a shorter, 7-year, time window between 2011-2017 (data on crimes); measuring the outcome as the log of and the asinh transformation of the number of cases; a permutation of the suitability index and alternative definitions of the index; and, the introduction of state-by-year fixed effects. Therefore, the claim of a causal link between avocado production and a reduction in the number of drug cartel attacks per 100'000 population in highly suitable municipalities is uncertain, although the results can be seen as suggestive evidence of a reduction in attacks. If anything, the results show that the rate of attacks per 100'000 people did not increase in more suitable municipalities, as none of the robustness checks nor the main estimation find a positive correlation between the suitability to produce avocados and the drug cartel attacks in Mexican municipalities. The reader should consider these results with prudence.

1.6.2 Michoacán and the export market case (Section 1.5)

In this section I repeat the robustness checks previously described, this time for the municipalities in the state of Michoacán.[29] A discussion of each test, as well as the Tables of results and Figures are presented in the Appendix section 1.G.2. Table 1.11 below summarizes the findings.[30] Overall, the results are mildly robust to different tests, although in some cases I lose the statistically significance. They suggest a potential increase in certain types of crimes in export-oriented municipalities, although results must be cautiously analyzed.

Table 1.11: Summary of robustness checks on the number of drug cartel attacks and crimes per 100'000 population in the state of Michoacán

Robustness check	Drug cartel attacks	Crimes
1. Alternative measures of the outcome	-	✓
2. Exclusion of years and municipalities	✓	✓*
3. Wild cluster bootstrap	✓	-
4. Permutation of the USDA-approved status	✓	✓
5. Alternative definition of the suitability index	-	-

Note: ✓ indicates robustness, - indicates partial robustness (i.e. non-significance but similar magnitude/sign of the coefficient), and ✕ indicates lack of robustness. * stands for results on demand, due to large number of estimations.

The results of a reduction in homicides across municipalities in Mexico, and of a non-decrease in homicides in Michoacán, are highly robust and provide evidence of a causal effect. However, the findings regarding drug cartel attacks and non-lethal crimes, while suggestive of a causal relationship, are sensitive to some tests and model specifications. As such, their interpretation requires caution. However, if anything, the results suggest that export-oriented municipalities in Michoacán did not experience a reduction in drug cartel attacks, as observed in other municipalities across Mexico. Moreover, there is evidence that crimes, notably property-related offenses, may have increased in those municipalities.

Several factors could explain the limited robustness of the results regarding drug cartel attacks and other crimes. First, measurement error and underreporting, which are more prevalent for these crime types than for homicides, might bias the estimates. Homicides are generally more accurately reported, even in developing countries, due to

[29] Bear in mind that some of the robustness checks cannot be replicated here because all municipalities correspond to the same state. For example, conservative clustering of the standard errors at the state level, or the introduction of a state-by-year fixed effect.

[30] I exclude the discussion of the results on homicides as they are non-significant in the main estimation.

their severity and higher likelihood of official documentation (Soares, 2004). Specifically, data on drug cartel attacks is derived from newspaper reports, which may omit incidents due to lack of information or fear of retaliation, among other challenges.

Second, the avocado index might be capturing something else than just the suitability to produce this fruit. For example, avocado suitability could correlate with overall agricultural suitability or even with the potential for cultivating illegal crops such as marijuana or poppy, which have historically been central to drug cartel activities For instance, De Haro-Lopez (2024) shows that municipalities unsuitable for avocado production are also unsuitable for poppy cultivation, while those highly suitable for avocado production often exhibit medium to high suitability for poppy cultivation. Therefore, it is possible that the avocado suitability index may partly reflect suitability for illegal crops, that can potentially influence the results on drug cartel attacks and crimes.

Finally, the availability of municipality-level disaggregated crime data begins only in 2011, limiting the time horizon for analysis. This start date captures the effects of the avocado export boom over a decade after the first municipalities were allowed to export avocados to the U.S. It would be possible that crime patterns change between the early stages of the avocado boom (before 2010) and once the market is stabilized (after 2011). Therefore, a longer time horizon would help in providing deeper insights into the dynamics of crime during the early phases of market expansion and subsequent stabilization. Unfortunately, this data is not available at the municipal level.

In summary, while the findings provide robust evidence of a causal effect on homicides, the results for drug cartel attacks and non-lethal crimes require more nuanced interpretation. Extensions to this chapter could address data limitations and explore the role of other factors, such as illegal crop cultivation or the role of the Mexican war on drugs (the so-called "Guerra contra el narco").

1.7 Conclusion

Recent media reports claim that Mexico's avocado export boom over the past 20 years has driven increased violence across avocado-producing regions in the country, primarily due to drug cartels seeking to exploit this lucrative market. I empirically test these claims using diverse data sources and exploiting the biophysical suitability of each municipality to produce avocados with movements in the international price of the fruit.

The findings reveal that, in the medium to long term, the avocado boom has reduced homicides and drug cartel attacks across Mexican municipalities, consistent with the opportunity cost mechanism often linked to labor-intensive agricultural booms. These results align with broader evidence on how agricultural growth can decrease violence by increasing legal economic opportunities.

However, the picture changes in the western state of Michoacán, where avocado production is predominantly export-driven. Following the lifting of an 83-year import ban, municipalities that received early approval to export avocados to the U.S. have experienced increases in drug cartel attacks and property crimes, while failing to show reductions in homicides. This outcome underscores the rapacity effect: the substantial economic gains tied to export markets appear to outweigh the opportunity costs of violence, incentivizing criminal organizations to extract rents from this legal market.

This dual effect on violence within the Mexican avocado sector highlights how a production boom of the same commodity can generate contrasting effects within a single country. This chapter contributes to the growing body of evidence suggesting that while agricultural booms can reduce violence, the expansion of export markets may offset these benefits, particularly in regions where armed or illegal groups are already present (Crost and Felter, 2020; Estancona and Tiscornia, 2023), and in sectors that share traits that facilitate the intrusion of criminal organizations, such as many small and fragmented producers and highly observable profits.

These findings contribute to a nuanced understanding of the conditions under which agricultural booms may reduce or exacerbate violence, or both. They also stress the importance of tailoring policy responses to account for context-specific dynamics, especially in regions where the economic gains from exports intersect with institutional weaknesses and active criminal organizations.

From a policy perspective, these findings underscore the critical importance of addressing institutional weaknesses in export-oriented agricultural sectors. In contexts like Michoacán, where weak property rights and fragmented production coexist with lucrative export markets, large efforts are needed to prevent criminal organizations from capturing economic gains. Strengthening local governance, protecting smallholder farmers, and enhancing law enforcement capacity are essential steps to curb violence while fostering sustainable agricultural growth.

Appendix

Chapter 1 Appendix

1.A Descriptive Statistics

Table 1.A.1: Descriptive Statistics - Municipalities by Suitability Index

	Avocado Suitability		
	0	1	Test
N	2,107 (85.1%)	368 (14.9%)	
Cultivated area (ha)	105.97 (413.10)	690.79 (2805.37)	<0.001
Avocado Production (Ton.)	813.91 (3816.18)	6793.44 (28722.07)	<0.001
Temperature (°C)	19.60 (4.20)	20.73 (2.67)	<0.001
Precipitation (mm)	996.33 (617.32)	1375.82 (341.42)	<0.001
Altitude (masl)	1286.79 (845.22)	1157.00 (679.24)	0.005
Area (sq. km)	878.20 (2288.10)	325.85 (512.22)	<0.001
Gini Index	0.41 (0.05)	0.40 (0.05)	<0.001
Poverty rate	37.40 (15.81)	32.64 (17.12)	<0.001
Literacy (%)	84.90 (10.10)	76.52 (12.29)	<0.001
Population (log.)	9.39 (1.55)	9.23 (1.29)	0.052
Homicides (1990-2019)	7.74 (30.12)	5.08 (17.42)	0.108
Drug cartel attacks (2000-2018)	12.85 (28.75)	10.95 (25.80)	0.406

Note: The Table presents the mean and standard deviation (in parentheses) for each of the variables across the sample period.

Table 1.B.1: Biophysical requirements of avocado

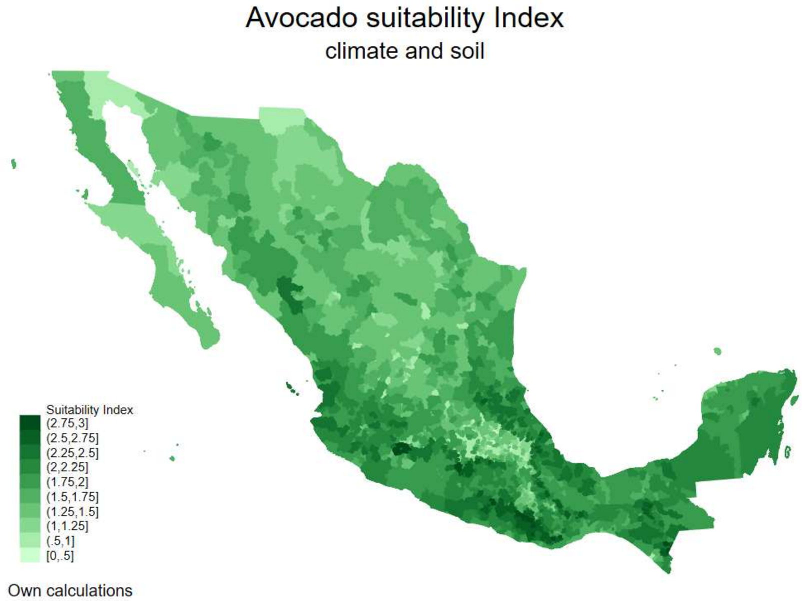
Criteria	**S1**	**S2**	**S3**	**N**
Climate				
Mean annual temperature (°C)	18–26	15–18; 26–30	10–15; 30–45	< 10; > 45
Mean minimum temperature of coldest month (°C)	> 16	13–16	8–13	< 8
Mean annual precipitation (mm)	1200–1800	1000–1200; 1800–2000	750–1000; 2000–2500	< 750; > 2500
Land and Soil				
Slope (%)	0–8	8–16	16–30	> 30
Soil texture	4–12	2–3	1	-
Soil pH	5–6.5	4.5–5; 6.5–7.5	4.3–4.5; 7.5–8.3	< 4.3; > 8.3
Soil salinity (ECe)	0–3	3–4	4–5	> 5
Depth of the soil profile (cm)	> 100	80–100	50–80	< 50
Organic matter (wt, %)	> 5.0	2.5–5.0	1.0–2.5	< 1.0
Cation Exchange Capacity (meq/100 g)	> 40	20–40	10–20	< 10
Height (msal)	1500–2000	800–1500	0–800; 2000–2500	> 2500

Soil texture classification follows USDA soil taxonomy: 1 = clay, 2 = silty clay, 3 = sandy clay, 4 = clay loam, 5 = silty clay loam, 6 = sandy clay loam, 7 = loam, 8 = silty loam, 9 = sandy loam, 10 = silt, 11 = loamy sand, 12 = sand.
Source: Grüter et al. (2022).

1.B Suitability index and actual production of avocados

Figure 1.B.1: Map of climate and soil suitability index, and production of avocados in Mexican municipalities

(a) Suitability index



(b) Real production

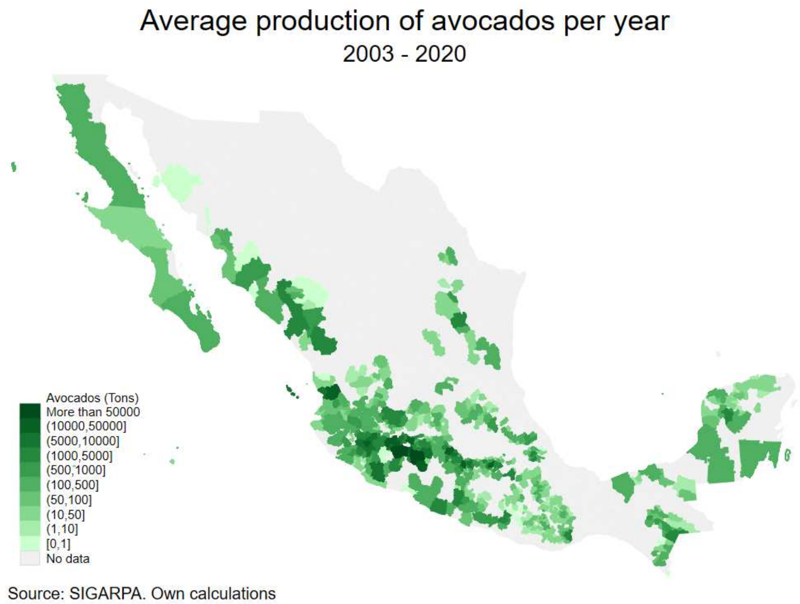


Figure 1.B.2: Suitability index and production of avocados in Mexican municipalities

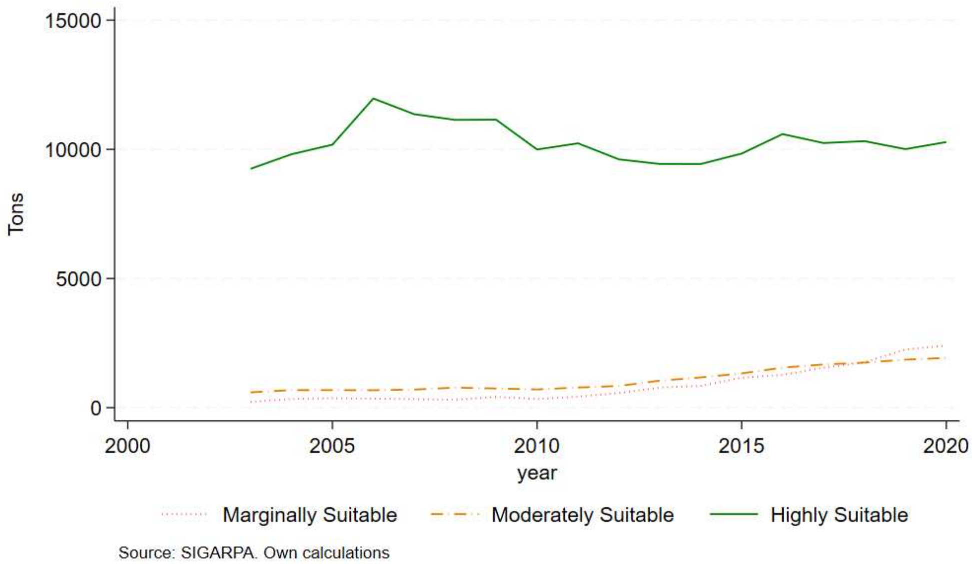


Table 1.B.2: Soil and climatic suitability index and actual avocado production

	Total production of avocados in municipality m in year t				
	Only Suitability		Suitability and Price		
	(1)	(2)	(3)	(4)	(5)
Moderately suitable (S2)	-0.38	-0.38	-0.28	-0.29	
	(0.44)	(0.43)	(0.39)	(0.39)	
Highly suitable (S1)	9.06**	9.03**	9.49***	9.50***	
	(3.35)	(3.36)	(3.44)	(3.44)	
Municipality area ha (log)	1.15**	1.16**	1.16**	1.17***	
	(0.45)	(0.45)	(0.45)	(0.45)	
Avocado price (lag)			0.69***		
			(0.22)		
Moderately suitable (S2) × Avocado price (lag)			-0.15	-0.15	0.04
			(0.24)	(0.24)	(0.24)
Highly suitable (S1) × Avocado price (lag)			-0.69	-0.70	1.74**
			(0.56)	(0.56)	(0.83)
Observations	9032	9032	9032	9032	9007
Year F.E.	No	Yes	No	Yes	Yes
Municipality F.E.	No	No	No	No	Yes
Sample mean of Y	2.96	2.96	2.96	2.96	2.96

Base category is Marginally suitable (S3) index. Two-way clustered standard errors at the municipality and year level in parenthesis. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

Figure 1.B.3: Suitability index and land cultivated with avocados in Mexican municipalities

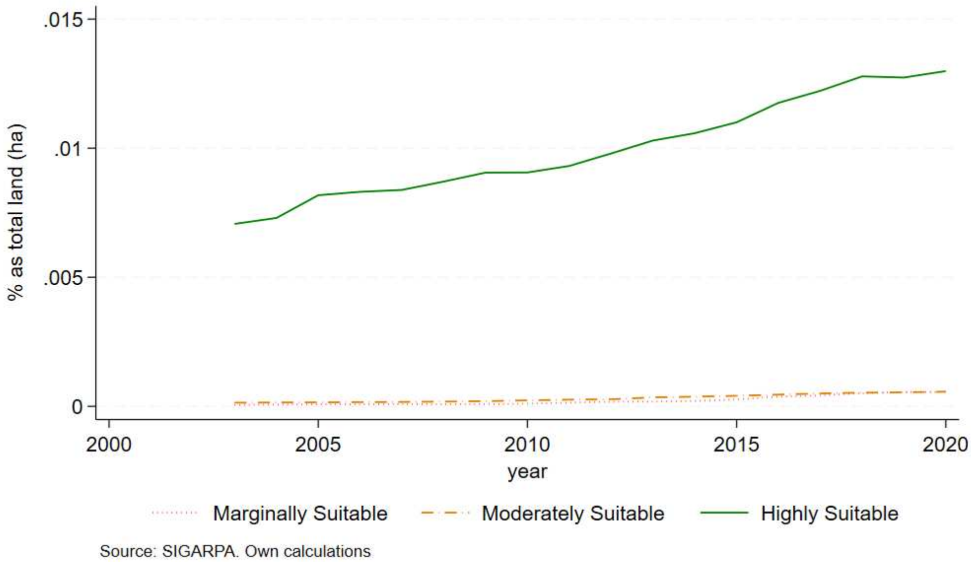


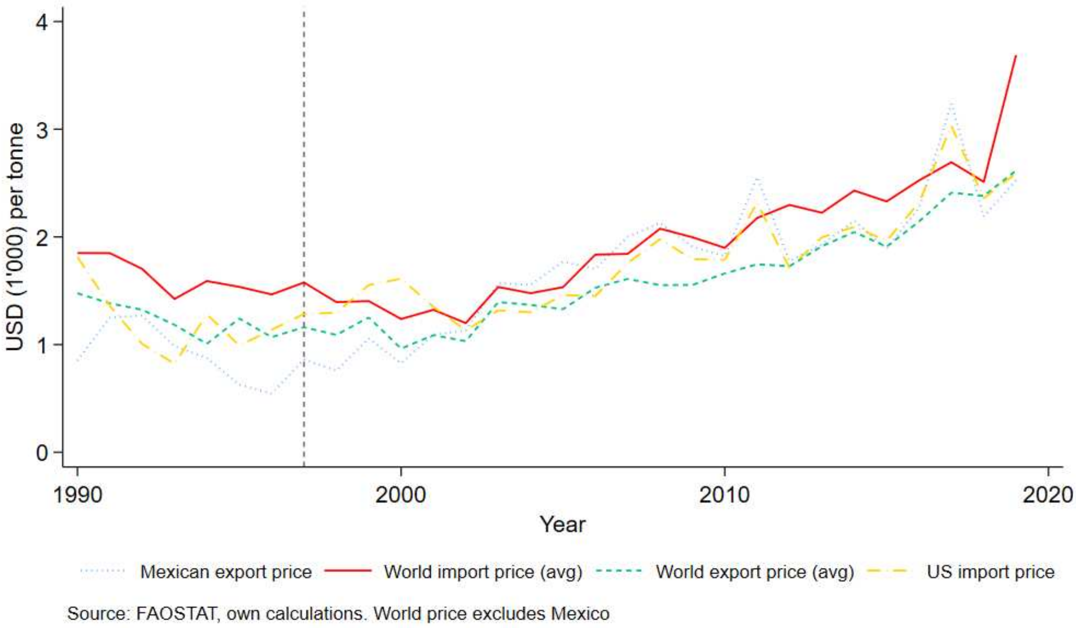
Table 1.B.3: Soil and climatic suitability index and actual avocado planted area

	Total planted area (ha) in municipality m in year t				
	Only Suitability		Suitability and Price		
	(1)	(2)	(3)	(4)	(5)
Moderately suitable (S2)	-59.27	-59.57	-42.39	-42.65	
	(53.40)	(53.31)	(44.60)	(44.91)	
Highly suitable (S1)	871.19**	867.99**	931.96**	931.55***	
	(328.92)	(329.21)	(337.84)	(341.64)	
Municipality area ha (log)	120.22**	122.11**	121.84**	122.25***	
	(44.27)	(44.27)	(44.47)	(44.17)	
Avocado price (lag)			82.99***		
			(27.95)		
Moderately suitable (S2) × Avocado price (lag)			-26.80	-26.88	4.36
			(27.14)	(32.34)	(25.89)
Highly suitable (S1) × Avocado price (lag)			-96.51***	-96.59	154.84*
			(21.14)	(62.46)	(76.24)
Observations	9032	9032	9032	9032	9007
Year F.E.	No	Yes	No	Yes	Yes
Municipality F.E.	No	No	No	No	Yes
Sample mean of Y	319	319	319	319	320

Base category is Marginally suitable (S3) index. Two-way clustered standard errors at the municipality and year level in parenthesis. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

1.C Avocado price measures

Figure 1.C.1: World import price and other price measures



1.D Homicides: Interaction with lead price $(t+1)$

Table 1.D.1: Effect of avocado suitability and world (import) prices in t+1 on homicide rate

	Homicide rate in municipality m in year t (1998-2019)					
	(1)	(2)	(3)	(4)	(5)	(6)
Avocado price (lag)	6.59***	6.30***				
	(1.61)	(1.63)				
Suitability Index=1 × Avocado price (lag)	-3.90**	-4.02**	-3.90**	-4.03**	-2.96*	-3.03*
	(1.62)	(1.64)	(1.62)	(1.65)	(1.71)	(1.72)
Suitability Index=1 × Avocado price (lead)	0.39	0.37	0.39	0.36	1.49	1.41
	(1.32)	(1.33)	(1.32)	(1.33)	(1.44)	(1.42)
Observations	49602	49602	49602	49602	49602	49602
Municipality F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.			Yes	Yes	Yes	Yes
State time trend					Yes	Yes
Controls		Yes		Yes		Yes
Sample mean of Y	15.9	15.9	15.9	15.9	15.9	15.9

Outcome: number of homicides per 100,000 population in the municipality. Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Two-way clustered standard errors at the municipality and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

1.E Drug cartel attacks: Pseudo-Poisson likelihood estimation

Table 1.E.1: Effect of avocado suitability and world price on drug cartel violent attacks (Pseudo-Poisson)

	No. of attacks in municipality m (2000-2018)				
	(1)	(2)	(3)	(4)	(5)
Suitability Index=1	0.06	0.02			
	(0.22)	(0.23)			
Avocado price (lag)	0.42		0.50		
	(0.30)		(0.30)		
Suitability Index=1 × Avocado price (lag)	0.07***	0.12***	0.04	0.08*	-0.24***
	(0.01)	(0.02)	(0.03)	(0.05)	(0.08)
Observations	46132	46132	27189	27189	27189
Controls	Yes	Yes	Yes	Yes	Yes
Year F.E.		Yes		Yes	Yes
Municipality F.E.			Yes	Yes	Yes
State time trend					Yes
Sample mean of Y	4.75	4.75	8.06	8.06	8.06

Fixed effects models are estimated with Poisson pseudo-likelihood regression with multiple levels of fixed effects. Two-way clustered standard errors at the municipality and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

1.F Crimes: 2011 - 2022

Mexico's Executive Secretariat of the National System of Security (SESNSP) data that collect information on the number of reported crimes at the municipality level starts in 2011. Starting in 2018, SESNSP made a change in the mathodology and classification of crimes into different categories. In an attempt to harmonize the old and new classification, I went through all types of crimes and assigned them into the standard categories I use in my analysis. Here I present the results of the estimation that covers the period after the change in methodology in 2017 and expands the analysis up to 2022.

Table 1.F.1 presents the results for all municipalities in Mexico. Results show a reduction in the overall index of criminality in higjly suitable municipalities, suggesting evidence of a reduction not only in homicides and drug cartel attacks, but also in crimes. Results by type of crime show a decrease in reported threats and an increase in kidnaps in highly suitable municipalities. However, I cannot rule out whether the results are mainly driven by the effect of avocado prices or by the change in methodology and the classification of crimes into different categories.

Table 1.F.1: Effect of avocado suitability and world price on number of crimes (by type) between 2011-2022

	Crime rate in municipality m in year t (2011-2022)							
	Crime	Category 1			Category 2		Category 3	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Index	Extortion	Threat	Kidnap	Robbery	Theft	Injuries	Other
Suitability Index=1 × Avocado price (lag)	-0.05**	-0.33	-1.33**	1.07***	4.39	-9.35	-7.02	-3.44**
	(0.02)	(0.20)	(0.53)	(0.33)	(4.63)	(6.19)	(7.96)	(1.37)
Observations	20015	20015	20015	20015	20015	20015	20015	20015
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State time trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample mean of Y	.00127	2.73	11.3	17.6	143	154	268	40.7

Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Two-way clustered standard errors at the municipality and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

Table 1.F.2 below presents the results for crimes in Michoacán in the period 2011-2022. The crime index shows that criminality in export-oriented municipalities increased during this period. The increase in criminality is mainly driven by more cases of threats, with a possibly increase in crime property as well (although estimates for robbery and theft are less precisely estimated).

Table 1.F.2: Effect of avocado suitability and world price on crime rate (by type) between 2011-2022 - Michoacán

	Crime rate in municipality m in year t (2011-2022)							
	Crime	Category 1			Category 2		Category 3	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Index	Extortion	Threat	Kidnap	Robbery	Theft	Injuries	Other
Suitability Index=1 × Avocado price (lag)	-0.30***	-0.34	-11.31***	-5.04	-22.79*	-25.77	22.26	-10.65*
	(0.07)	(0.31)	(2.31)	(5.63)	(11.10)	(17.92)	(22.20)	(5.12)
USDA=1 × Avocado price (lag)	0.08	-0.34	1.67	7.25**	14.09	13.34	0.34	-5.95
	(0.06)	(0.45)	(2.08)	(2.50)	(11.13)	(14.26)	(10.30)	(3.97)
Suitability Index=1 × USDA=1 × Avocado price (lag)	0.27**	-0.71	17.47***	-1.80	24.60	44.02	-44.11	14.21*
	(0.12)	(0.48)	(4.88)	(7.04)	(20.37)	(26.56)	(37.34)	(7.54)
Observations	940	940	940	940	940	940	940	940
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample mean of Y	.0107	1.44	15.6	29.9	93.6	115	120	21.4
Test p-val: $\beta 5 + \beta 7 = 0$	.744	.069	.172	.224	.914	.357	.268	.494
Test p-val: $\beta 6 + \beta 7 = 0$	.005	.13	.001	.449	.082	.03	.221	.225

Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Two-way clustered standard errors at the municipality and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

1.G Robustness checks

1.G.1 Robustness checks of results in Section 1.4

1.G.1.1 Comparing outcomes in same time period

As a first check, I compare the different outcomes -homicides, drug cartel attacks, and non-lethal crimes- using the same time window. Unfortunately, there is no municipal-level data for all outcomes since 1990 (only for homicides), and the results in section 1.4 exploit all the available years for each outcome, which differs depending on the data source. First, I compare the homicide rate and the drug cartel attacks rate for the period 2000-2018, which is the period covered by the OCVED project data (years with data on drug cartel attacks). Table 1.G.1 shows that the coefficient for the homicide rate is negative and statistically significant in this restricted time frame as well, following the same pattern of the period 1990-2019 for which there is full available data on homicides.

Table 1.G.1: Homicide and Drug Cartel Attacks rate (2000-2018)

	Homicide rate		Attacks rate	
	(1)	(2)	(3)	(4)
Suitability Index=1 × Avocado price (lag)	-3.07***	-1.34*	-11.77**	-3.29*
	(0.79)	(0.64)	(4.67)	(1.72)
Observations	44878	44878	46132	46132
Controls	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
Municipality F.E.	Yes	Yes	Yes	Yes
State time trend		Yes		Yes
Sample mean of Y	16.2	16.2	26.3	26.3

Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Two-way clustered standard errors at the municipality and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

Second, I compare all the outcomes within the period 2011-2017, for which there is information on all outcomes.[31] Results are presented in Table 1.G.2 and show no statistically effect on homicides or attacks. Unfortunately, in this reduced time period the coefficient is not precisely estimated and I cannot reject the null of similar violence patterns among high- and low-suitable municipalities.

Table 1.G.2: Homicide, Drug Cartel Attacks, and Crime rate (2011-2017)

	Homicide	Attacks	Category 1			Category 2		Category 3	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
			Extortion	Threat	Kidnap	Robbery	Theft	Injuries	Other
Suitability Index=1 × Avocado price (lag)	-0.39	3.85	-0.20	1.97	1.23	14.91	3.39	32.79	7.47
	(2.35)	(8.80)	(0.33)	(2.64)	(2.72)	(16.03)	(8.78)	(24.47)	(6.62)
Observations	16534	16996	12731	12731	12731	12731	12731	12731	12731
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State time trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample mean of Y	20.6	38.6	2.63	10.3	22.7	164	165	263	34

Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Two-way clustered standard errors at the municipality and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

[31] Municipal-level crime data starts in 2011 but I restrict the analysis to 2017 because of the change in the Secretariat of the National System of Security's (SESNSP) methodology for classifying crimes after that year.

1.G.1.2 Alternative measures of the outcome variable

I also evaluate the robustness of the results to alternative measures of the outcome variables. I measure the outcomes as the log. transformation of the number of cases (homicides, drug cartel attacks, crimes) rather than the number of cases per 100'000 people., and then I do the same but with the inverse hyperbolic sine (*asinh*) transformation of the number of cases. The results for the number of homicides are robust to these transformations (Tables 1.G.3 and 1.G.4), and roughly indicate a reduction of 3%, on average, in the number of homicides in municipalities that are highly suitable for avocado-growing. The results for the number of drug cartel attacks (Tables 1.G.5 and 1.G.6) are robust as well when the estimation includes year and municipality fixed effects, but fail to be statistically significant at the 10% for the estimation that includes the state time trend.

In the case of crimes, the results show a statistically significant effect for some of the crimes, in particular when measured as $log(crime)$ (Table 1.G.7).[32] The estimated coefficients are all negative (indicating a reduction in criminality in highly suitable municipalities) and statistically significant for extortion, threats, and theft. With the *asinh* transformation the coefficients are also negative, although not significant. Taken together, these results would further validate the findings in the main section of a reduction in violence in highly suitable municipalities. I keep the number of cases per 100'000 pop. as the main estimation as it is common practice in the literature and in policy to report crimes this way.

[32]Results in the main estimation (Table 1.5, Section 1.4) indicate no difference in non-lethal crimes between high- and low-suitable municipalities.

Log. of homicides

Table 1.G.3: Effect of avocado suitability and world price on homicides (log)

	(Log of) Homicides in municipality m in year t (1990-2019)				
	(1)	(2)	(3)	(4)	(5)
Suitability Index=1	0.09**	0.09**			
	(0.04)	(0.04)			
Avocado price (lag)	0.15***		0.13***		
	(0.02)		(0.02)		
Suitability Index=1 × Avocado price (lag)	-0.09***	-0.09***	-0.09***	-0.09***	-0.03*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Observations	68498	68498	68498	68498	68498
Controls	Yes	Yes	Yes	Yes	Yes
Year F.E.		Yes		Yes	Yes
Municipality F.E.			Yes	Yes	Yes
State time trend					Yes
Sample mean of Y	1.04	1.04	1.04	1.04	1.04

Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Two-way clustered standard errors at the municipality and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

Asinh of homicides

Table 1.G.4: Effect of avocado suitability and world price on homicides (asinh)

	Homicides (asinh) in municipality m in year t (1990-2019)				
	(1)	(2)	(3)	(4)	(5)
Suitability Index=1	0.12**	0.12**			
	(0.04)	(0.04)			
Avocado price (lag)	0.18***		0.15***		
	(0.03)		(0.03)		
Suitability Index=1 × Avocado price (lag)	-0.10***	-0.10***	-0.10***	-0.10***	-0.03*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Observations	68498	68498	68498	68498	68498
Controls	Yes	Yes	Yes	Yes	Yes
Year F.E.		Yes		Yes	Yes
Municipality F.E.			Yes	Yes	Yes
State time trend					Yes
Sample mean of Y	1.3	1.3	1.3	1.3	1.3

Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Two-way clustered standard errors at the municipality and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

Log. of drug-cartel attacks

Table 1.G.5: Effect of avocado suitability and world price on drug cartel attacks (log)

	Log. of attacks in municipality m (2000-2018)				
	(1)	(2)	(3)	(4)	(5)
Suitability Index=1	-0.06*	-0.06*			
	(0.03)	(0.03)			
Avocado price (lag)	0.20***		0.16***		
	(0.04)		(0.04)		
Suitability Index=1 × Avocado price (lag)	-0.06***	-0.06***	-0.06***	-0.06***	-0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Observations	46132	46132	46132	46132	46132
Controls	Yes	Yes	Yes	Yes	Yes
Year F.E.		Yes		Yes	Yes
Municipality F.E.			Yes	Yes	Yes
State time trend					Yes
Sample mean of Y	.421	.421	.421	.421	.421

Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Two-way clustered standard errors at the municipality and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

Asinh of drug-cartel attacks

Table 1.G.6: Effect of avocado suitability and world price on drug cartel attacks (asinh)

	Asinh transf. of attacks in municipality m (2000-2018)				
	(1)	(2)	(3)	(4)	(5)
Suitability Index=1	-0.08*	-0.08*			
	(0.04)	(0.04)			
Avocado price (lag)	0.24***		0.20***		
	(0.04)		(0.04)		
Suitability Index=1 × Avocado price (lag)	-0.08***	-0.08***	-0.07***	-0.07***	-0.03
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Observations	46132	46132	46132	46132	46132
Controls	Yes	Yes	Yes	Yes	Yes
Year F.E.		Yes		Yes	Yes
Municipality F.E.			Yes	Yes	Yes
State time trend					Yes
Sample mean of Y	.515	.515	.515	.515	.515

Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Two-way clustered standard errors at the municipality and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

Log. of crimes

Table 1.G.7: Effect of avocado suitability and world price on crimes (log. of)

	Log. of crimes in municipality m in year t (2011-2017)						
	Category 1			Category 2		Category 3	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Extortion	Threat	Kidnap	Robbery	Theft	Injuries	Other
Suitability Index=1 × Avocado price (lag)	-0.11**	-0.10**	-0.04	-0.05	-0.14*	0.01	0.02
	(0.04)	(0.04)	(0.03)	(0.06)	(0.06)	(0.05)	(0.04)
Observations	12731	12731	12731	12731	12731	12731	12731
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State time trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample mean of Y	.538	.886	1.59	3.03	2.92	3.49	1.67

Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Two-way clustered standard errors at the municipality and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

Asinh of crimes

Table 1.G.8: Effect of avocado suitability and world price on crimes (asinh)

	Asinh of crimes in municipality m in year t (2011-2017)						
	Category 1			Category 2		Category 3	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Extortion	Threat	Kidnap	Robbery	Theft	Injuries	Other
Suitability Index=1 × Avocado price (lag)	-0.08	-0.09	-0.03	0.02	-0.09	0.06	0.13
	(0.05)	(0.06)	(0.04)	(0.09)	(0.10)	(0.06)	(0.07)
Observations	12731	12731	12731	12731	12731	12731	12731
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State time trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample mean of Y	.671	1.11	1.97	3.55	3.41	4.06	2.02

Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Two-way clustered standard errors at the municipality and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

1.G.1.3 Exclusion of years and states

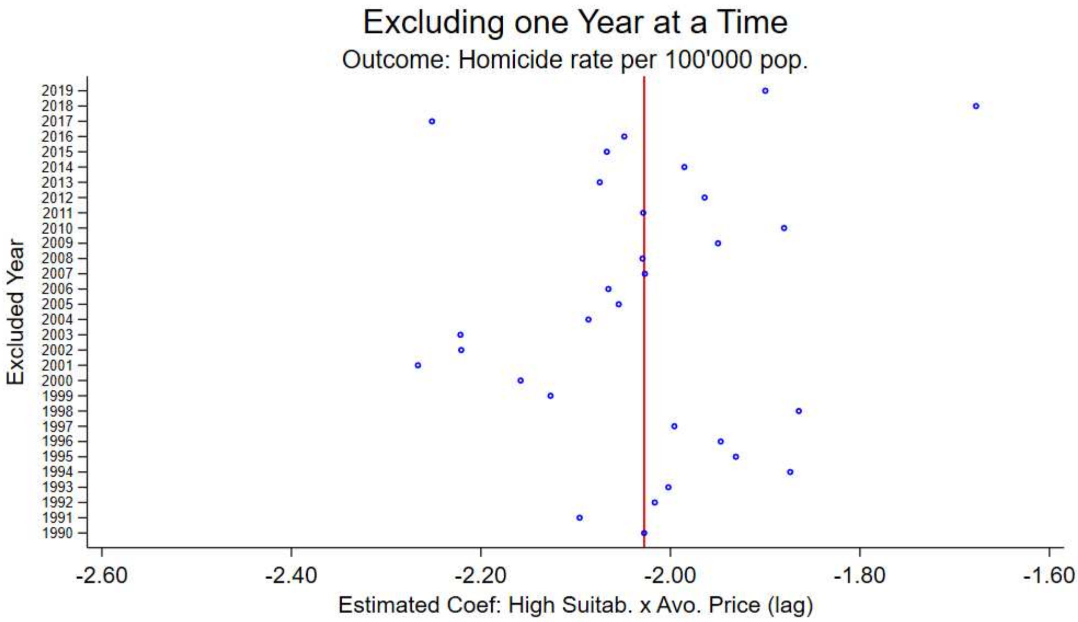
As a third robustness check, I estimate equation 1.1 excluding one year at a time, and excluding one state at a time, to check if there are years or states that are potentilly driving the results. I plot the coefficient and the p-values of the estimations that exclude one year at a time, and compare them to the coefficient and the p-value of the main estimation. The results for the homicide rate (Fig. 1.G.1) are robust to the exclusion of years, showing that the results are not driven by a particular time. All the p-values lie within the 5% significance level and the coefficients are centered around the main estimation result. In the case of the drug cartel attacks (Fig. 1.G.2), the results show a bit more of variability and sensitivity to the exclusion of a few years (2002, 2003, 2010, and 2018). All coefficients are negative as in the main estimation, but for those specific years they fail to be statistically significant at the 10% (although they are fairly close to the thereshold).

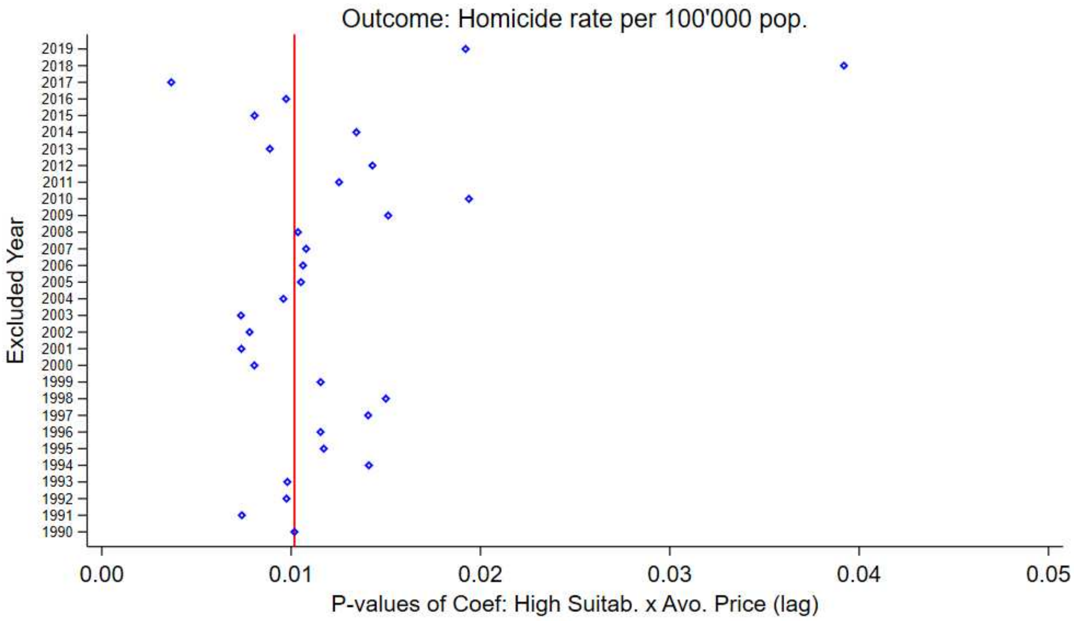
I then conduct the same check, but to the exclusion of each of the 32 states of Mexico at a time. The results for the homicide rate (Fig. 1.G.3 are highly robust to the exclusion of individual states and are precisely estimated. The only exception is when the estimation excludes the state of Oaxaca, where the estimated β is close to zero and statistically non significant. This can be due to the fact that Oaxaca is divided into 570 municipalities, almost a quarter of all the 2460 municipalities across Mexico. The result excluding Oaxaca would indicate a potential lack of power after dropping more than 20% of the observations with respect to the main estimation. The results for the drug cartel attacks (Fig. 1.G.4) follow a similar pattern: when excluding Oaxaca the coefficient is not significant. This is also the case of Chiapas, Coahuila, and Yucatán. Overall, out of the 32 states the results for the drug cartel attacks are highly robust.

Excluding one year at a time

Homicides

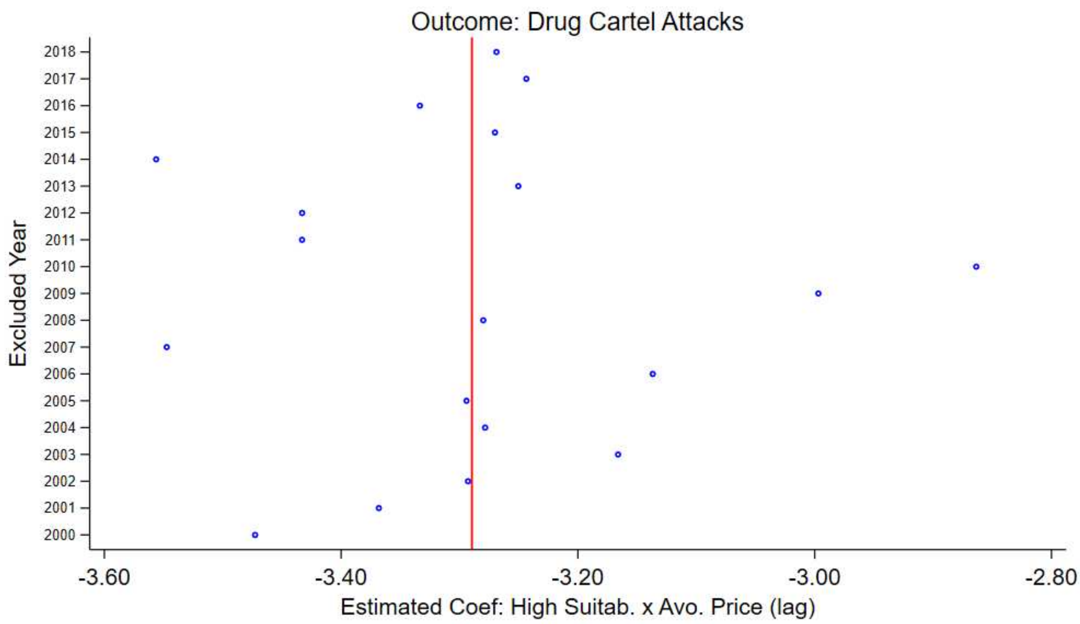
Figure 1.G.1: Coefficients and p-values of regressions excluding one year at a time: homicides

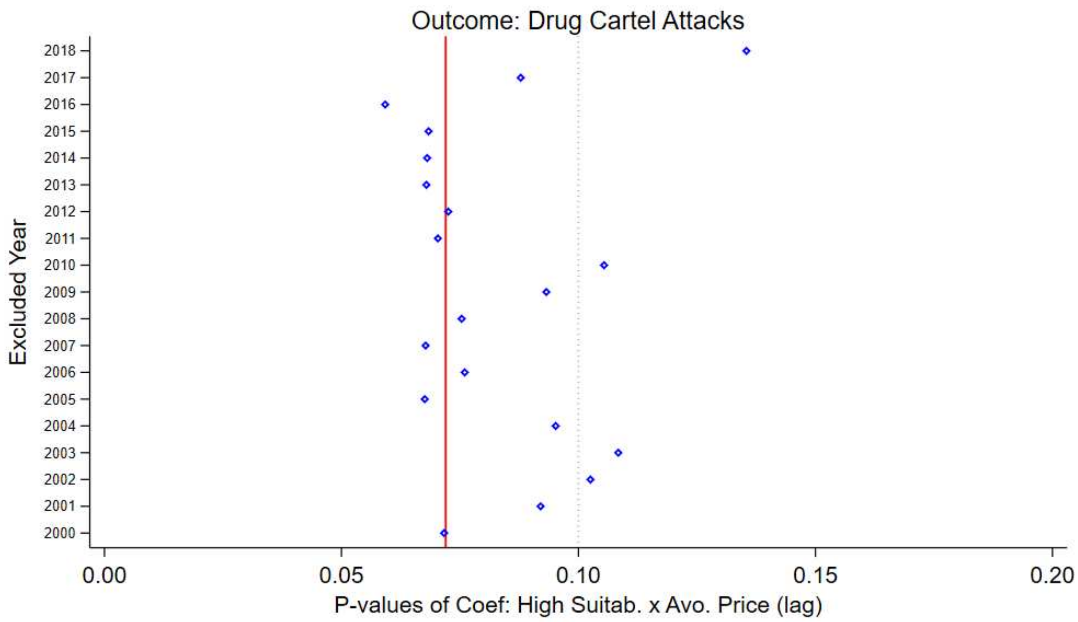




Drug cartel attacks

Figure 1.G.2: Coefficients and p-values of regressions excluding one year at a time: drug cartel attacks

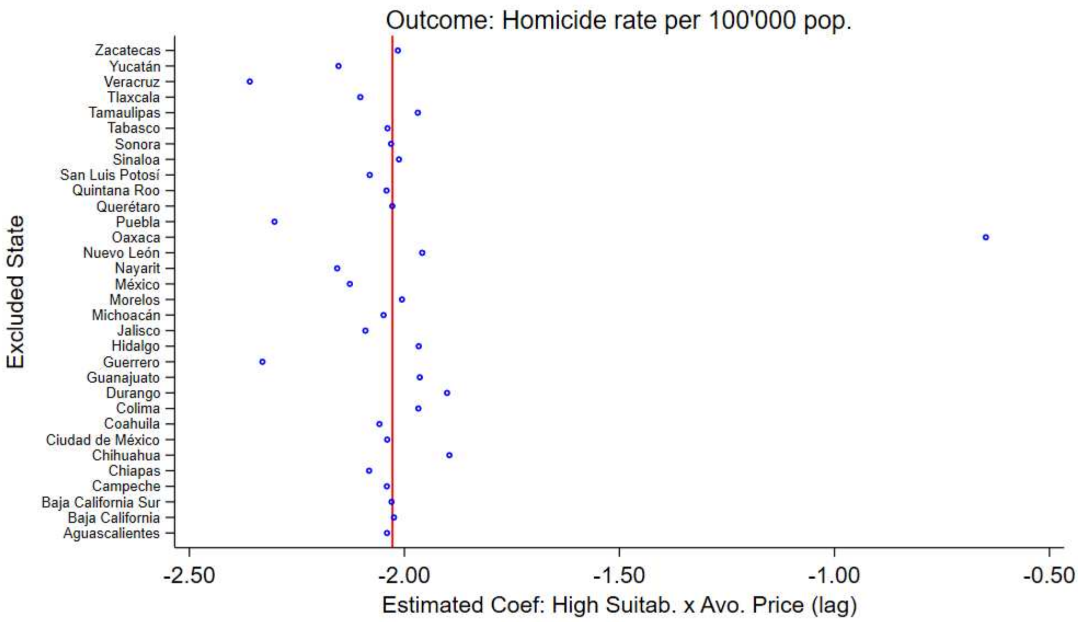


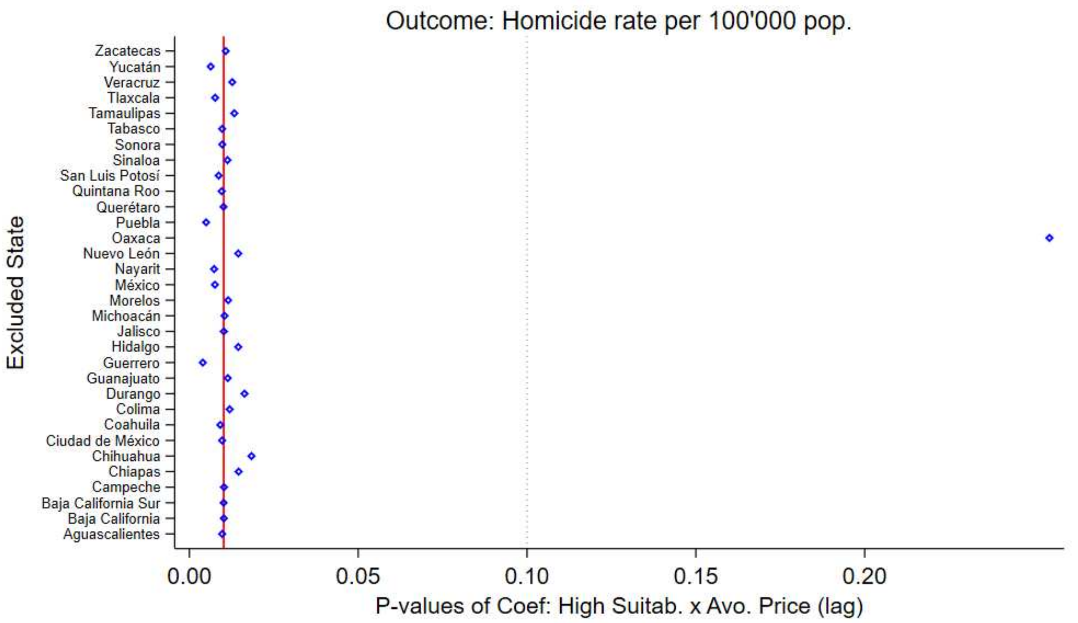


Excluding one state at a time

Homicides

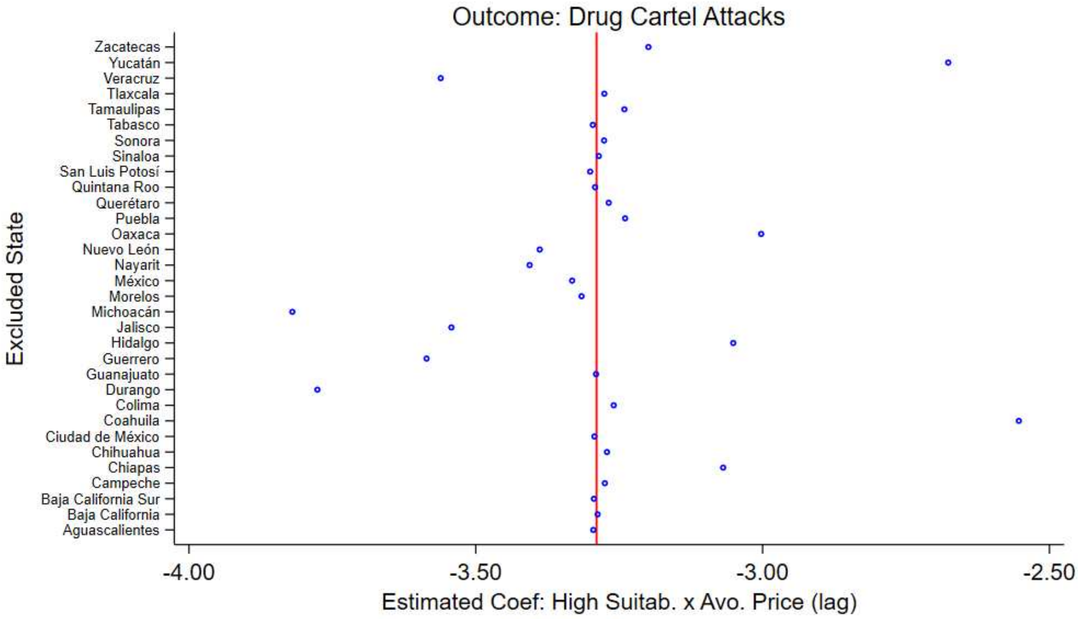
Figure 1.G.3: Coefficients and p-values of regressions excluding one state at a time: homicides

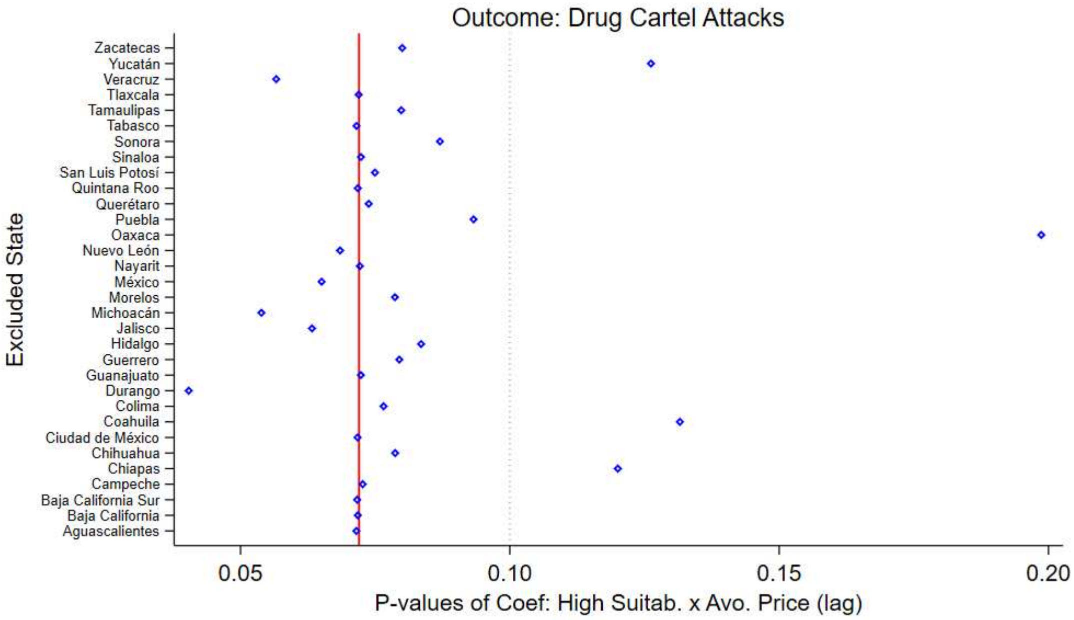




Drug cartel attacks

Figure 1.G.4: Coefficients and p-values of regressions excluding one state at a time: drug cartel attacks





1.G.1.4 Clustered standard errors at the state level

My main estimation strategy clusters the standard errors at the municipality and year level (two-way clustering). Here, I conduct a most conservative estimation that cluster the standard errors at the state level. Table 1.G.9 and Table 1.G.10 show that the estimation on the homicide rate is robust as well to this conservative clustering approach.

Homicides

Table 1.G.9: Effect of avocado suitability and world price on homicide rate (per 100,000 pop.)

	Homicide rate in municipality m in year t (1990-2019)				
	(1)	(2)	(3)	(4)	(5)
Suitability Index=1	4.94	4.95			
	(4.28)	(4.29)			
Avocado price (lag)	6.13***		5.13***		
	(1.01)		(0.82)		
Suitability Index=1 × Avocado price (lag)	-4.66***	-4.64***	-4.73***	-4.71***	-2.03*
	(1.65)	(1.63)	(1.69)	(1.68)	(1.08)
Observations	68498	68498	68498	68498	68498
Controls	Yes	Yes	Yes	Yes	Yes
Year F.E.		Yes		Yes	Yes
Municipality F.E.			Yes	Yes	Yes
State time trend					Yes
Sample mean of Y	16.7	16.7	16.7	16.7	16.7

Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Clustered standard errors at the state level are reported in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

Table 1.G.10: Effect of avocado suitability and world price on homicide rate (per 100'000 pop.)

	Homicide rate in municipality m in year t (1990-2019)							
	Before (1990-1997)				After (1998-2019)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Suitability Index=1	15.61**				2.53			
	(6.65)				(3.80)			
Avocado price (lag)		2.33				4.86***		
		(2.10)				(1.56)		
Suitability Index=1 × Avocado price (lag)	2.67*	2.73*	2.54*	1.04	-3.59**	-3.70**	-3.71**	-1.74**
	(1.38)	(1.35)	(1.34)	(1.28)	(1.38)	(1.42)	(1.42)	(0.83)
Observations	16534	16534	16534	16534	51964	51964	51964	51964
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes		Yes	Yes	Yes		Yes	Yes
Municipality F.E.		Yes	Yes	Yes		Yes	Yes	Yes
State time trend				Yes				Yes
Sample mean of Y	17.9	17.9	17.9	17.9	16.3	16.3	16.3	16.3

Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Clustered standard errors at the state level are reported in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

The results for the drug cartel attacks rate in Table 1.G.11 confirm as well the robustness of the estimation for this outcome. Table 1.G.12 presents the results for crimes.

Attacks by drug cartels

Table 1.G.11: Effect of avocado suitability and world price on rate of drug cartel attacks (per 100,000 pop.)

	Attacks rate in municipality m (2000-2018)				
	(1)	(2)	(3)	(4)	(5)
Suitability Index=1	-19.54**	-19.43**			
	(8.26)	(8.24)			
Avocado price (lag)	13.86**		18.70**		
	(5.44)		(8.19)		
Suitability Index=1 × Avocado price (lag)	-10.65**	-10.74**	-11.61**	-11.77**	-3.29**
	(4.84)	(4.82)	(5.22)	(5.24)	(1.32)
Observations	46132	46132	46132	46132	46132
Controls	Yes	Yes	Yes	Yes	Yes
Year F.E.		Yes		Yes	Yes
Municipality F.E.			Yes	Yes	Yes
State time trend					Yes
Sample mean of Y	26.3	26.3	26.3	26.3	26.3

Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Clustered standard errors at the state level are reported in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

Crimes

Table 1.G.12: Effect of avocado suitability and world price on crime rate (by type)

	Crime rate in municipality m in year t (2011-2017)						
	Category 1			Category 2		Category 3	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Extortion	Threat	Kidnap	Robbery	Theft	Injuries	Other
Suitability Index=1 × Avocado price (lag)	-0.20	1.97	1.23	14.91	3.39	32.79	7.47
	(0.33)	(2.33)	(2.15)	(19.75)	(12.71)	(30.20)	(7.53)
Observations	12731	12731	12731	12731	12731	12731	12731
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State time trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample mean of Y	2.63	10.3	22.7	164	165	263	34

Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Clustered standard errors at the state level are reported in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

1.G.1.5 Wild Cluster Bootstrap (WCB) p-values and CI

Below report the results of a wild bootstrap estimation (Cameron et al., 2008) with 1000 random repetitions with clustering at the municipality level. The bootstrap p-values and confidence intervals of both the estimation on the homicide rate (Table 1.G.13) and the drug cartel attacks per 100'000 population (Table 1.G.14) report similar and robust statistical significance as in the main estimation.

Homicides

Table 1.G.13: Homicide rate (per 100'000 pop.) - Wild bootstrap inference

	Coef	t-stat	Bootstr. p-value	[95% conf.	interval]
1990 - 2019					
High Suitab. x Avocado price (lag)	-2.03	-3.43	0.002	-3.254	-0.914
1990 - 1997					
High Suitab. x Avocado price (lag)	1.04	0.18	0.922	-8.214	10.231
1998 - 2019					
High Suitab. x Avocado price (lag)	-1.74	-3.08	0.002	-2.830	-0.664

The table reports the wild bootstrap estimation using 1000 repetitions for a regression where the dependent variable is the homicide rate (per 100'000 pop.) and the estimation method is OLS regression with high-dimensional fixed effects. The estimation follows the same dependent and indepedent variables as in the main estimation.

Drug cartel attacks

Table 1.G.14: Drug cartel attacks (per 100'000 pop.)- Wild bootstrap inference

	Coef	t-stat	Bootstr. p-value	[95% conf.	interval]
Drug cartel attacks					
High Suitab. x Avocado price (lag)	-3.29	-1.77	0.058	-6.619	0.170

The table reports the wild bootstrap estimation using 1000 repetitions for a regression where the dependent variable is the rate of drug cartel attacks (per 100'000 pop.) and the estimation method is OLS regression with high-dimensional fixed effects. The estimation follows the same dependent and indepedent variables as in the main estimation.

1.G.1.6 Permutation of the Suitability Index

As a sixth check, I validate whether the results of the main estimation are sensitive to 1000 random permutations of the suitability index across municipalities. The squared brackets [] in Table 1.G.15 shows that the homicide rate results are robust to the random permutations, reassuring of the causality of the results found in Tables 1.2 and 1.3 in section 1.4. In the case of drug cartel attacks, results in Table 1.G.16 show that the estimation that includes the state time trend is sensitive to the permutations of the suitability index. In more than 67% of the random permutations, the simulation predicted a placebo coefficient that is larger (in absolute value) than the real suitability index, threatening the validity of the results on a reduction in the rate of drug cartel attacks in highly suitable municipalities.

Homicides

Table 1.G.15: Effect of avocado suitability and world price on homicide rate (per 100'000 pop.) - Permutation of the Suitability Index

	Homicide rate in municipality m in year t					
	All years		Before (1990-1997)		After (1998-2019)	
	(1)	(2)	(3)	(4)	(5)	(6)
Suitability Index=1 × Avocado price (lag)	-4.71	-2.03	2.54	1.04	-3.71	-1.74
	(0.00)	(0.01)	(0.54)	(0.80)	(0.00)	(0.01)
	[0.00]	[0.00]	[0.30]	[0.64]	[0.00]	[0.00]
Observations	68498	68498	16534	16534	51964	51964
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Municipality F.E.	Yes	Yes	Yes	Yes	Yes	Yes
State time trend		Yes		Yes	No	Yes
Sample mean of Y	17.4	17.4	19.9	19.9	16.6	16.6

The table presents the results of a permutation test of the Suitability Index with 1000 random permutations, where the dependent variable is the homicide rate. The parentheses ( ) present the p-value of the original estimation. The squared brackets [ ] contain the p-value of the regressions with the permutation test. Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Two-way clustered standard errors at the state and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

Drug cartel attacks

Table 1.G.16: Effect of avocado suitability and world price on attacks rate (per 100'000 pop.) - Permutation of the Suitability Index

	Rate of attacks	
	(1)	(2)
Suitability Index=1 × Avocado price (lag)	-11.77	-3.29
	(0.02)	(0.07)
	[0.15]	[0.67]
Observations	46132	46132
Controls	Yes	Yes
Year F.E.	Yes	Yes
Municipality F.E.	Yes	Yes
State time trend		Yes
Sample mean of Y	23.8	23.8

The table presents the results of a permutation test of the Suitability Index with 1000 random permutations, where the dependent variable is the rate of drug cartel attacks. The parentheses ( ) present the p-value of the original estimation. The squared brackets [ ] contain the p-value of the regressions with the permutation test. Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Two-way clustered standard errors at the state and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

1.G.1.7 Alternative definitions of the suitability index

My suitability index consist of climatic and soil requirements for the optimal production of avocados. Nevertheless, for some municipalities there is no information on soil characteristics, and as Grüter et al. (2022) note, climate requirements are (e.g. rainfall, temperature) more important limiting factors than land and soil requirements when assessing the suitability to grow different types of crops, including avocados. Moreover, De Haro-Lopez (2023, 2024) uses only temperature and precipitation data to construct her avocado suitability index. Therefore, below I present the results of estimating equation 1.1 using only the climatic component of the suitability index.

Climatic suitability index

Results for the homicide rate in Tables 1.G.17 and 1.G.18 show that the magnitude and statistically significance of the interaction coefficient of the (climatic) suitability index and the avocado price (lag) is mostly the same as in the main estimation. Table 1.G.19 presents the results on the estimation of drug cartel attacks, and Table 1.G.20 for non-lethal crimes. The results show less robust results. In the case of the rate of drug cartel attacks, the coefficient in the estimation that includes the state time trend (Col. 5) is no longer statistically significant, although the magnitude of the coefficient is similar to the main estimation and the direction indicates a reduction in drug cartel attacks.

Table 1.G.17: Effect of avocado suitability and world price on homicide rate (per 100,000 pop.)

	Homicide rate in municipality m in year t (1990-2019)				
	(1)	(2)	(3)	(4)	(5)
High Suitability (clim.)=1	5.30***	5.31***			
	(1.42)	(1.42)			
Avocado price (lag)	6.22***		5.25***		
	(0.85)		(0.79)		
High Suitability (clim.)=1 × Avocado price (lag)	-4.28***	-4.29***	-4.34***	-4.35***	-2.00**
	(0.97)	(0.97)	(0.99)	(0.99)	(0.75)
Observations	68498	68498	68498	68498	68498
Controls	Yes	Yes	Yes	Yes	Yes
Year F.E.		Yes		Yes	Yes
Municipality F.E.			Yes	Yes	Yes
State time trend					Yes
Sample mean of Y	16.7	16.7	16.7	16.7	16.7

Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Two-way clustered standard errors at the municipality and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

Table 1.G.18: Effect of avocado suitability and world price on homicide rate (per 100'000 pop.)

	Homicide rate in municipality m in year t (1990-2019)							
	Before (1990-1997)				After (1998-2019)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High Suitability (clim.)=1	16.13***				2.84**			
	(2.35)				(1.10)			
Avocado price (lag)		2.17				4.91***		
		(2.05)				(1.13)		
High Suitability (clim.)=1 × Avocado price (lag)	2.96*	3.02	2.86	1.86	-3.19***	-3.32***	-3.33***	-1.60**
	(1.36)	(3.06)	(3.10)	(3.29)	(0.71)	(0.74)	(0.74)	(0.57)
Observations	16534	16534	16534	16534	51964	51964	51964	51964
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes		Yes	Yes	Yes		Yes	Yes
Municipality F.E.		Yes	Yes	Yes		Yes	Yes	Yes
State time trend				Yes				Yes
Sample mean of Y	17.9	17.9	17.9	17.9	16.3	16.3	16.3	16.3

Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Two-way clustered standard errors at the municipality and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

Table 1.G.19: Effect of avocado suitability and world price on drug cartel violent attacks

	Attacks rate in municipality m (2000-2018)				
	(1)	(2)	(3)	(4)	(5)
High Suitability (clim.)=1	-15.19**	-15.16**			
	(6.32)	(6.20)			
Avocado price (lag)	13.98***		18.75**		
	(3.35)		(7.55)		
High Suitability (clim.)=1 × Avocado price (lag)	-8.97*	-8.96**	-9.81*	-9.88*	-1.72
	(4.27)	(4.18)	(4.77)	(4.80)	(2.02)
Observations	46132	46132	46132	46132	46132
Controls	Yes	Yes	Yes	Yes	Yes
Year F.E.		Yes		Yes	Yes
Municipality F.E.			Yes	Yes	Yes
State time trend					Yes
Sample mean of Y	26.3	26.3	26.3	26.3	26.3

Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Two-way clustered standard errors at the municipality and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

Table 1.G.20: Effect of avocado suitability and world price on number of crimes (by type)

	Crime rate in municipality m in year t (2011-2017)						
	Category 1			Category 2		Category 3	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Extortion	Threat	Kidnap	Robbery	Theft	Injuries	Other
High Suitability (clim.)=1 × Avocado price (lag)	-0.05	0.81	0.65	5.44	0.79	35.32	2.69
	(0.46)	(2.10)	(2.20)	(13.16)	(7.23)	(20.99)	(5.36)
Observations	12731	12731	12731	12731	12731	12731	12731
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State time trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample mean of Y	2.63	10.3	22.7	164	165	263	34

Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Two-way clustered standard errors at the municipality and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

Continuous measure of the suitability index

I also estimate the main equation using the continuous measure of the suitability index. Remember that the suitability index goes from 0 to 3, and in the main estimation I use a categorical variable for highly suitable municipalities, those with an index of 2.5 or more. Table 1.G.21 and Table 1.G.22 for homicides show that the coefficient of the interaction between the continuous suitability index and the lagged avocado price is negative and statistically significant, as in the main estimation. Although the magnitude is lower, the results show that municipalities that are more suitable to produce avocados experience a reduction in the homicide rate per 100'000 pop. when the international import price of avocado increases by one standard deviation. This result is statistically significant at the 5%. In the main specification I use the binary variable for ease of interpretation. Results for drug cartel attacks and non-lethal crimes exhibit the same non-significant results as with the climatic component of the suitability index.

Table 1.G.21: Effect of avocado suitability and world price on homicide rate (per 100,000 pop.)

	Homicide rate in municipality m in year t (1990-2019)				
	(1)	(2)	(3)	(4)	(5)
suitability_cont	5.21***	5.22***			
	(1.05)	(1.05)			
Avocado price (lag)	11.53***		11.13***		
	(1.73)		(1.72)		
suitability_cont × Avocado price (lag)	-3.26***	-3.27***	-3.58***	-3.61***	-1.14**
	(0.77)	(0.77)	(0.82)	(0.82)	(0.54)
Observations	68498	68498	68498	68498	68498
Controls	Yes	Yes	Yes	Yes	Yes
Year F.E.		Yes		Yes	Yes
Municipality F.E.			Yes	Yes	Yes
State time trend					Yes
Sample mean of Y	16.7	16.7	16.7	16.7	16.7

Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Two-way clustered standard errors at the municipality and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

Table 1.G.22: Effect of avocado suitability and world price on homicide rate (per 100'000 pop.)

	Homicide rate in municipality m in year t (1990-2019)							
	Before (1990-1997)				After (1998-2019)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
suitability_cont	13.54***				3.26***			
	(1.22)				(0.88)			
Avocado price (lag)		-1.23				9.47***		
		(4.05)				(1.89)		
suitability_cont × Avocado price (lag)	1.56	2.09	1.81	0.41	-2.30***	-2.76***	-2.79***	-1.27**
	(1.71)	(2.09)	(2.18)	(2.21)	(0.63)	(0.69)	(0.69)	(0.50)
Observations	16534	16534	16534	16534	51964	51964	51964	51964
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes		Yes	Yes	Yes		Yes	Yes
Municipality F.E.		Yes	Yes	Yes		Yes	Yes	Yes
State time trend				Yes				Yes
Sample mean of Y	17.9	17.9	17.9	17.9	16.3	16.3	16.3	16.3

Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Two-way clustered standard errors at the municipality and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

Table 1.G.23: Effect of avocado suitability and world price on drug cartel violent attacks

	Attacks rate in municipality m (2000-2018)				
	(1)	(2)	(3)	(4)	(5)
suitability_cont	-12.14	-12.10			
	(8.29)	(8.29)			
Avocado price (lag)	28.51***		36.88**		
	(9.40)		(16.81)		
suitability_cont × Avocado price (lag)	-8.70	-8.69	-10.63	-10.79	-4.03
	(5.40)	(5.41)	(6.63)	(6.66)	(3.41)
Observations	46132	46132	46132	46132	46132
Controls	Yes	Yes	Yes	Yes	Yes
Year F.E.		Yes		Yes	Yes
Municipality F.E.			Yes	Yes	Yes
State time trend					Yes
Sample mean of Y	26.3	26.3	26.3	26.3	26.3

Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Two-way clustered standard errors at the municipality and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

Table 1.G.24: Effect of avocado suitability and world price on number of crimes (by type)

	Crime rate in municipality m in year t (2011-2017)						
	Category 1			Category 2		Category 3	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Extortion	Threat	Kidnap	Robbery	Theft	Injuries	Other
suitability_cont × Avocado price (lag)	-0.17	0.32	-0.87	-23.89	0.13	-6.62	2.07
	(0.51)	(1.16)	(1.38)	(24.98)	(10.27)	(13.13)	(3.17)
Observations	12731	12731	12731	12731	12731	12731	12731
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State time trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample mean of Y	2.63	10.3	22.7	164	165	263	34

Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Two-way clustered standard errors at the municipality and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

1.G.1.8 State-by-year fixed effect

The main estimation includes, besides year and municipality fixed effects, a state-level time trend to allow each of the 32 states to follow a specific linear trend over time in the outcome variables. However, this assumption can be too restrictive if the outcome varies in a non-linear manner within each state. Therefore, in section 1.G.1.8 I estimate equation 1.1 with a state-by-year fixed effect instead of the state-level time trend, a more flexible but less parsimonious approach that allows to capture any state-specific year-specific shocks, such as the launch of the "War on Drugs" in Michoacán in 2006. Results for the homicide rate (Tables 1.G.25 and 1.G.26) show that results are robust (and almost of the same magnitude) to the introduction of state-by-year fixed effects, showing that there are no state-year specific shocks that drive or alter the results.

Homicides

Table 1.G.25: Effect of avocado suitability and world price on homicide rate (per 100,000 pop.)

	Homicide rate in municipality m in year t (1990-2019)				
	(1)	(2)	(3)	(4)	(5)
Suitability Index=1	4.94***	4.95***			
	(1.51)	(1.51)			
Avocado price (lag)	6.13***		5.13***		
	(0.84)		(0.78)		
Suitability Index=1 × Avocado price (lag)	-4.66***	-4.64***	-4.73***	-4.71***	-2.23***
	(1.00)	(1.00)	(1.02)	(1.02)	(0.74)
Observations	68498	68498	68498	68498	68498
Controls	Yes	Yes	Yes	Yes	Yes
Year F.E.		Yes		Yes	Yes
Municipality F.E.			Yes	Yes	Yes
State-by-Year F.E.					Yes
Sample mean of Y	16.7	16.7	16.7	16.7	16.7

Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Two-way clustered standard errors at the municipality and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

Table 1.G.26: Effect of avocado suitability and world price on homicide rate (per 100'000 pop.)

	Homicide rate in municipality m in year t (1990-2019)							
	Before (1990-1997)				After (1998-2019)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Suitability Index=1	15.61***				2.53**			
	(2.74)				(1.17)			
Avocado price (lag)		2.33				4.86***		
		(2.02)				(1.13)		
Suitability Index=1 × Avocado price (lag)	2.67	2.73	2.54	1.07	-3.59***	-3.70***	-3.71***	-1.62**
	(2.29)	(3.87)	(3.93)	(3.88)	(0.80)	(0.84)	(0.83)	(0.64)
Observations	16534	16534	16534	16534	51964	51964	51964	51964
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes		Yes	Yes	Yes		Yes	Yes
Municipality F.E.		Yes	Yes	Yes		Yes	Yes	Yes
State-by-Year F.E.				Yes				Yes
Sample mean of Y	17.9	17.9	17.9	17.9	16.3	16.3	16.3	16.3

Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Two-way clustered standard errors at the municipality and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

Drug cartel attacks

In the case of drug cartel attacks (Table 1.G.27) the results are not robust, as the coefficient fails to be statistically significant at the 10%. At least, it is reassuring to find that the direction of the coefficient is also negative, suggestive of a possible reduction in the drug cartel attacks per 100'000 inhabitants in highly avocado-suitable municipalities.

Table 1.G.27: Effect of avocado suitability and world price on drug cartel violent attacks

	Attacks rate in municipality m (2000-2018)				
	(1)	(2)	(3)	(4)	(5)
Suitability Index=1	-19.54***	-19.43***			
	(6.71)	(6.65)			
Avocado price (lag)	13.86***		18.70**		
	(3.25)		(7.41)		
Suitability Index=1 × Avocado price (lag)	-10.65**	-10.74**	-11.61**	-11.77**	-2.58
	(3.95)	(3.83)	(4.61)	(4.67)	(1.66)
Observations	46132	46132	46132	46132	46132
Controls	Yes	Yes	Yes	Yes	Yes
Year F.E.		Yes		Yes	Yes
Municipality F.E.			Yes	Yes	Yes
State-by-Year F.E.					Yes
Sample mean of Y	26.3	26.3	26.3	26.3	26.3

Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Two-way clustered standard errors at the municipality and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

Crimes

In the case of crimes, results are mostly similar to the ones in the main estimation (i.e. non-significant), except for extortion cases. With the introduction of the state-by-year fixed effect, the estimated coefficient is now statistically significant and indicate a reduction in the number of (reported) cases of extortion in highly suitable municipalities for the production of avocados across Mexico. This negative coefficient would help in validating the hypothesis of a reduction in crimes and violence. If anything, it does not hurt the robustness of the results as no coefficient for crimes is positive. De Haro-Lopez (2024) finds a similar result of reduction in extortion cases in her study of municipalities of 7 states in Mexico, covering the same period.

Table 1.G.28: Effect of avocado suitability and world price on number of crimes (by type)

	Crime rate in municipality m in year t (2011-2017)						
	Category 1			Category 2		Category 3	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Extortion	Threat	Kidnap	Robbery	Theft	Injuries	Other
Suitability Index=1 × Avocado price (lag)	-0.58*	1.02	0.04	4.55	1.08	17.66	3.45
	(0.28)	(2.53)	(2.64)	(13.96)	(7.99)	(20.25)	(5.83)
Observations	12731	12731	12731	12731	12731	12731	12731
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-by-Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample mean of Y	2.63	10.3	22.7	164	165	263	34

Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Two-way clustered standard errors at the municipality and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

1.G.2 Robustness checks of results in Section 1.5 (Michoacán)

1.G.2.1 Comparing outcomes in same time period

Table 1.G.29 presents the estimation of the number of homicides in municipalities across Michoacán restricted to the period 2000-2018 (years with data on drug cartel attacks). There is no change in the results.

Table 1.G.29: Homicide and Drug Cartel Attacks per 100'000 pop. (2000-2018)

	Homicide rate				Attacks rate			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Suitability Index=1 × Avocado price (lag)	-2.43	-2.03	-2.35	-1.60	-4.78	-8.01	0.45	-3.71
	(4.81)	(4.42)	(4.71)	(4.27)	(9.90)	(10.11)	(8.19)	(8.63)
USDA_ever=1 × Avocado price (lag)	-2.02	-1.95	-2.63	-2.41	-9.82	-12.65	-0.43	-4.33
	(1.86)	(1.86)	(2.08)	(2.22)	(8.65)	(8.56)	(8.12)	(7.98)
Suitability Index=1 × USDA_ever=1 × Avocado price (lag)	3.96	3.84	3.86	3.55	21.23	24.05*	21.39	25.37*
	(5.30)	(4.94)	(5.42)	(5.02)	(13.35)	(12.72)	(13.45)	(12.72)
Observations	1786	1786	1786	1786	1786	1786	1786	1786
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.		Yes		Yes		Yes		Yes
Municipality F.E.			Yes	Yes			Yes	Yes
Sample mean of Y	22.4	22.4	22.4	22.4	36.8	36.8	36.8	36.8
Test p-val: $\beta 6 + \beta 7 = 0$	.722	.716	.821	.831	.372	.332	.11	.0732

Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Two-way clustered standard errors at the municipality and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

Table 1.G.30 estimate all outcomes for the period 2011-2017, which cover the years with data on non-lethal crimes at the municipality level. Two results are worth noting.

Table 1.G.30: Homicide, Drug C. Attacks, and Crime rate (2011-2017)

	Homicide	Attacks	Category 1			Category 2		Category 3	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
			Extortion	Threat	Kidnap	Robbery	Theft	Injuries	Other
Suitability Index=1 × Avocado price (lag)	-35.83	1.73	-0.44	-9.91	-2.43	-29.47**	-44.53**	61.02	6.66
	(20.66)	(59.47)	(0.97)	(7.77)	(9.50)	(11.97)	(15.19)	(33.13)	(4.42)
USDA_ever=1 × Avocado price (lag)	6.64	73.31	-1.08	-2.21	14.56**	56.91*	30.18*	12.77	-1.36
	(5.96)	(38.74)	(0.62)	(3.16)	(5.29)	(28.26)	(14.24)	(14.83)	(3.66)
Suitability Index=1 × USDA_ever=1 × Avocado price (lag)	50.57*	34.66	-0.40	21.80*	-12.40	49.05	51.42*	-119.55**	-7.27
	(22.75)	(84.71)	(0.71)	(9.55)	(12.68)	(44.91)	(22.01)	(46.18)	(4.85)
Observations	658	658	658	658	658	658	658	658	658
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample mean of Y	25.5	72.8	1.75	12.4	36.6	85.5	98.9	89.9	10.6
Test p-val: $\beta 6 + \beta 7 = 0$	.0352	.181	.146	.0749	.863	.0276	.00758	.0508	.0896

Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Two-way clustered standard errors at the municipality and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

First, during this shorter period, there is a statistically significant increase in the number of homicides per 100'000 inhabitants in avocado-growing municipalities authorized to export to the US. In particular, this effect is more salient compared to other municipalities that are also authorized to export but do not have the same production suitability. Put differently, the increase in homicides is concentrated in municipalities with large levels of production and that export to the US. Compared to the longer period 1998-2019 where there are no effects on homicides, this result would suggest that lethal violence increased once the market is established, and not in the early periods.

De Haro-Lopez (2024) also finds an increase in homicides during the period 2011-2017 in main avocado-producing municipalities across 7 western states in Mexico. Second, the results on drug cartels attacks are not statistically significant (as it is the case in the period 2000-2018). The coefficients are less precisely estimated, but they are still suggestive of an increase in attacks in USDA-approved municipalities.

1.G.2.2 Alternative measures of the outcome variable

I estimate equation 1.2 measuring the outcomes as either the $log(y)$ or as the inverse hyperbolic sine transformation *asinh*. In the case of drug cartel attacks, the coefficients are less precisely estimated when measured as both the log or the asinh transformation. Despite the lack of significance, the coefficients still have the expected direction and the results are suggestive of an increase in drug cartel attacks in avocado-producing and exporter municipalities. For the estimation of non-lethal crimes, the results for threats, robbery, and theft are robust and statistically significant as in the estimation that measures the number of cases per 100'000 population. The only crime for which the estimation is not significant is for kidnaps. Overall, these results are robust and validate the findings of an increase in some non-lethal crimes in municipalities of Michoacán that grow avocados and are oriented towards the export market.

Log. of homicides

Table 1.G.31: Effect of avocado suitability and world price on homicides (log)

	(Log of) Homicides in municipality m in year t (1990-2019)			
	(1)	(2)	(3)	(4)
Suitability Index=1 × Avocado price (lag)	-0.01	0.02	-0.02	0.01
	(0.09)	(0.07)	(0.12)	(0.10)
USDA_ever=1 × Avocado price (lag)	-0.12**	-0.11*	-0.11*	-0.08
	(0.05)	(0.05)	(0.06)	(0.06)
Suitability Index=1 × USDA_ever=1 × Avocado price (lag)	0.04	0.03	0.03	0.02
	(0.11)	(0.10)	(0.14)	(0.13)
Observations	2726	2726	2726	2726
Controls	Yes	Yes	Yes	Yes
Year F.E.		Yes		Yes
Municipality F.E.			Yes	Yes
Sample mean of Y	1.46	1.46	1.46	1.46
Test p-val: $\beta 6 + \beta 7 = 0$	.534	.499	.593	.622

Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Two-way clustered standard errors at the municipality and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

Asinh of homicides

Table 1.G.32: Effect of avocado suitability and world price on homicides (asinh)

	Homicides (asinh) in municipality m in year t (1990-2019)			
	(1)	(2)	(3)	(4)
Suitability Index=1 × Avocado price (lag)	-0.02	0.01	-0.04	-0.00
	(0.11)	(0.09)	(0.14)	(0.13)
USDA_ever=1 × Avocado price (lag)	-0.14**	-0.12*	-0.12	-0.09
	(0.06)	(0.06)	(0.07)	(0.07)
Suitability Index=1 × USDA_ever=1 × Avocado price (lag)	0.06	0.04	0.04	0.02
	(0.13)	(0.12)	(0.17)	(0.16)
Observations	2726	2726	2726	2726
Controls	Yes	Yes	Yes	Yes
Year F.E.		Yes		Yes
Municipality F.E.			Yes	Yes
Sample mean of Y	1.83	1.83	1.83	1.83
Test p-val: $\beta6 + \beta7 = 0$	.568	.538	.629	.665

Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Two-way clustered standard errors at the municipality and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

Log. of drug-cartel attacks

Table 1.G.33: Effect of avocado suitability and world price on drug cartel attacks (log)

	Log. of attacks in municipality m (2000-2018)			
	(1)	(2)	(3)	(4)
Suitability Index=1 × Avocado price (lag)	0.07	0.02	0.10	0.04
	(0.13)	(0.15)	(0.13)	(0.15)
USDA_ever=1 × Avocado price (lag)	-0.02	-0.06	0.02	-0.05
	(0.14)	(0.14)	(0.15)	(0.15)
Suitability Index=1 × USDA_ever=1 × Avocado price (lag)	0.27	0.31	0.25	0.31
	(0.21)	(0.22)	(0.22)	(0.22)
Observations	1786	1786	1786	1786
Controls	Yes	Yes	Yes	Yes
Year F.E.		Yes		Yes
Municipality F.E.			Yes	Yes
Sample mean of Y	.718	.718	.718	.718
Test p-val: $\beta6 + \beta7 = 0$	.166	.179	.145	.169

Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Two-way clustered standard errors at the municipality and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

Asinh of drug-cartel attacks

Table 1.G.34: Effect of avocado suitability and world price on drug cartel attacks (asinh)

	Asinh transf. of attacks in municipality m (2000-2018)			
	(1)	(2)	(3)	(4)
Suitability Index=1 × Avocado price (lag)	0.09	0.04	0.13	0.06
	(0.16)	(0.18)	(0.15)	(0.18)
USDA_ever=1 × Avocado price (lag)	-0.03	-0.08	0.02	-0.06
	(0.16)	(0.16)	(0.17)	(0.17)
Suitability Index=1 × USDA_ever=1 × Avocado price (lag)	0.30	0.35	0.28	0.35
	(0.24)	(0.26)	(0.25)	(0.26)
Observations	1786	1786	1786	1786
Controls	Yes	Yes	Yes	Yes
Year F.E.		Yes		Yes
Municipality F.E.			Yes	Yes
Sample mean of Y	.872	.872	.872	.872
Test p-val: $\beta 6 + \beta 7 = 0$	.204	.223	.179	.213

Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Two-way clustered standard errors at the municipality and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

Log. of crimes

Table 1.G.35: Effect of avocado suitability and world price on crimes (log. of)

	Log. of crimes in municipality m in year t (2011-2017)						
	Category 1			Category 2		Category 3	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Extortion	Threat	Kidnap	Robbery	Theft	Injuries	Other
Suitability Index=1 × Avocado price (lag)	-0.24	-0.62	0.13	-0.19	-0.25*	0.49**	0.36
	(0.22)	(0.45)	(0.23)	(0.12)	(0.11)	(0.20)	(0.22)
USDA_ever=1 × Avocado price (lag)	-0.18	0.08	0.27	0.55**	0.52**	0.12	0.06
	(0.09)	(0.12)	(0.15)	(0.20)	(0.17)	(0.14)	(0.14)
Suitability Index=1 × USDA_ever=1 × Avocado price (lag)	0.15	1.07*	-0.40	0.20	0.09	-0.77**	-0.27
	(0.28)	(0.49)	(0.27)	(0.28)	(0.24)	(0.30)	(0.23)
Observations	658	658	658	658	658	658	658
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample mean of Y	.291	.995	2.02	2.69	2.73	2.79	.997
Test p-val: $\beta 6 + \beta 7 = 0$	.925	.0509	.608	.0125	.0323	.0509	.294

Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe) Two-way clustered standard errors at the municipality and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

Asinh of crimes

Table 1.G.36: Effect of avocado suitability and world price on crimes (asinh)

	Asinh of crimes in municipality m in year t (2011-2017)						
	Category 1			Category 2		Category 3	
	(1) Extortion	(2) Threat	(3) Kidnap	(4) Robbery	(5) Theft	(6) Injuries	(7) Other
Suitability Index=1 × Avocado price (lag)	-0.30	-0.82	0.17	-0.20	-0.25*	0.49*	0.42
	(0.28)	(0.55)	(0.27)	(0.12)	(0.11)	(0.22)	(0.28)
USDA_ever=1 × Avocado price (lag)	-0.23	0.13	0.33	0.61**	0.60**	0.12	0.07
	(0.12)	(0.15)	(0.19)	(0.22)	(0.20)	(0.14)	(0.17)
Suitability Index=1 × USDA_ever=1 × Avocado price (lag)	0.22	1.33*	-0.44	0.21	0.08	-0.80*	-0.31
	(0.35)	(0.60)	(0.31)	(0.31)	(0.26)	(0.33)	(0.28)
Observations	658	658	658	658	658	658	658
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample mean of Y	.375	1.26	2.52	3.25	3.29	3.38	1.26
Test p-val: $\beta6 + \beta7 = 0$	.978	.0454	.699	.0126	.0373	.0585	.295

Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Two-way clustered standard errors at the municipality and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

1.G.2.3 Exclusion of years and municipalities

Figure 1.G.5 shows that the main finding of an increase in the number of drug cartel attacks in highly-suitable export-oriented municipalities in Michoacán during 2000-2018 is not sensible to the exclusion of individual years. In only 2 out of the 18 year-period the p-values are above the 10% threshold of statistical significance. The estimated coefficients have all the main sign as the main β and are in the range of 20-31, with the main estimate being 25.37.

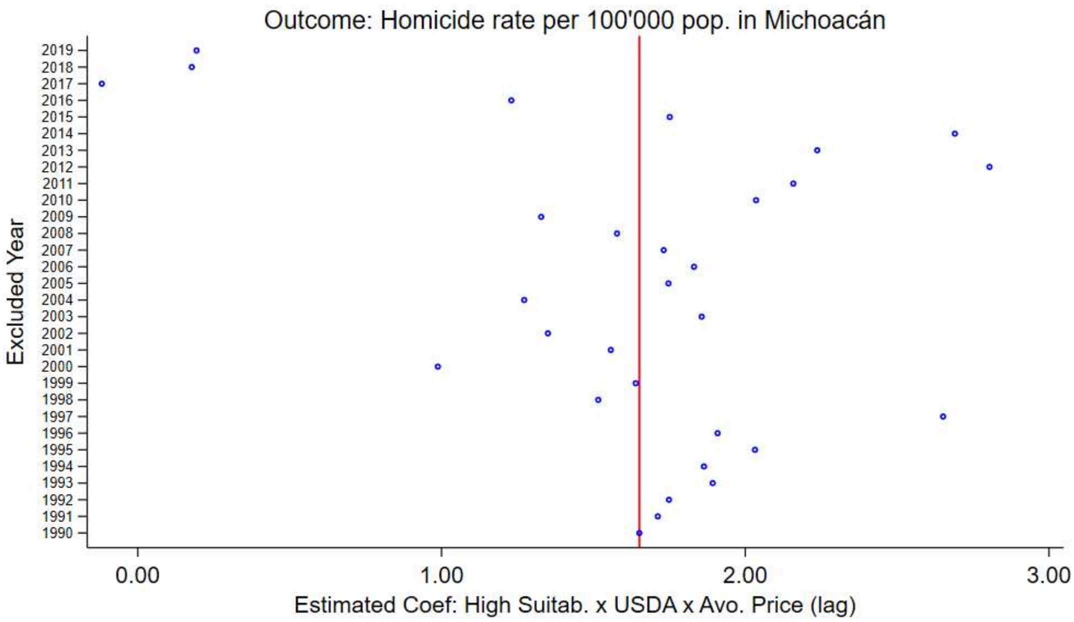
The exclusion of municipalities (one at a time) provide similar results in terms of robustness. Figure 1.G.8 shows that, out of the 113 municipalities, only the exclusion of 4 of them yield non-significant estimates at the 10%.[33] Similar to the exclusion of years, the estimated coefficients are all positive and are concentrated in the range 20-30 attacks per 100'000 population.

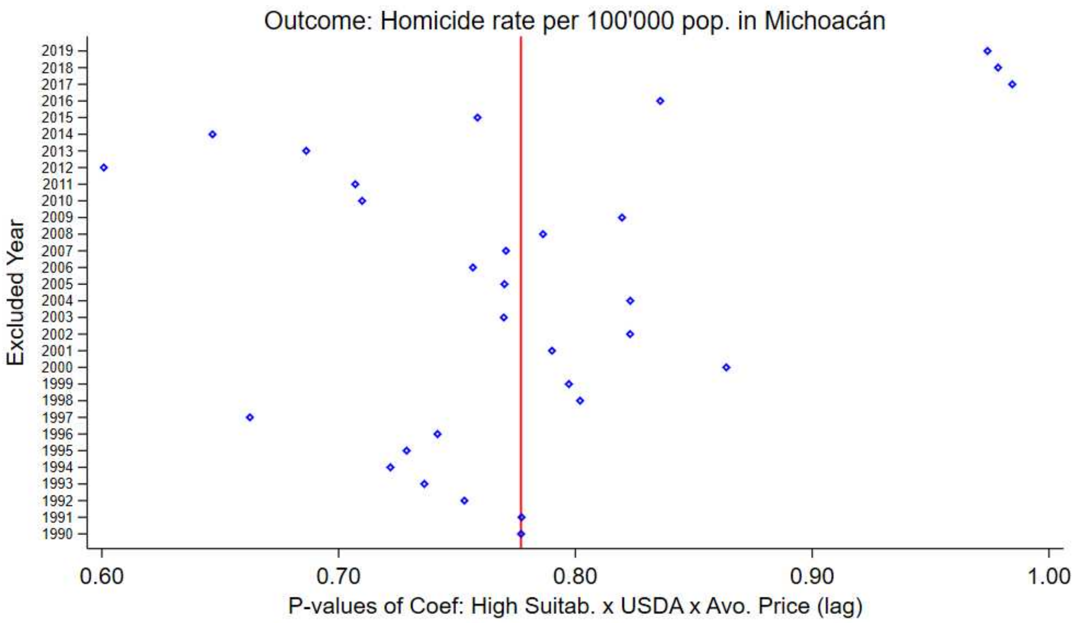
[33] These municipalities are: Jungapeo, Madero, Nocupétaro, and Tumbiscatío. Among those, Madero is the only municipality authorized to export avocados to the US since 1997.

Excluding one year at a time

Homicides

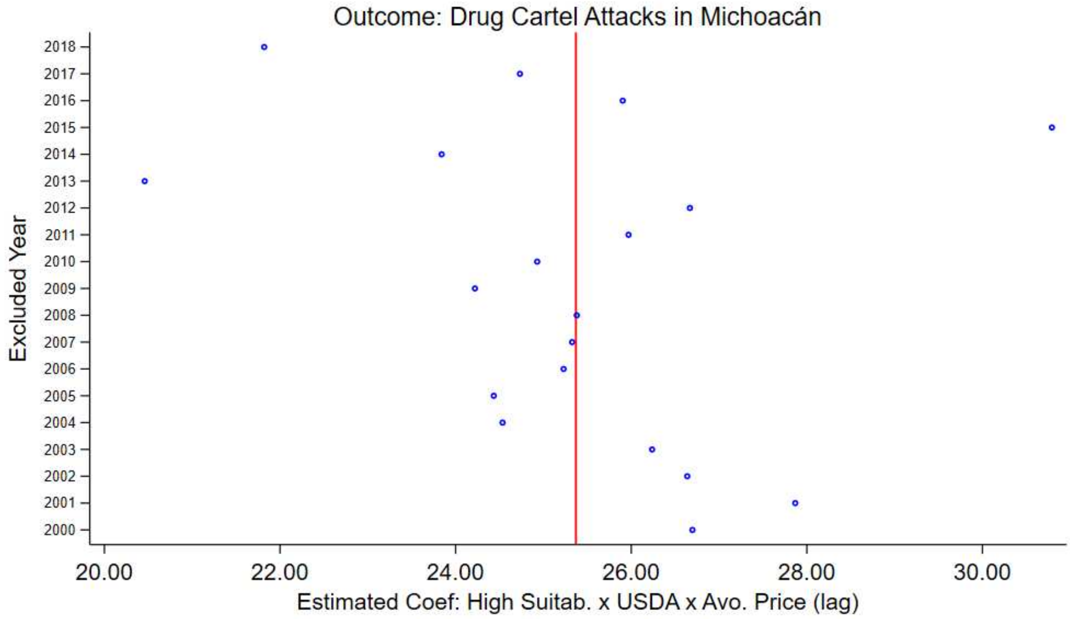
Figure 1.G.5: Coefficients and p-values of regressions excluding one year at a time: homicides (Michoacán)

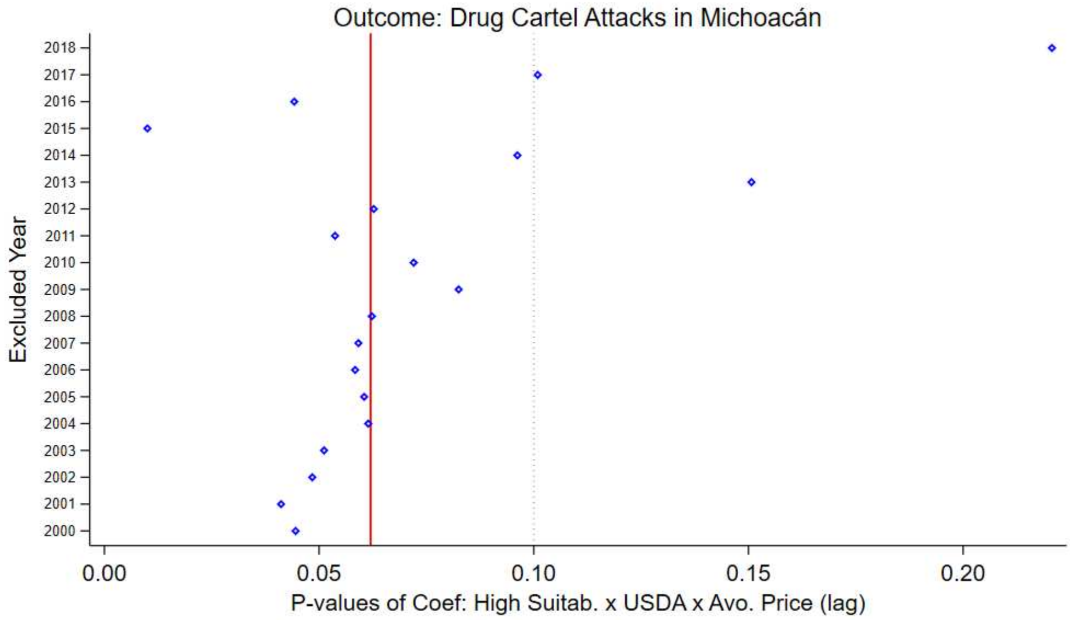




Drug cartel attacks

Figure 1.G.6: Coefficients and p-values of regressions excluding one year at a time: drug cartel attacks (Michoacán)

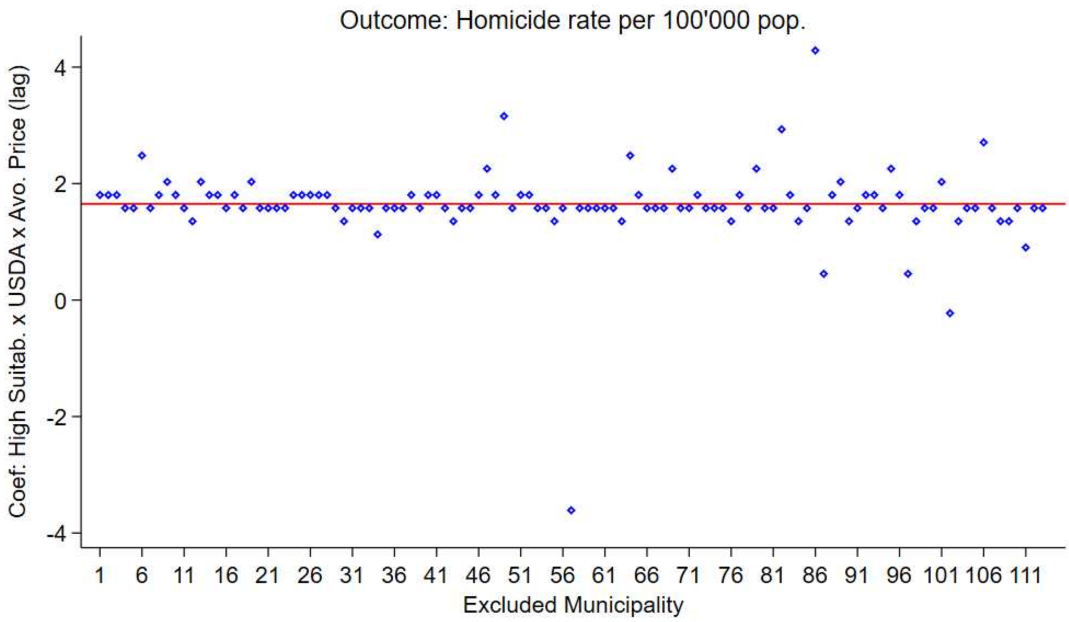


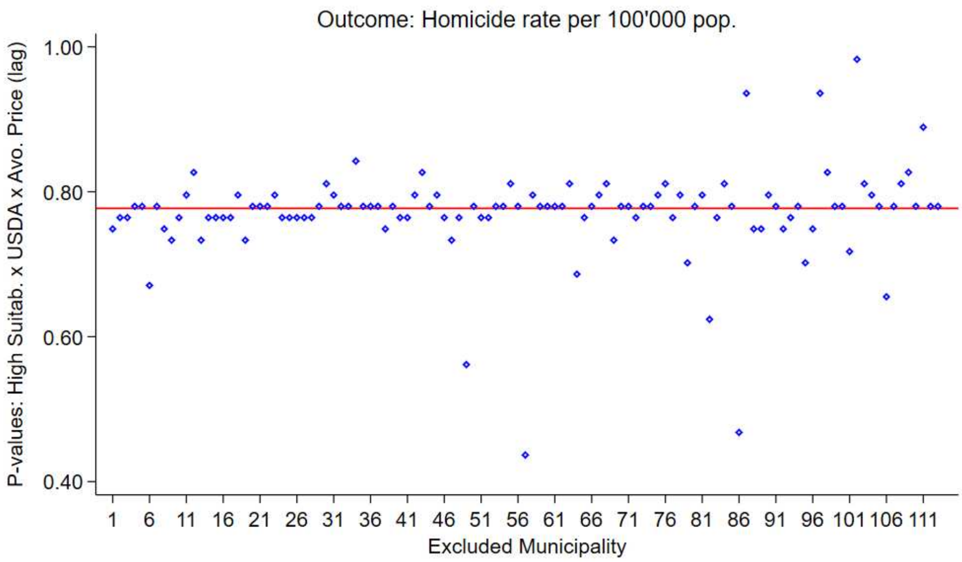


Excluding one municipality at a time

Homicides

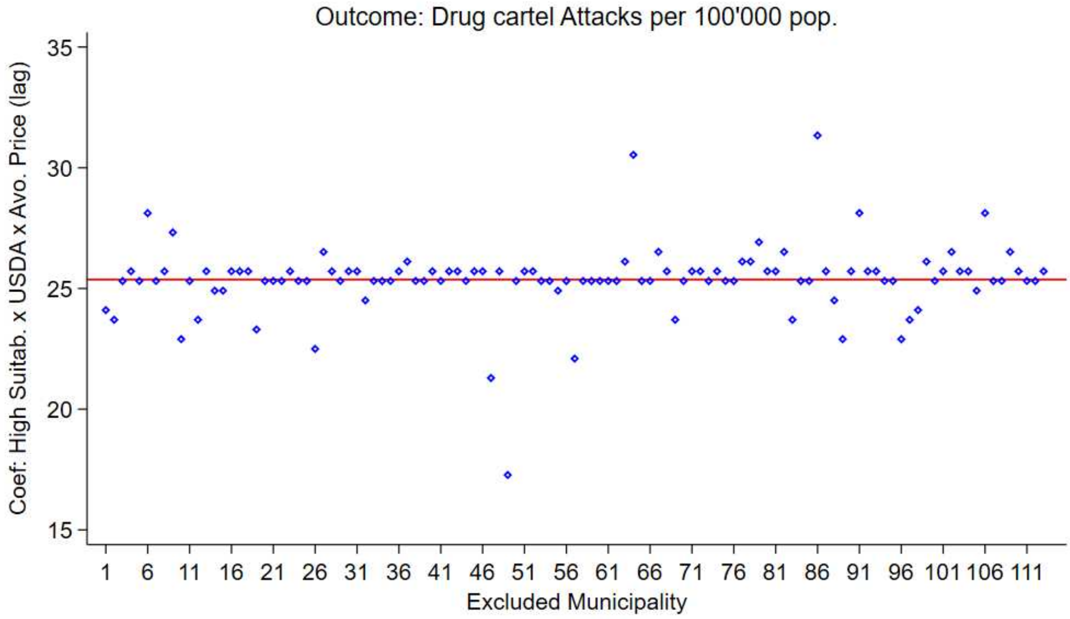
Figure 1.G.7: Coefficients and p-values of regressions excluding one municipality at a time: homicides (Michoacán)

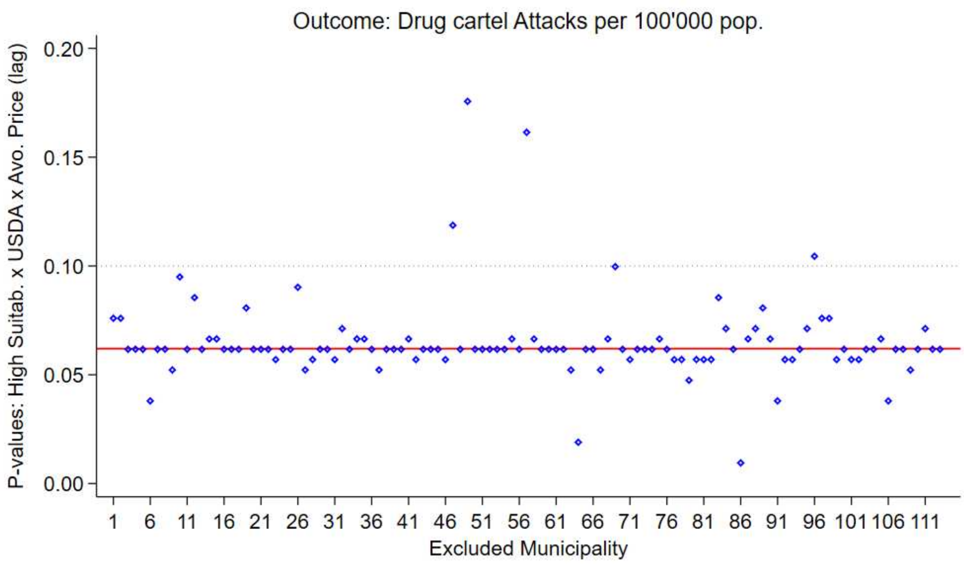




Drug cartel attacks

Figure 1.G.8: Coefficients and p-values of regressions excluding one municipality at a time: drug cartel attacks (Michoacán)





1.G.2.4 Wild Cluster Bootstrap (WCB) p-values and CI

I run a wildbootstrap estimation of the confidence intervals (CIs) for the main coefficients $\beta_5, \beta_6, \beta_7$ with 1000 repetitions, clustering at the municipality level. Table 1.G.37 show that the estimation on homicides does not change with the bootstrap estimation. Table 1.G.38 shows that the effects of an increase in drug cartel attacks in highly-suitable USDA-approved municipalities is still marginally significant at the 10%. Table 1.G.39 presents the results for crimes. The results for threats and kidnapping are robust to wild cluster bootstrap inference. However, the CIs for robbery ad theft a marginally larger and therefore less statistically significant.

Homicides

Table 1.G.37: Homicide rate in Michoacán (per 100'000 pop.) - Wild bootstrap inference

	Coef	t-stat	Bootstr. p-value	[95% conf.	interval]
1990 - 2019					
High Suitab. x Avocado price (lag)	-1.92	-0.43	0.832	-22.650	9.146
USDA x Avocado price (lag)	-1.55	-0.66	0.490	-6.471	3.628
High Suitab. x USDA x Avocado price (lag)	1.65	0.28	0.846	-10.688	18.366
1990 - 1997					
High Suitab. x Avocado price (lag)	24.20	0.79	0.644	-36.612	143.513
USDA x Avocado price (lag)	-4.36	-0.53	0.576	-20.702	12.221
High Suitab. x USDA x Avocado price (lag)	-23.13	-0.70	0.612	-135.785	38.918
1998 - 2019					
High Suitab. x Avocado price (lag)	-2.63	-0.75	0.636	-16.542	7.489
USDA x Avocado price (lag)	-2.10	-0.92	0.366	-6.808	2.908
High Suitab. x USDA x Avocado price (lag)	4.43	0.96	0.430	-5.221	16.493

The table reports the wild bootstrap estimation using 1000 repetitions for a regression where the dependent variable is the homicide rate (per 100'000 pop.) and the estimation method is OLS regression with high-dimensional fixed effects. The estimation follows the same dependent and indepedent variables as in the main estimation.

Drug cartel attacks

Table 1.G.38: Drug cartel attacks in Michoacán (per 100'000 pop.)- Wild bootstrap inference

	Coef	t-stat	Bootstr. p-value	[95% conf.	interval]
Drug cartel attacks					
High Suitab. x Avocado price (lag)	-3.71	-0.43	0.678	-22.532	20.195
USDA x Avocado price (lag)	-4.33	-0.50	0.646	-21.435	13.162
High Suitab. x USDA x Avocado price (lag)	25.37	1.80	0.102	-6.520	54.593

The table reports the wild bootstrap estimation using 1000 repetitions for a regression where the dependent variable is the rate of drug cartel attacks (per 100'000 pop.) and the estimation method is OLS regression with high-dimensional fixed effects. The estimation follows the same dependent and indepedent variables as in the main estimation.

Crimes

Table 1.G.39: Crime rate in Michoacán (per 100'000 pop.) - Wild bootstrap inference

	Coef	t-stat	Bootstr. p-value	[95% conf.	interval]
Crime Index					
High Suitab. x Avocado price (lag)	-0.23	-1.37	0.218	-0.723	0.153
USDA x Avocado price (lag)	0.12	0.76	0.408	-0.195	0.435
High Suitab. x USDA x Avocado price (lag)	0.17	0.66	0.536	-0.354	0.704
Extortion					
High Suitab. x Avocado price (lag)	-0.44	-0.60	0.530	-2.370	1.264
USDA x Avocado price (lag)	-1.08	-1.22	0.212	-2.840	0.615
High Suitab. x USDA x Avocado price (lag)	-0.40	-0.23	0.812	-4.119	3.265
Threat					
High Suitab. x Avocado price (lag)	-9.91	-0.97	0.328	-34.672	19.792
USDA x Avocado price (lag)	-2.21	-0.46	0.634	-11.437	6.688
High Suitab. x USDA x Avocado price (lag)	21.80	1.80	0.128	-6.745	48.686
Kidnap					
High Suitab. x Avocado price (lag)	-2.43	-0.20	0.874	-40.486	26.242
USDA x Avocado price (lag)	14.56	1.85	0.050	0.290	31.181
High Suitab. x USDA x Avocado price (lag)	-12.40	-0.81	0.414	-43.071	23.207
Robbery					
High Suitab. x Avocado price (lag)	-29.47	-1.48	0.176	-89.891	24.058
USDA x Avocado price (lag)	56.91	1.37	0.148	-23.400	143.727
High Suitab. x USDA x Avocado price (lag)	49.05	0.79	0.398	-81.630	182.008
Theft					
High Suitab. x Avocado price (lag)	-44.53	-1.41	0.232	-136.820	28.587
USDA x Avocado price (lag)	30.18	1.39	0.130	-11.648	74.228
High Suitab. x USDA x Avocado price (lag)	51.42	1.25	0.244	-39.175	138.370
Injury					
High Suitab. x Avocado price (lag)	61.02	1.35	0.208	-33.213	236.661
USDA x Avocado price (lag)	12.77	0.55	0.602	-32.667	60.814
High Suitab. x USDA x Avocado price (lag)	-119.55	-2.08	0.026	-251.927	-7.595
Other					
High Suitab. x Avocado price (lag)	6.66	1.34	0.234	-4.466	18.745
USDA x Avocado price (lag)	-1.36	-0.21	0.836	-13.205	11.362
High Suitab. x USDA x Avocado price (lag)	-7.27	-0.88	0.374	-24.701	9.783

The table reports the wild bootstrap estimation using 1000 repetitions for a regression where the dependent variable is the crime rate (per 100'000 pop.) and the estimation method is OLS regression with high-dimensional fixed effects. The estimation follows the same dependent and indepedent variables as in the main estimation.

1.G.2.5 Permutation of the USDA-approval status

I run a permutation of the USDA status at the municipality level with 1,000 random permutations. This permutation affects coefficients β_6 and β_7. Results for homicides in Table 1.G.40 indicate that results are not affected by the random permutations. Only coefficient β_7 for the period 1990-1997 present a result that would contradict the main estimation. Importantly for the main result, the estimations of the full period (1990-2019) and particularly the period after municipalities were granted the approval to export avocados to the US (1998-2019), are robust to the random permutations, both for β_6 and β_7.

Homicides

Table 1.G.40: Effect of avocado suitability and world price on homicide rate (per 100'000 pop.)

	Homicide rate in municipality m in year t		
	All years	Before (1990-1997)	After (1998-2019)
	(1)	(2)	(3)
Suitability Index=1 × Avocado price (lag)	-1.92	24.20	-2.63
	(0.68)	(0.32)	(0.46)
USDA=1 × Avocado price (lag)	-1.55	-4.36	-2.10
	(0.50)	(0.69)	(0.36)
	[0.86]	[0.76]	[0.77]
Suitability Index=1 × USDA=1 × Avocado price (lag)	1.65	-23.13	4.43
	(0.78)	(0.35)	(0.33)
	[0.14]	[0.07]	[0.10]
Observations	2726	658	2068
Controls	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes
Municipality F.E.	Yes	Yes	Yes
Sample mean of Y	26.3	36.4	23.1

The table presents the results of a permutation test of the USDA-approval status with 1000 random permutations, where the dependent variable is the homicide rate. The squared brackets [] contain the p-value of the regressions with the permutation test. Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Two-way clustered standard errors at the state and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

The permutation of the approval to export avocados to the US yield robust results for the outcome on drug cartel attacks as well. Table 1.G.41 shows that only in 5% of the permutations the simulation predicted a placebo coefficient that is larger (in absolute value) that the main estimated coefficient. This reassures the finding of an increase in drug cartel attacks in municipalities authorized to export avocados after the lift of the import ban in the US in 1997. De Haro-Lopez (2024) also finds that drug cartels, instead of fighting for territorial expansion, increased their attacks against civilians in avocado-suitable municipalities.

Drug cartel attacks

Table 1.G.41: Effect of avocado suitability and world price on attacks rate (per 100'000 pop.)

	Attacks in municipality m 2000-2018
	(1)
Suitability Index=1 × Avocado price (lag)	-3.71
	(0.67)
USDA=1 × Avocado price (lag)	-4.33
	(0.59)
	[0.87]
Suitability Index=1 × USDA=1 × Avocado price (lag)	25.37
	(0.06)
	[0.05]
Observations	1786
Controls	Yes
Year F.E.	Yes
Municipality F.E.	Yes
Sample mean of Y	35.9

The table presents the results of a permutation test of the USDA-approval status with 1000 random permutations, where the dependent variable is the attacks rate. The squared brackets [] contain the p-value of the regressions with the permutation test. Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Two-way clustered standard errors at the state and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

Table 1.G.42 shows that results for threats, robbery, and theft in highly-suitable export-oriented municipalities are robust to permutation of the USDA status. These results points toward an increase in those crimes in avocado-growing export-oriented municipalities for the period 2011-2017.

Crimes

Table 1.G.42: Effect of avocado suitability and world price on crime rate (per 100'000 pop.)

	(1) Index	(2) Extortion	(3) Threat	(4) Kidnap	(5) Robbery	(6) Theft	(7) Injuries	(8) Other
Suitability Index=1 × Avocado price (lag)	-0.23	-0.44	-9.91	-2.43	-29.47	-44.53	61.02	6.66
	(0.18)	(0.67)	(0.25)	(0.81)	(0.05)	(0.03)	(0.12)	(0.18)
USDA=1 × Avocado price (lag)	0.12	-1.08	-2.21	14.56	56.91	30.18	12.77	-1.36
	(0.29)	(0.13)	(0.51)	(0.03)	(0.09)	(0.08)	(0.42)	(0.72)
	[0.74]	[0.58]	[0.90]	[0.45]	[0.55]	[0.51]	[0.84]	[0.97]
Suitability Index=1 × USDA=1 × Avocado price (lag)	0.17	-0.40	21.80	-12.40	49.05	51.42	-119.55	-7.27
	(0.41)	(0.59)	(0.06)	(0.37)	(0.32)	(0.06)	(0.04)	(0.18)
	[0.14]	[0.16]	[0.07]	[0.13]	[0.10]	[0.10]	[0.03]	[0.09]
Observations	658	658	658	658	658	658	658	658
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample mean of Y	.047	2	12.2	37.6	89	104	93.4	11

The table presents the results of a permutation test of the USDA-approval status with 100 random permutations, where the dependent variable is the crime rate. The squared brackets [] contain the p-value of the regressions with the permutation test. Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Two-way clustered standard errors at the state and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

1.G.2.6 Alternative definitions of the suitability index

Below I present the results of estimating equation 1.2 using only the climatic component of the suitability index (i.e. precipitation and temperature). When only employing the climatic component, the results on homicides (Table 1.G.43) follow a similar pattern as in the main estimation. The new coefficients are statistically significant and suggest an increase in the number of homicides per 100'000 pop. in export oriented municipalities in the state of Michoacán. Nevertheless, the join test of the coefficients being different from zero is not statistically significant and I cannot reject the null hypothesis. Using the climatic component of the suitability index does not alter the results of the main estimation of no differences in homicides between export-oriented and non-exporter municipalities in Michoacán.

Climatic suitability index

Table 1.G.43: Effect of avocado suitability and world price on homicide rate (per 100'000 pop.) - Michoacán

	Homicide rate in municipality m in year t (1990-2019)			
	(1)	(2)	(3)	(4)
High Suitability (clim.)=1 × Avocado price (lag)	-8.69**	-8.06**	-8.15*	-7.91*
	(3.87)	(3.88)	(4.07)	(4.12)
USDA_ever=1 × Avocado price (lag)	-3.32*	-2.82	-3.66*	-2.85
	(1.89)	(2.07)	(2.12)	(2.31)
High Suitability (clim.)=1 × USDA_ever=1 × Avocado price (lag)	9.59**	9.81**	8.90*	9.65**
	(4.32)	(4.19)	(4.58)	(4.48)
Observations	2726	2726	2726	2726
Controls	Yes	Yes	Yes	Yes
Year F.E.		Yes		Yes
Municipality F.E.			Yes	Yes
Sample mean of Y	25.6	25.6	25.6	25.6
Test p-val: $\beta6 + \beta7 = 0$	.139	.0891	.251	.135

Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Two-way clustered standard errors at the municipality and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

The results on drug cartel attacks (Table 1.G.44) and crimes (Table 1.G.45) show that employing exclusively the climatic component of the suitability index can affect the results. In the case of drug cartel attacks the coefficient changes the direction of the effect, although it is not well estimated. Using the climatic component of the index suggests, if anything, that there was no an increase nor a decrease in the attacks in export-oriented municipalities. In the case of crimes, the coefficients are less precisely estimated but they suggest still an increase in property crimes in export-oriented municipalities.

Table 1.G.44: Effect of avocado suitability and world price on drug cartel violent attacks - Michoacán

	Attacks rate in municipality m in year t (2000-2018)			
	(1)	(2)	(3)	(4)
High Suitability (clim.)=1 × Avocado price (lag)	55.79*	53.79*	47.32*	44.51
	(29.36)	(30.20)	(25.90)	(26.42)
USDA_ever=1 × Avocado price (lag)	-1.69	-3.99	4.84	1.80
	(6.81)	(6.38)	(7.34)	(7.05)
High Suitability (clim.)=1 × USDA_ever=1 × Avocado price (lag)	-32.00	-32.35	-19.07	-19.21
	(30.77)	(31.62)	(27.69)	(27.91)
Observations	1786	1786	1786	1786
Controls	Yes	Yes	Yes	Yes
Year F.E.		Yes		Yes
Municipality F.E.			Yes	Yes
Sample mean of Y	36.8	36.8	36.8	36.8
Test p-val: $\beta6 + \beta7 = 0$	.296	.273	.605	.528

Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Two-way clustered standard errors at the municipality and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

Table 1.G.45: Effect of avocado suitability and world price on crime rate (by type) - Michoacán

	Crime rate in municipality m in year t (2011-2017)						
	Category 1			Category 2		Category 3	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Extortion	Threat	Kidnap	Robbery	Theft	Injuries	Other
High Suitability (clim.)=1 × Avocado price (lag)	-0.01	-1.91	1.03	-23.08	-4.18	11.01	2.19
	(1.83)	(7.69)	(8.50)	(15.28)	(9.06)	(22.13)	(3.52)
USDA_ever=1 × Avocado price (lag)	-1.28*	0.43	12.86**	65.64**	34.17**	-0.63	-0.64
	(0.60)	(2.87)	(4.59)	(24.68)	(13.94)	(14.65)	(4.39)
High Suitability (clim.)=1 × USDA_ever=1 × Avocado price (lag)	-0.40	12.05	-15.70	19.08	11.05	-62.32	-6.59
	(1.92)	(10.55)	(11.36)	(51.75)	(23.04)	(37.15)	(8.36)
Observations	658	658	658	658	658	658	658
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample mean of Y	1.75	12.4	36.6	85.5	98.9	89.9	10.6
Test p-val: $\beta6 + \beta7 = 0$	.392	.272	.801	.138	.106	.132	.304

Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Two-way clustered standard errors at the municipality and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

Continuous measure of the suitability index

The tables below show the estimation of equation 1.2 using the continuous measure of the suitability index to produce avocados. The higher the index, the more the potential of a municipality to produce avocados. Results on homicides (Table 1.G.46) show the same pattern of no differences across export-oriented municipalities and the others. In the case of drug cartel attacks, the coefficient is less precisely estimated but still suggest an increase in the number of attacks in USDA-approved municipalities. Finally, the results on crimes show the same statistically significant increase in threats, and in (less precisely estimated) cases of robbery and theft.

Table 1.G.46: Effect of avocado suitability and world price on homicide rate (per 100'000 pop.) - Michoacán

	Homicide rate in municipality m in year t (1990-2019)			
	(1)	(2)	(3)	(4)
suitability_cont × Avocado price (lag)	1.33	1.69	2.43	2.52
	(2.18)	(2.12)	(2.46)	(2.34)
USDA_ever=1 × Avocado price (lag)	-3.16	-2.48	0.43	0.46
	(6.46)	(6.33)	(6.97)	(6.83)
USDA_ever=1 × suitability_cont × Avocado price (lag)	0.52	0.48	-1.64	-1.20
	(3.34)	(3.27)	(3.52)	(3.41)
Observations	2726	2726	2726	2726
Controls	Yes	Yes	Yes	Yes
Year F.E.		Yes		Yes
Municipality F.E.			Yes	Yes
Sample mean of Y	25.6	25.6	25.6	25.6
Test p-val: $\beta6 + \beta7 = 0$	.438	.552	.746	.843

Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Two-way clustered standard errors at the municipality and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

Table 1.G.47: Effect of avocado suitability and world price on drug cartel violent attacks - Michoacán

	Attacks rate in municipality m in year t (2000-2018)			
	(1)	(2)	(3)	(4)
suitability_cont × Avocado price (lag)	9.63	8.33	5.25	3.48
	(8.86)	(9.19)	(8.26)	(8.14)
USDA_ever=1 × Avocado price (lag)	-14.06	-18.49	-21.71	-28.64
	(21.21)	(21.59)	(23.07)	(22.95)
USDA_ever=1 × suitability_cont × Avocado price (lag)	4.21	5.16	13.13	14.89
	(11.02)	(11.19)	(11.10)	(10.66)
Observations	1786	1786	1786	1786
Controls	Yes	Yes	Yes	Yes
Year F.E.		Yes		Yes
Municipality F.E.			Yes	Yes
Sample mean of Y	36.8	36.8	36.8	36.8
Test p-val: $\beta6 + \beta7 = 0$	.414	.277	.519	.311

Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Two-way clustered standard errors at the municipality and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

Table 1.G.48: Effect of avocado suitability and world price on crime rate (by type) - Michoacán

	Crime rate in municipality m in year t (2011-2017)						
	Category 1			Category 2		Category 3	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Extortion	Threat	Kidnap	Robbery	Theft	Injuries	Other
suitability_cont × Avocado price (lag)	1.26	-4.79	1.42	-55.77**	-19.62	55.05*	9.18
	(1.25)	(5.50)	(5.87)	(17.66)	(16.95)	(24.76)	(6.87)
USDA_ever=1 × Avocado price (lag)	3.84	-32.41*	51.38**	-75.42	-53.84	239.40**	11.50
	(3.12)	(14.11)	(19.36)	(101.61)	(42.21)	(79.43)	(23.77)
USDA_ever=1 × suitability_cont × Avocado price (lag)	-2.56	17.05*	-19.76*	72.39	43.89	-124.03**	-7.40
	(1.59)	(7.42)	(9.97)	(48.19)	(24.26)	(40.64)	(11.51)
Observations	658	658	658	658	658	658	658
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample mean of Y	1.75	12.4	36.6	85.5	98.9	89.9	10.6
Test p-val: $\beta6 + \beta7 = 0$	.45	.0711	.0188	.958	.622	.0289	.754

Fixed effects models are estimated with linear regression with multiple levels of fixed effects (Stata: reghdfe). Two-way clustered standard errors at the municipality and year level in parenthesis. Where indicated, control regressors include the lagged US retail price of cocaine, population size, Gini index, and standardized values of poverty and illiteracy rates in the municipality. Significance levels: * p<0.10 ** p<0.05 *** p<0.01.

Chapter 2

Informal labor exchange teams and participation on the labor market: Evidence from rural Tanzania

2.1 Introduction

Labor markets are inherently incomplete. Employers face the challenge of finding the right employees and then motivating them to perform accordingly. While these problems are pervasive, they are exacerbated in rural economies of poor countries where financial frictions, the seasonality and the limited scaling of production processes lead to strong fluctuations in the demand for labor. Therefore, the benefits of long-term relationships in managing these frictions – which allow for lower search and incentive costs – often cannot be realized. While long-term personal interactions between community members have been successfully used to reduce credit market imperfections in remote areas, less is known about whether similar arrangements can improve the efficiency of labor markets.

In this chapter, we show that informal long-term arrangements between community members to help each other in own farm production, so-called *labor-exchange teams*, improve members' attractiveness on the labor market. In our study villages, some women (and only women) engage in labor exchange. We observe that those who are part of a team have higher chances of being hired when paid labor is available than women who are not part of a team. This, however, only holds if they are hired as a team as opposed to individually, and is particularly pronounced for tasks that are costly to monitor for the employer.

This chapter is joint work with Christelle Dumas (University of Fribourg) and Matthias Fahn (University of Hong Kong). We thank Anik Ashraf, Holger Herz, and participants at the 2024 German Development Conference and the 7th Conference of the Development Economics Network Switzerland for their helpful comments. A version of this chapter has been disseminated as a working paper (See Arciniegas et al. (2025)). This chapter differs from the working paper only in minor stylistic adjustements. We received financial support from the research initiative 'Structural Transformation and Economic Growth' (STEG), a programme funded by the UK's Foreign, Commonwealth & Development Office (FCDO), contract reference STEG_LOA_1465_Dumas. The views expressed here are not necessarily those of FCDO.

We propose a theoretical explanation that is based on the notion that cooperation in a team is supported by an informal relational contract that is enforced through repeated interaction. In our model, team members collectively agree that any member's low effort will be penalized by suspending cooperation within the labor exchange team for their own farm production. This heightened penalty for low effort strengthens the employer's incentives for the team, encouraging greater effort from the team members. As a result, employers find it more appealing to hire these teams, especially when monitoring is expensive. Therefore, the ongoing interaction among team members for their own farm production substitutes for the absence of long-term employment relationships.

More precisely, we analyze an infinitely repeated game in which two agents engage in their own farm production and can achieve efficiency gains by helping each other. Cooperation requires a self-enforcing agreement between agents, maintained by the threat of dissolving the team if someone deviates. Since workers are risk averse, those with less wealth have more to lose from a deviation and are therefore more likely to be part of such an agreement ("team"). Each period, agents may also receive employment offers, where they earn a market wage and must decide how much effort to put in. Greater effort increases the likelihood of producing high-value output for the employer (principal). The employer faces two decisions: the level of monitoring and whether to hire individuals or groups.

The employer can choose limited monitoring, observing only the output value, or extensive monitoring, which is costlier but allows direct observation of effort. Workers are incentivized through punishment for non-performance, defined as low-value output under limited monitoring or low effort under extensive monitoring.

When hiring, the employer can hire individuals or a group of workers. A group consists of several individuals working together on the employer's farm and may be part of a labor exchange team for their own farm production. Under limited monitoring, hiring a team is advantageous because team members can observe each other's effort. Teams can form side agreements to exert higher effort than would be optimal individually, benefiting both the team – who thereby can internalize the positive effect one agent's effort has on the other agent's utility – and the employer. This agreement is enforceable as deviations not only increase the risk of punishment by the employer but also lead to the dissolution of the team. This added punishment results in higher effort levels from the agents and, consequently, greater profits for the employer.

We derive testable predictions from the model, that we can test using data collected from 300 households in several rural villages in north-west Tanzania. The data were collected from women and from employers. The sample was designed so that half of the women were part of a labor exchange team. We first established a baseline at the beginning of the agricultural season, and then interviewed the respondents every week for eight consecutive weeks. This allows us to obtain precise information on their farming activities, whether individual own farm production, team production or transactions on the agricultural labor market. We show that the predictions of the model are borne out by the data: women from lower socio-economic backgrounds, i.e., those from a less affluent environment, are more likely to participate in labor exchange teams. Moreover, being a member of such a team provides additional opportunities for paid employment, especially for tasks where effort is harder to observe.

Given that our dataset is fully observational, we address the risk of omitted variable bias in the following way. We include additional covariates, which presumably capture heterogeneity in the willingness and ability to work, as well as differences in productivity. Second, we run a matching estimation, to accommodate a possible misspecification in our covariates. Last, we use Cinelli and Hazlett (2019) to assess to which extent our result might be driven by unobservable characteristics. We show that to explain our result, an extreme confounder that explains 100 percent of the residual variance of the outcome would have to explain at least 23 percent of the residual variance of the treatment to fully account for the observed estimated effect. Stated differently, this shows that even if we cannot establish that our estimate is fully causal, we can reject that the true causal effect of labor exchange teams on propensity to be hired is equal to zero.

Other mechanisms may also explain some of our results but the totality of our findings is unlikely explained by these alternative mechanisms. In particular, given that team participation increases only the propensity to be hired as a group and does so for tasks which are more difficult to monitor suggests that signalling, lower transaction costs and networking mechanisms cannot fully account for the results. We also provide evidence that the benefits of hiring a team are limited by the liquidity constraints of the employers, who are unable to hire a whole group despite its efficiency.

Our research contributes to several strands of literature. First, our research addresses the question of the link between community ties and the market. Recent microeconomic data provides conflicting views on whether social ties have a positive influence on labor market outcomes (Mas and Moretti, 2009), a negative influence (Bandiera et al., 2013; Akerlof et al., 2023; Ashraf, 2022), or have ambiguous effects (Bandiera et al., 2009, 2010).[1] This suggests that these social links can play out differently, depending on the nature of the link, the market environment and the type of pressure exerted on individuals. In our case, we are interested in the consequences of relational contracts (i.e. arrangements that have been chosen by individuals) on employment prospects in a developing country setting.

[1] Additional angles to this question include a historical perspective, suggesting that social ties were important for establishing transactions in contexts where it was difficult to enforce them (Greif, 1989, 1993; Landa, 1981), as well as theoretical contributions (Kranton, 1996; Ishiguro, 2016; Bodoh-Creed, 2019).

We also contribute to a second strand of literature on labor market imperfections in rural areas of poor countries, which have been largely documented (Shapiro and Stiglitz, 1984; de Janvry et al., 1991; Bharadwaj, 2015; Dillon et al., 2019). Besides tests of market efficiency, a smaller literature looks into how informal arrangements may help reaching efficiency or approach it. This is the case, for instance, of sharecropping. Stiglitz (1974) shows that sharecropping can be an efficient solution when the landowner/employer cannot observe the worker's level of effort. The reduced information asymmetry among the community also implies that the worker has a comparative advantage in supervising all the hired labor (Eswaran and Kotwal, 1985). We document a similar informational advantage for women labor-exchange teams. Takasaki et al. (2014) find that labor exchange in Amazonia substitutes for the market and allows an efficient allocation of labor. However, the mechanism through which the efficient allocation is obtained cannot be tested with their method, and it is not clear whether it is only due to the flexibility the arrangement provides or if it is explained by reduced information asymmetries, as we suggest.

Third, we contribute to the literature on labor exchange, which remains scarce, despite the fact that it remains common in various sub-Saharan countries and other developing countries around the world. In SSA, labor exchange groups have been documented in Cameroon (Geschiere, 1995), in Zimbabwe (Worby, 1995), in DR Congo (Suehara, 2006), in Uganda (Shiraishi, 2006), and in Ethiopia Mekonnen and Dorfman (2017). Labor exchange has been shown to take two main forms (Krishnan and Sciubba, 2009). The symmetrical form consists of a well-defined group of individuals who join forces and rotate the person who benefits from the work according to a pre-established schedule (this is also known as a rotating labor association (Wang, 2019)). The asymmetrical form consists of calling "work parties", during which many individuals work on a plot in exchange for food and drink; reciprocity is expected but may take place in the distant future. The organization of the exchange of labor that we describe in this article belongs to the former category and has been shown to require the constitution of homogeneous groups (Krishnan and Sciubba, 2009).

The mere existence of labor exchange is interesting because it does not increase the amount of work provided on the farm (since, by design, every hour received must be compensated for by an hour provided on someone else's plot). First, it seems that team members benefit from increased motivation due to sharing tedious tasks with peers (Bevan and Pankhurst, 1996; Mekonnen and Dorfman, 2017). The arrangement also makes it possible to have more labor on the farm at a key time, despite the absence of a paid labor market (Moore, 1975) or the impossibility of hiring for lack of cash (Bassett, 2002). Although the total workforce does not increase, working in a group means that a larger area can be covered in a given time, which is often more efficient and also means that the farmer can react quickly to weather forecasts for rainfall.

Last, our qualitative interviews before the data collection revealed that economies of scale may be achieved with a larger workforce. The estimates of the benefits of belonging to a labor-exchange agreement are strikingly high, as Mekonnen and Dorfman (2017) find an increase in productivity by 30% in Ethiopia. Fumagalli and Martin (2023) also find that creating labor exchange groups reduces child labor in Mozambique, which is consistent with the idea that labor exchange teams reduce labor market imperfections (Dumas, 2013; Bharadwaj, 2015).[2] Our paper contributes to this literature by highlighting an additional benefit of labor exchange: reducing monitoring costs and providing women with more paid-work opportunities.

We organize the rest of the chapter as follows: Section 2.2 describes the data and documents facts that are crucial to the understanding of the context. Section 2.3 is devoted to the theoretical model and the predictions it provides, while Section 2.4 provides the empirical analysis and the tests of these predictions. Section 2.5 presents a battery of validity tests on the robustness of the results. Section 2.6 discusses alternative explanations and other market effects. Section 2.7 concludes.

2.2 Data and Context

2.2.1 Data

We use data collected in the Bukoba Rural district (Kagera region) in northwestern Tanzania (see the map in Figure 2.D.1). Ten villages were surveyed, and 89 labor exchange teams were identified in these villages during the listing phase. In each village, we sampled ten women participating in labor exchange teams (WLT), ten women not participating in such teams (WNLT) and ten richer farmers who hire workers on a regular basis (we call them "landlords"). This sample allows us to compare labor outcomes between women who form teams and those who do not, as well as to identify preferences for the different types of labor supply. Sampled women also had to meet the following criteria: they had to farm their own plots and had to be between 18 and 55 years old. In addition, no more than two women from the same team could be surveyed. Thus, the total sample consists of 300 respondents, of which 200 are women.

We focus on women because previous qualitative interviews revealed that only women engage in labor teams in Bukoba, and also because the majority of agricultural labor supply is provided by women, as is the case on average in Tanzania (Palacios-Lopez

[2] A few papers also assess whether the existence of labor-exchange teams is explained by trust and social capital but find conflicting results (Tu and Bulte, 2010; Wang, 2019).

et al., 2017)[3] Men tend to look for alternative jobs, such as mechanics or carpenters, in neighboring towns. Women, because they are less mobile than men (van den Broeck and Kilic, 2019), have to find a job in their village.

The survey consists of a baseline that took place during the last two weeks of February 2023, and an eight-week follow-up which began in March 2023. The baseline survey was conducted in person, the follow-up survey was conducted by telephone.[4] The entire survey was conducted during the long rainy season, when most agricultural activities take place.

The baseline questionnaire includes, for all respondents, the household roster, and modules on education and labor of household members, land and agriculture, housing and assets, and measures of welfare and assistance. Women's questionnaires include two additional modules on empowerment and health measures. Core to our analysis, each survey included a set of specific questions to capture the hiring behavior of landlords and the women's farming and economic activities. Specific questions related to labor exchange were also asked to team members.

The follow-up questionnaire consisted of a two-modules questionnaire asking respondents, every week, about the activities done in each of the past seven days and about the activities they expected to do during the upcoming week. This design has the objective of limiting measurement error associated with long-term recall in standard end-of-season agricultural questionnaires (Arthi et al., 2018). Given that most activities are defined by half-day (e.g. morning, afternoon), we collect information for each half-day of the previous week.

2.2.2 Labor teams

We first document the existence and organization of labor exchange teams. In the ten villages that were surveyed, all women participating in a team were listed. If we compare the number of participating women with an estimate of the female population in these villages, we find that about 9% of women between the ages of 18 and 55 exchange labor.[5] This figure ranges from 3% to 21% in our sample of villages.

Based on our survey, we find that the teams are quite large, with an average of ten women. In the week prior to the baseline, women worked on their own plots for an average of six half-days per week, and team members spent 1.38 half-days farming

[3] Palacios-Lopez et al. (2017) estimate the female share of agricultural labor in Tanzania at 52%. van den Broeck and Kilic (2019) estimate that participation in off-farm employment of rural women in Tanzania was between 34% and 40% using LSMS data for 2011 and 2013, respectively.

[4] Enumerators were instructed to choose a day of the week (e.g., Tuesday) that was convenient for the respondent and to call systematically on that day.

[5] As of today, the detailed census of 2022 has not been released. However, we combine the 2012 Tanzanian census (information at the village level) with the 2022 census (information at the ward level) to estimate the population of each age and gender in the ten surveyed villages.

together, demonstrating the importance of the team to those who are part of it. Among team members, most (89%) participate in only one team and 9% participate in two teams.

The organization of team activities is rather fixed. This means that the women have a fixed schedule of when they meet. This would usually be a few pre-determined mornings when they meet to farm a member's plot. The schedule that determines who benefits from the joint work is usually well defined, but there may be discussions if some members are willing to switch.[6] In addition to this standard pre-defined organization, chosen by 83% of the groups, women say they can meet spontaneously on additional days to work together (86%). Exclusion from the team is rare[7] and the teams are long-lasting, as the average duration of an existing team in our sample is 6.3 years. These statistics suggest that the bonds of labor teams are persistent and quite strong.

Table 2.2.1 provides the motivations of women for participating in labor exchange teams. Most reasons pertain to gains either due to returns to scale or enhanced motivation by working with other people. 46% of women say that being a member of a team gives them access to wage work, and this is the aspect we are particularly interested in this chapter, as to the best of our knowledge it has not been documented before.

Table 2.2.1: Reasons to join a labor exchange team

Reason	(%)
It allows me to cultivate a larger plot than alone	70
We support each other while working together	52
It allows me to have access to wage work and get extra money	46
It allows me to cultivate the plot, otherwise I could not do it myself	43
It is more efficient to work with other women	19
It allows me to work independently of my husband	6

Sample: All 100 women who are members of a WLT.
The survey asked the respondents: *"Why did you decide to join/create this labour-exchange group?"*. Multiple answers were allowed.

2.2.3 Labor demand

Very few landowners hire workers on a permanent or long-term basis. The main reason for this is that agricultural activities fluctuate according to the season and the demand for work is very low at certain times. Table 2.B.1 shows the share of surveyed employers

[6] This understanding is based on qualitative interviews conducted prior to the survey collection in May 2022.

[7] Only 8 of the work-sharing teams in our sample have experienced exclusion or replacement of a previous member. Only one case was due to "the person being lazy or not productive enough," while the rest consisted of the member voluntarily leaving the group.

who may hire workers for each farming task. The main task requiring hired labor is land preparation (73%), followed by weeding (52%) and sowing/planting (40%). Only a quarter of employers hire external labor for harvesting. As a result, workers are mostly hired on a casual basis, either by the day (or half-day) or by the task to be performed. The labor market is therefore best characterized as a spot market, and the low connectivity between villages makes it unlikely that workers will be hired from outside the village.

The survey collects information on the perceived benefits of group versus individual hiring from the employer's perspective. Recall that the definition of group work is that several workers are hired jointly. If the payment is task-based, the whole group will be paid jointly. These groups may be a labor exchange team but this is not necessarily the case. Table 2.2.2 lists the reasons why employers might prefer individual hiring. The main reasons given are that the employer does not have sufficient need to hire a full group, and because individual workers are easy to find and hire. Interestingly, 35% say they would not be able to hire a group due to lack of liquidity. However, employers also see clear advantages in hiring a group (Table 2.2.3): 77% say they are more efficient, 39% that they monitor each other, 37% that they usually work together. While some of these options may cover multiple mechanisms, the monitoring argument that we develop in the next sections suggests that employers may be able to outsource the supervision of workers when they hire a team.

Table 2.2.2: Why employers prefer to hire individuals

Reason	(%)
I just need one or two individuals	47
I do not have enough money to hire a group	35
I can find them easily	34
They are available when needed	23
I am used to working with them	6
Groups can create problems	3
Other reason	2

Sample: All employers who declare hiring individuals for at least one agricultural task.
The survey asked the respondents: *"Why do you prefer to hire individuals for [TASK]?"*. Multiple answers were allowed.

2.2.4 Constraints in the labor market

Although groups are said to be more efficient, 87% of the labor market transactions we observe are individual hires. We explain this by the liquidity constraints faced by

Table 2.2.3: Why employers prefer to hire teams

Reason	(%)
They do a larger task in the same amount of time	77
They monitor each other	39
They usually work together	37
I've known them for a long time	9
I have more trust in a group	8
Easier to hire a full group	6
Reliability	3

Sample: All employers who declare hiring teams for at least one agricultural task.
The survey asked the respondents: *"Why do you prefer to hire labor teams for [TASK]?"*. Multiple answers were allowed.

employers. Using the follow-up survey, we compare the landlords' planned activities for the coming week with the realized activities reported in the next interview. In the majority of weeks, such a discrepancy was reported by the landlord.[8] In 86% of cases, the stated reason is that the employer was unable to hire because of a liquidity constraint. In only 9% of cases was this due to the unavailability of workers.

We also ask the women if they would be willing to work the next day. The job description in the question is well defined and is a very common task for women in the area (planting beans). 60% would accept, while 40% say they have other activities planned. In additional questions, we ask them their reservation wage for this task. We interpret this majority of women willing to accept a paid work for the next day as evidence of an oversupply in the labor market. First, far fewer than this 60% will have the opportunity to work. Second, we believe that this figure underestimates the actual willingness of women to provide wage work, as we ask the question for the following day, leaving women limited possibility to reorganize. Therefore, we believe that in these village economies, labor demand is usually binding. This assessment is consistent with the findings of Dillon et al. (2019) of excess labor supply in rural Tanzania.

2.3 Model

Next, we build a theoretical model based on the findings above. The model is simplified in some dimensions and intended to capture the relevant trade-offs while still being tractable. We then use the model to derive predictions about who is more likely to participate in labor exchange teams, and how membership in exchange teams affects labor market prospects.

[8] In 57% of the employer-week observations, there were activities for which the employer had planned to hire workers for the previous seven days, but which did not ultimately take place.

2.3.1 Setup

There are two workers/agents $i \in \{1, 2\}$ ("she"), each endowed with some wealth that generates a continuous consumption flow W^i, and one employer/principal ("he")[9], who can potentially interact over an infinite time horizon with periods $t = 1, 2, ...$ All players share a common discount factor δ.

The principal is risk neutral, agents are risk averse, and their per-period preferences are characterized by the utility function $u(c_t^i)$, where c_t^i is agent i's per-period consumption, and $u'(\cdot) > 0$, $u''(\cdot) < 0$.

Agents can either have their own farm production or – if offered employment – work for the principal. In the following, we will first describe farm production and then the fundamentals underlying paid labor.

2.3.1.1 Farm Production

In every period, agents can engage in *individual* farm production and generate a net value $\theta > 0$. They can also help each other, at private cost $\alpha > 0$. If agent j helps agent i, agent i's value from farm production is $\gamma\theta$, with $\gamma > 1$. For simplicity, we assume that the agent can still create her own value if helping the other, transfers between agents are not possible. We call it a "team" if agents help each other, making the details of the team arrangement precise below.

Note that we choose this specification of teamwork in which mutual help can happen in every period solely for simplicity. A model in which agents can take turns helping each other (and then not work on their own farm) would generate the same qualitative results. However, the analysis would involve more cases since we always had to distinguish between an agent giving and an agent receiving help.

2.3.1.2 Paid Labor

In any period, the principal requires the input of both agents with probability p. We assume this probability is exogenous and does not depend on the arrangement between agents (which, as we will show below, are associated with different profits to the principal). Assuming that agents that generate more profits are hired more frequently would further increase the benefits of being in a team but have no further qualitative implications.

[9]Please note that, while it differs from the usual conventions in the literature, we use the pronoun "she" for agents and "he" for principals.

This choice reflects our empirical setting, where workers are predominantly female and employers are predominantly male.

If they are hired by the principal, the agents cannot engage in their own farm production. Instead, they choose work effort $e \in [0, 1/2)$ at individual effort costs $e^2/2$. Then, an output with value $\vartheta \leq 1/2$ is realized with probability $e_1 + e_2$, and no output with probability $1 - e_1 - e_2$. Thus, the total net value generated by the agents' effort is $(e_1 + e_2)\vartheta - e_1^2/2 - e_2^2/2$, and efficient, "first-best," effort is characterized by

$$e_1^{FB} = e_2^{FB} = \vartheta.$$

The principal pays a salary s to each agent, which is exogenously given and determined by factors outside our model such as norms or market conditions[10].

Moreover, the principal can choose between limited and extensive monitoring. With *limited monitoring*, the principal only observes the output; with *extensive monitoring*, he observes each agent's effort. We normalize the costs of limited monitoring to zero, the costs of extensive monitoring are $m > 0$. Agents, however, are able to mutually observe each other's effort at no cost.

To provide incentives to exert effort, the principal can impose a punishment on agents for non-performance and reduce each agent's utility by a value q, with $0 < q < \vartheta/2$. Non-performance means low output in case of limited monitoring, and "low" effort in case of extensive monitoring (below, we make precise what we mean by low effort). We assume q to be exogenously given, it may originate from reduced future employment opportunities, lower future payments, reputational losses, and so on. This formulation with an exogenous punishment q is a short-cut for a more complicated informal long-term employment contract, which however would yield qualitatively very similar results. For simplicity, we assume that q is not subtracted from the principal's utility and that, once it has been imposed on agents, nothing changes in their future relationship.

Finally, we assume s is sufficiently high and/or q is sufficiently small for the agents to find it worthwhile to work for the principal and forego the value from home production. This assumption incorporates evidence that paid labor is very popular among individuals in our data.

2.3.1.3 Timing

The timing within one period is as follows: At the beginning of a period, agents decide whether to form a team or not. Then, they either may receive an offer by the principal. If they receive an offer and accept it, they receive the salary s and then make their effort decisions. At the end of the period they receive the punishment q if performance has not been satisfactory, after which the period ends. If they reject an offer or do not receive

[10]See Breza et al. (2019) for the role of norms in sustaining high wages on labor markets

one in the first place, agents engage in their own farm production and simultaneously decide whether to help each other or not.

In the following, our aim is to characterize subgame perfect equilibria, with a particular focus on the conditions needed to sustain cooperation between agents, and on arrangements maximizing the principal's profits.

2.3.2 Team Arrangement

Here, we explore the conditions under which agents find it optimal to form a team. Arrangement between agents are not verifiable, thus cooperation requires a self-enforcing agreement. If paid labor is not offered in a period, agents engage in their own farm production. Then, if the agent works on her own, her per-period utility is $u(W^i + \theta)$, where W^i is an exogenous consumption flow generated by the agent's wealth and θ the net benefit from individual farm production. If, on top, both agents help each other, an agent's per-period utility is $u(W^i + \gamma\theta) - \alpha$ in every other period.[11] Therefore, cooperation is desired if $u(W^i + \gamma\theta) - \alpha > u(W^i + \theta)$ holds. However, this condition is not sufficient for a team arrangement to work.

In addition, it must be optimal for each agent to cooperate, instead of not helping the other agent and but only enjoying the benefits of being helped. Any arrangement cannot be legally enforced, thus we derive the conditions under which a standard grim trigger strategy can sustain cooperation. It follows that, after one agent deviated and did not cooperate in the team, the team breaks up, and agents have to engage in individual farm production in all subsequent periods. In addition, we take into account that the utility from being hired by the principal in future periods can also depend on whether the agents are part of a well-functioning team. Therefore, we denote the utility agents obtain when being employed by u_a^E, where $a \in \{I, T\}$ captures the nature of the agents' arrangement for home production, with $a = I$ standing for individual and $a = T$ standing for team production. As we will see below, $u_I^E \neq u_T^E$.

From now on, we omit i-subscripts to simplify notation. Then, an agent's expected utility stream if the team arrangement is honored in every period equals

$$\begin{aligned}
&\sum_{\tau=t}^{\infty} \delta^{\tau-t} \left[(1-p)\left(u(W+\gamma\theta)-\alpha\right)+pu_T^E\right] \\
=&\frac{(1-p)\left(u(W+\gamma\theta)-\alpha\right)+pu_T^E}{1-\delta}.
\end{aligned}$$

If an agent is not part of a team, her expected utility stream is

[11] Our assumption that an agent's utility is additive on consumption and helping costs is solely made for simplicity.

$$\frac{(1-p)u(W+\theta)+pu_I^E}{1-\delta}.$$

If an agent decides to deviate from the agreement, she only receives but does not give help in the given period. Thereafter, the team breaks up. Therefore, an agent's utility in the period where she deviates is $u(W+\gamma\theta)$ (instead of $u(W+\gamma\theta)-\alpha$ if she also provides help) and – provided cooperation is desired – it is optimal for an agent to help the other, if

$$\begin{aligned}&u(W+\gamma\theta)-\alpha+\delta\frac{(1-p)\left(u(W+\gamma\theta)-\alpha\right)+pu_T^E}{1-\delta}\\&\geq u(W+\gamma\theta)+\delta\frac{(1-p)u(W+\theta)+pu_I^E}{1-\delta}\end{aligned}$$

$$\Leftrightarrow \alpha\leq\bar{\alpha}\equiv\delta\frac{(1-p)\left[u(W+\gamma\theta)-u(W+\theta)\right]+p\left(u_T^E-u_I^E\right)}{1-\delta p}.$$

Thus, $\bar{\alpha}$ determines the threshold of the cost of helping above which cooperation in a team is not feasible. If it is larger, it is "easier" to sustain teamwork, thus we are interested in how several variables affect its size. Relatedly, we define

$$\Delta\equiv\frac{(1-p)\left[u(W+\gamma\theta)-\alpha-u(W+\theta)\right]+p\left(u_T^E-u_I^E\right)}{1-\delta}$$

as an agent's expected (net) benefit of teamwork. The size of Δ will be particularly relevant later on, when we establish links between teamwork and paid labor. Comparative statics of $\bar{\alpha}$ and Δ are collected in Proposition 2.1.

Proposition 2.1. *Assume $\bar{\alpha},\Delta>0$. Then, $d\bar{\alpha}/d\delta, d\Delta/d\delta>0$. Moreover, $d\bar{\alpha}/dW, d\Delta/dW<0$ if p is sufficiently small.*

A higher δ makes the future more valuable, thus increases the (future) benefits of cooperation and therefore also of $\bar{\alpha}$. Importantly, the discount factor δ not only captures time preferences, but also the frequency of interaction, where more frequent interaction is associated with a higher δ. This link will become important later on when we analyze the principal's benefits of hiring a team. A higher wealth level W reduces an agent's marginal utility. Therefore, the benefits of cooperation ceteris paribus go down. The total impact of a higher W on $\bar{\alpha}$ and Δ must take into account that the benefits from paid labor are affected as well. There, note that in our data the frequency of paid labor is rather low (compared to home production), thus we would argue that the effect of W on paid labor can be neglected. All this allows us to state our first prediction:

Prediction 2.1. *Women from wealthier households are less likely to be part of a team.*

2.3.3 Employment Relationship

With probability p, the principal offers an employment contract to the agents. We abstract from the possibility that the principal only needs one agent, or that he might go for someone else. We interpret the following results in the sense that a more profitable arrangement is more likely to actually be chosen by the principal. As described above, an employment offer contains a salary s for each agent, effort levels e_i associated with effort costs $e_i^2/2$, and a punishment q upon non-performance. Moreover, the principal chooses between limited monitoring at which he observes the output at no cost, and extensive monitoring at which he observes each agent's effort at cost m. In the following, we first analyze optimal arrangements under limited and under extensive monitoring, and then discuss the principal's choice.

2.3.3.1 Limited Monitoring

Under limited monitoring, we distinguish between two possible agreements. The first, *bilateral agreements*, assumes that either the agents have not formed a team, or that what happens in the employment relationship has no effect on the team. The second, *multilateral agreement,* assumes that agents have formed a team and have the following side-agreement: They promise each other to exert a given effort level in the employment relationship (recall that they can mutually observe each other's effort at no cost). If one of them deviates, also the team breaks up.

In the following, we use B or M superscripts for bilateral and multilateral agreements.

2.3.3.1.1 Bilateral Agreements

Under a bilateral agreement, each agent receives a punishment q if output is low. Thereby, agent i's optimal effort e_i^B maximizes her utility

$$\begin{aligned}
&(e_1^B + e_2^B)u(W+s) + \left(1 - (e_1^B + e_2^B)\right)(u(W+s) - q) - (e_i^B)^2/2 \\
=&u(W+s) - \left(1 - (e_1^B + e_2^B)\right) q - (e_i^B)^2/2 \\
\Rightarrow& e_i^B = q.
\end{aligned}$$

As stated before, our data suggests that paid labor is very popular among individuals, hence we assume that an agent's participation constraint,

$$u(W+s) - \left(1 - (e_1^B + e_2^B)\right) q - (e_i^B)^2/2 \geq \bar{u}, \tag{PC}$$

where $\bar{u} = u(W + \gamma\theta) - \alpha$ if agents are members of a team, and $\bar{u} = u(W + \theta)$ otherwise, is satisfied.

Therefore, with limited monitoring and bilateral agreements, the principal's per-period profits are are $\pi^B = \left(e_1^B + e_2^B\right)\vartheta - 2s$, or

$$\pi^B = 2\left(q\vartheta - s\right).$$

An agent's utility is

$$u^{EB} = u(W + s) - \left(1 - \frac{3}{2}q\right)q.$$

Before proceeding, it is important to note that if the principal decided to hire only one agent (perhaps due to financial constraints), this agent would still exert an effort level of q, resulting in profits of $q\vartheta - s$. Thus, if hiring one agent is profitable, the same applies to hiring two agents. Additionally, since the production function is additive with respect to the agents' efforts, there is no intrinsic complementarity between them. However, we will demonstrate how a multilateral agreement can endogenously create complementarity between the agents.

2.3.3.1.2 Multilateral Agreement

In a multilateral agreement, agents who have formed a team for farm production "promise" each other to exert some effort level e^M. Before we describe the multilateral agreement in more detail, we first discuss why agents would prefer to commit to effort levels that exceed the effort under bilateral agreements, $e^B = q$. With limited monitoring, each agent receives a punishment q if output is low, and the probability for this depends on the sum of effort levels. Therefore, each agent's likelihood of being punished not only depends on her own, but also on the other agent's effort. Put differently, an agent's effort exerts a positive externality on the other agent's utility, and this externality is not taken into account when making individually optimal decisions in a bilateral agreement.

Therefore, each agent's utility is maximized if this externality is taken into account and effort maximizes the agents' *joint* utility,

$$\begin{aligned}
&2(e_1^M + e_2^M)u(W + s) + 2\left(1 - (e_1^M + e_2^M)\right)(u(W + s) - q) - (e_1^M)^2/2 - (e_2^M)^2/2 \\
=&2u(W + s) - 2\left(1 - (e_1^M + e_2^M)\right)q - (e_1^M)^2/2 - (e_2^M)^2/2,
\end{aligned}$$

i.e., if each agent chooses

$$e^{M*} = 2q.$$

Next, we derive the conditions under which e^{M*} can be enforced. Any level of e^M exceeding e^B requires punishing a deviation, which involves a lower *future* utility of a deviating agent. In our case, agents who work in a farm production team can be punished by a break up of the team – and having bilateral agreements in future instances of being hired by the principal. Furthermore, the optimal deviation for an agent is independent of the other agent's effort and equal to the bilateral effort $e^B = q$.

Therefore, an agent will find it optimal to exert some effort level $e^M > e^B$ if the following incentive compatibility (IC) condition is satisfied.

$$\begin{aligned} &u(W+s) - (e^M)^2/2 - \left(1 - 2e^M\right) q + \delta \frac{(1-p)\left(u(W+\gamma\theta) - \alpha\right) + pu_T^E}{1-\delta} \\ \geq &u(W+s) - (e^B)^2/2 - \left(1 - e^B - e^M\right) q + \delta \frac{(1-p)u(W+\theta) + pu_I^E}{1-\delta}. \end{aligned} \tag{IC}$$

The left hand side gives the utility of honoring the multilateral agreement, the right hand side displays the utility of a deviation. There, it is immediate that any effort exceeding e^B is only possible if agents work in a farm production team, because otherwise, continuation utilities (the terms involving discounting) would coincide.

Taking into account $e^B = q$ and the definition

$$\Delta = \frac{(1-p)\left[u(W+\gamma\theta) - \alpha - u(W+\theta)\right] + p\left(u_T^E - u_I^E\right)}{1-\delta},$$

the (IC) condition becomes

$$e^M q - (e^M)^2/2 \geq q^2/2 - \delta\Delta. \tag{IC}$$

If $e^{M*} = 2q$ satisfies (IC), agents can enforce that effort. Otherwise, they will go for the largest effort for which (IC) holds. It turns out that this effort equals $e = q + \sqrt{2\delta\Delta}$, which implies that

$$e^M = \min\left\{q + \sqrt{2\delta\Delta},\, 2q\right\}.$$

In any case, $e^M > e^B$ for $\delta\Delta > 0$.

Finally, we again assume that e^M satisfies an agent's (PC) constraint, which is

$$u(W+s) - (e^M)^2/2 - \left(1 - 2e^M\right) q \geq u(W+\gamma\theta) - \alpha. \tag{PC}$$

Therefore, with limited monitoring and multilateral agreements, the principal's per-period profits are are $\pi^M = 2e^M\vartheta - 2s$, or

$$\pi^M = 2\left[\min\left\{q + \sqrt{2\delta\Delta},\, 2q\right\}\vartheta - s\right]$$

An agent's utility is

$$u^{EM} = u(W+s) - (e^M)^2/2 - \left(1 - 2e^M\right)q.$$

It immediately follows that

$$\begin{aligned}\pi^M &> \pi^B \\ u^{EM} &> u^{EB},\end{aligned}$$

which is collected in the following proposition.

Proposition 2.2. *Assume limited monitoring has been chosen. Then, effort and utility levels, as well as the principal's profits under a multilateral agreement are higher than under bilateral agreements. Moreover, effort and profits with a multilateral agreement (weakly) increase in the frequency of interaction, δ.*

The principal prefers a multilateral regime because the side arrangement between agents, in which both promise each other to exert effort and in which a deviation leads to a break-up of the team for farm production, increases the effort the agents exert for given compensation and punishment levels. Note that this result would even be stronger if exerting the punishment q was costly for the principal since higher effort reduces the likelihood that a given punishment must be exercised.

2.3.3.1.3 Discussion

When analyzing teamwork versus individual farm production, we have derived the benefits of the former,

$$\Delta \equiv \frac{(1-p)\left[(u(W+\gamma\theta) - \alpha) - u(W+\theta)\right] + p\left(u_T^E - u_I^E\right)}{1-\delta}.$$

The difference $u_T^E - u_I^E > 0$ illustrates that the benefits of teamwork increase in the opportunity to be hired by the principal. Furthermore, hiring teams benefits the principal because effort is higher. The specific friction of the labor relationship, however, is *not* crucial for our results. If, for example, we also modeled employment as a repeated interaction governed by a relational contract (i.e., payments would not automatically be enforced but needed to be self-enforcing), then teamwork would still be beneficial. The reason is that the relational contract between agents in which a deviation would lead to a breakup of the team would also increase the efficiency of a relational contract between principal and agents (see Che and Yoo (2001), Kvaløy and Olsen (2006)).

2.3.3.2 Extensive Monitoring

If the principal decides to extensively monitor the agents with cost $m > 0$, he can observe effort. Then, q is contingent on effort, and the output realization is irrelevant for the specifics of the arrangement. It will also be irrelevant whether agents are in a team of farm production.

Now, the principal requires an effort level e^{ext} from each agent, which again must satisfy the agent's (IC) constraint,

$$u(W + s) - (e^{ext})^2/2 \geq u(W + s) - q. \tag{IC}$$

The highest effort for which this holds is $\sqrt{2q}$. As before, any e^{ext} would need to satisfy an agent's participation constraint,

$$u(W + s) - (e^{ext})^2/2 \geq \bar{u}, \tag{PC}$$

which we again assume to hold. It follows that

$$e^{ext} = \sqrt{2q},$$

which is larger than e^M (and consequently e^B).

Therefore,

$$\pi^{ext} = 2\left(\sqrt{2q}\vartheta - s\right) - m$$

and

$$u^{ext} = u(W + s) - 2q/2.$$

2.3.3.3 Principal's Choice

The principal has the choice between limited and extensive monitoring. Extensive monitoring is costly but allows for higher effort which the principal prefers (given salaries and punishments are fixed). Clearly, extensive monitoring is optimal if m is sufficiently small. Therefore, the next proposition follows from the previously derived results.

Proposition 2.3. *There exist cutoffs m^1 and m^2 such that, for $m < m^1$, extensive monitoring is optimal in any case. For $m \in [m^1, m^2]$, extensive monitoring is optimal* *if the hired agents do not work in a team, whereas limited monitoring is optimal if they work in a team. For $m > m^2$, limited monitoring is optimal.*

Put differently, multilateral agreements between agents are particularly beneficial for the principal if monitoring costs are relatively high; in this case, less monitoring should be observed on average if teams are hired.

All these results yield the following predictions.

Prediction 2.2. *Team members are more likely to be hired on the extensive and intensive margin, however only if they are hired as a group.*

Prediction 2.3. *The hiring propensity for group labor increases in the frequency of interactions of teams.*

Prediction 2.4. *Teams are more likely to be hired for tasks with high monitoring costs m. For these tasks, there is less monitoring for the employer if teams are hired.*

The rent that needs to be paid to motivate the agents is smaller with the multilateral arrangement (presuming the outside option then is not too high). If we assume that agents who work in a team have such a multilateral arrangement, the principal clearly prefers to hire teams over individuals, however only as groups (Prediction 2.2). Finally, because the cost of hiring teams decreases in $\delta\Delta$, teams that interact more frequently are more likely to be hired (Prediction 2.3).

2.4 Empirical analysis

In this section, we use data from the baseline and follow-up surveys to test the main predictions of the theoretical model.

2.4.1 Team membership

We first identify the characteristics of women who are more likely to participate in labor exchange teams. To do so, we build several variables obtained from the baseline survey. All these variables are described in Appendix 2.A. Table 2.4.1 shows that the main determinant of woman's participation to a labor sharing agreement is wealth (as proxied by her ownership of durable goods). This is consistent with prediction 2.1 and reflects the lower marginal utility of the benefits of cooperation for wealthier women. One standard deviation in the wealth score decreases the probability of participation by 21ppt. Conditional on wealth, the women's other characteristics do not seem to affect their participation.

Table 2.4.1: Determinants of participation in a labor team

	Prob. in WLT
	(1)
Age	0.05
	(0.03)
Age sq.	-0.00*
	(0.00)
Household size	0.03
	(0.02)
Married	0.04
	(0.09)
No. of children below age 2	-0.11
	(0.10)
Literate	0.01
	(0.09)
HH total land (ha)	-0.06
	(0.08)
Health PCA score (std)	-0.05
	(0.03)
Housing PCA score (std)	0.03
	(0.06)
Durable goods PCA score (std)	-0.21***
	(0.07)
Prod. Assets PCA score (std)	0.03
	(0.07)
Median wage in the village (log)	-0.03
	(0.11)
Observations	200
Sample mean of Y	.5
Pseudo R2	.074

Sample: all women surveyed during the baseline survey. Logit estimation; coefficients report the average marginal effects (AME). Robust standard errors are reported in parenthesis. Significance levels: $*p < 0.10 **p < 0.05 ***p < 0.01$.

2.4.2 Paid work

Prediction 2.2 states that team members are more likely to be hired by a landowner, and that this effect should be driven by group work. Table 2.4.2 displays the probability of women having obtained agricultural paid work during the eight weeks of the follow-up survey.

Column (1) estimates individual paid work, column (2) estimates group paid work, while column (3) estimates any paid work. Almost half of the women performed individual work during the survey, while only 20% performed paid group work during this period. Overall, slightly more than half of the women provided farm paid work. We find that having a labor-sharing agreement strongly affects the probability of providing paid group work and has no effect on individual work. In total, this increases the probability

Table 2.4.2: Women and paid work - extensive margin

	Prob. of providing paid work Farm labor		
	(1) Individual	(2) Group	(3) Total
Woman in Labor Team	-0.02	0.40***	0.12*
	(0.07)	(0.06)	(0.07)
Observations	200	200	200
Sample mean of Y	.45	.2	.52
Pseudo R2	.117	.284	.158

Sample: all women surveyed during the eight rounds of follow-up survey. Data aggregated across the eight rounds.
Logit estimation; coefficients report the average marginal effects (AME). All estimations include the controls used in Table 2.4.1 (coefficients not shown). Robust standard errors are reported in parenthesis. Significance levels: $*p < 0.10 * *p < 0.05 * * * p < 0.01$.
Note. Col. (3) = Col. (1) + Col. (2)

of providing farm paid work by 12ppt. Table 2.B.2 in the Appendix provides the effect of the covariates and we confirm that women from higher socioeconomic backgrounds are less likely to sell farm labor (prediction 2.1), and this comes only from the individual labor.

In Table 2.4.3, we analyze the number of times the women performed each activity over the eight follow-up weeks. The number of times is collected as half days of activity and should be understood as roughly three hours of work. Panel A shows the OLS estimates. We confirm that women in teams have more paid farm work as a group (+1.22 half-days over the eight weeks), but we do not find any effect on individual employment (column (1)). However, in this specification, the effect on total farm paid work is not significantly different from zero. While this 1.22 half-days over eight weeks may seem marginal, it should be noted that an average woman receives only 3.52 half-days of any farm paid work during the same period.

Panels B and C correspond to a Negative Binomial regression. A Negative Binomial may be more appropriate than the linear regression since the values of the outcome variables are constrained to be positive and usually take low values (in particular for paid work).[12] Panel B provides the coefficients obtained from the Negative Binomial regression, while Panel C provides the average marginal effects.

[12] We have tested whether a Poisson specification is rejected against the Negative Binomial and this is the case; thus we only present the Negative Binomial.

Table 2.4.3: Women and paid work - intensive margin

	No. of times providing paid work Farm labor		
	(1) Individual	(2) Group	(3) Total
Panel A			
Woman in Labor Team	-0.45	1.22***	0.77
	(0.73)	(0.26)	(0.80)
Panel B			
Woman in Labor Team	0.25	19.20***	0.65***
	(0.26)	(0.72)	(0.25)
Panel C			
Woman in Labor Team	0.87	12.08***	2.67**
	(1.00)	(2.74)	(1.35)
Observations	200	200	200
Sample mean of Y	2.91	.61	3.52

Sample: all women surveyed during the eight rounds of follow-up survey. Data aggregated across the eight rounds.
Panel A: OLS regression. Panel B: Negative Binomial regression. Panel C: Marginal effects after Negative Binomial regression. All estimations include the controls used in Table 2.4.1 (coefficients not shown).
Robust standard errors are reported in parenthesis. Significance levels: $*p < 0.10 **p < 0.05 ***p < 0.01$.

The effects that are obtained on paid group work are extremely large; this is due to the fact that women who are not in a labor-sharing arrangement (almost) never provide group work. Therefore, the proportional increase is estimated to be extremely high. More interesting is the column (3), which combines individual and group work. Here, the estimates are more reliable because both WLT and WNLT provide some paid work, albeit at a low level. While the coefficient was not significant in the OLS specification, it is very significant in the Negative Binomial specification. We find that participation in a labor-sharing arrangement increases the number of paid farm work by 65%, or 2.67 additional half days on average. For the rest of the chapter, we focus on the effects on group paid work and therefore use the OLS specification.

Finally, we test prediction 2.3 (teams that interact more frequently have a higher chance of being hired) by focusing on women who are team members. For these women, we compute the number of team interactions they had during the eight weeks of the survey. By team interactions, we mean the exchange of labor for own farm production with team members. We thus create a dummy indicator if the number of team interactions is higher than the sample median. Results are presented in Table 2.4.4.

Table 2.4.4: Paid farm work, heterogeneity by the intensity of interactions in the team

	Extensive and intensive margins of paid work for WLT					
	Did paid farm work (Y/N)			No. of times of paid farm work		
	(1)	(2)	(3)	(4)	(5)	(6)
	Individual	Group	Total	Individual	Group	Total
High Team interactions	-0.07	0.18*	0.09	-0.82	1.14**	0.32
	(0.09)	(0.09)	(0.09)	(1.15)	(0.53)	(1.30)
Observations	100	100	100	100	100	100
Sample mean of Y	.48	.4	.62	2.88	1.21	4.09
(Pseudo) R2	.089	.107	.093	.052	.188	.042

Sample: Women in labor teams (WLT) surveyed during the eight rounds of follow-up survey. Data aggregated across the eight rounds.
Logit estimation for Cols 1-3 (coefficients report the average marginal effects), and OLS estimation for Cols 4-6. All estimations include the set of controls used in Table 2.4.1 (coefficients not shown). 'High Team interactions' is an indicator of whether the woman belongs to a labor team where members had interactions above the median level observed across teams during the follow-up survey. Robust standard errors are reported in parenthesis. Significance levels: $*p < 0.10 **p < 0.05 ***p < 0.01$.

Table 2.4.4 shows that high interactions in the team increase the probability of obtaining paid work and the number of paid work activities. This result is also interesting for asserting the validity of our model and estimation. First, by focusing on women who participate in labor teams, we remove the unobserved heterogeneity between women who exchange labor and those who do not. Thus, among a more homogeneous group of women who choose to exchange labor, we see that the intensity of this informal arrangement affects the women's labor market prospects. Second, the number of interactions between women in a team is likely difficult for employers to observe. This suggests that the effect of the team interactions is due to changes in behavior and incentives of team members rather than a signalling effect for the employer. This team self-monitoring mechanism is the mechanism we have in the model.

We now turn to the wage difference depending on whether the woman is hired individually or in a group. To do this, we use all labor market transactions that are recorded in the woman's questionnaire. Table 2.B.3 shows that the wage does not depend on whether the woman was hired in a group or individually, conditional on her characteristics. Most likely, the lower rent is compensated by other productivity gains associated with group work. From a developmental perspective, it is also important to note that women who engage in labor exchange teams are not penalized by a lower wage in the market.

2.4.3 Monitoring

We now proceed to test prediction 2.4. To do so, we first identify the agricultural tasks for which effort is more difficult to observe. As mentioned above, employers are more likely to hire for pre-harvest activities: land preparation, sowing/planting and weeding. Our priors were that sowing/planting is the activity for which it is most difficult to observe the agents' effort. It is particularly difficult because it is only when the plant starts to grow that employers can check whether the task has been done correctly. In addition, employers are sometimes concerned that some seeds may be stolen by the workers, as they stated in the qualitative interviews before the survey. Sowing/planting is also a task where stakes are higher. If not implemented correctly, the harvest will be poor. By comparison, weeding is done at multiple times during the season and it is possible to compensate for a sub-optimal effort in a previous period. These categorization of tasks into three categories: easy observation of effort (post-harvest tasks); difficult observation of effort (pre-harvest tasks) and very difficult observation of effort (sowing/planting) matches the analysis in Bharadwaj (2015).

Table 2.4.5 presents the hiring preferences of landowners by type of task. The questionnaire asks employers whether they prefer to hire individuals or groups for each agricultural task. Overall, employers prefer to hire individuals, but this may be driven by their liquidity constraints. However, groups are relatively more attractive for sowing/-planting activities. This observation is consistent with the idea that worker effort is more difficult to observe for this task, and therefore employers would prefer to hire teams for this activity.

Table 2.4.5: Hiring preferences by agricultural task (% by task)

Task	Individuals	Groups	Indifferent
Land Preparation	59	33	8
Sowing/Planting	53	41	6
Weeding	59	38	3
Other	81	19	0
Harvesting	77	19	4
Total	64	32	4

Sample: All employers. Sample size: 100. Total number of observations: 397 (100 landlords x 7 activities) landlords-activities in which there is a hiring. The table shows the hiring preference for each task (row percentage)
The survey asked the respondents: *"Please tell me, for [TASK], if you prefer to hire external workers (individuals or groups), or if you prefer to do that activity with household members"*. Only one landlord indicated a preference for doing that activity with household members for land preparation (not shown in the Table).

We can also use the supervision time reported by employers to explore this hypothesis. In the baseline questionnaire, we ask how long they supervise their workers for a full day's work, by agricultural task.[13] We did not ask separate questions depending

[13]We ask only for their preferred hiring mode, leading to a fairly low number of observations.

on how many workers were active in the field, therefore the supervision time cannot be computed per active worker in the plot. As there are presumably more workers in the field when they hire a group, the table overestimates the supervision time per worker in the Groups column compared to the Individuals column.

Table 2.4.6: Average supervision time (hours) by agricultural task and type of hiring.

Task	Individuals	Groups	Ratio
Land Preparation	0.97	0.85	1.14
No. of obs.	*58*	*33*	
Sowing/Planting	1.11	0.83	1.33
No. of obs.	*46*	*36*	
Weeding	1.06	0.96	1.10
No. of obs.	*53*	*34*	
Harvesting	1.37	1.67	0.82
No. of obs.	*40*	*10*	
Total	1.11	0.95	1.16
No. of obs.	*197*	*113*	

Sample: Employers who declare to prefer either individuals or groups for each agricultural task.
Ratio corresponds to the average supervision time of individuals divided by the average supervision time of groups.
The survey asked the respondents: *"For a standard day of work on [TASK], how much time do you spend on the plot checking what your hired workers are doing?"*.

Table 2.4.6 shows that, on average, supervision time is lower for groups, confirming the self-monitoring advantage of teamwork. More interestingly, the discrepancy between supervision time for individuals and supervision time for groups is largest for sowing/planting activities. These results confirm prediction 2.4: monitoring effort in sowing/planting is costly, so employers are more likely to use groups for this task; and in this case, they provide less supervision. For other pre-harvest tasks, the supervision time is lower for groups than for individuals, but the difference is less marked. Finally, the result is reversed for harvesting tasks, as expected. The higher supervision cost for groups is likely explained by the fact that more workers are operating at the same time. However, given that employers rarely hire for this task, we will mostly focus on pre-harvest tasks in what follows.

We then use the detailed information on women's farm activities to assess whether teams have a comparative advantage in sowing/planting. Using all farm activities performed during the survey, we first look at own farm production (first two columns of table 2.4.7). The first column is for team members (WLT), the second one for the other women (WNLT). More than half of the time is spent on weeding, slightly less than 30% of the time on sowing/planting and roughly 15% of the time on land preparation. Harvesting is a very small proportion of time because the survey was conducted at the beginning of the agricultural season. In terms of level, we see little difference between the activities undertaken by team members and the others in own farm production. Weeding attracts two percent more of women's own farm time if they are in a labor team; some other proportions appear as statistically different from each other but the difference is even lower. The last three columns present the same statistics for agricultural paid work. Here, a much larger share of activities is devoted to sowing/planting by women in labor teams (+10% of their time). This table reveals that the comparative advantage of women in teams is indeed in the activity for which effort is more difficult to observe.

Table 2.4.7: Comparison between WLT and WNLT in own farm production vs paid work (%), by agricultural tasks

	Own farm prod.			Paid work		
Task	WLT	WNLT	p-val	WLT	WNLT	p-val
Land Preparation	14.87%	15.76%	*0.26*	13.21%	17.54%	*0.16*
Sowing/Planting	28.81%	30.36%	*0.08*	35.85%	25.61%	*0.01*
Weeding	55.24%	53.11%	*0.04*	49.81%	56.84%	*0.10*
Harvesting	1.08%	0.75%	*0.03*	1.13%	0.00%	*0.06*
Total	100%	100%		100%	100%	
Observations	4,834	5,049		265	285	

Percentages within columns. Sample: All surveyed women (both WNLT and WLT) who declared to have done any agricultural task (this excludes non-farming work and household chores). The level of observation is a half-day for each day of the week across the eight follow-up rounds. Column "p-val" reports the p-value of a two-sample test of proportions between WLT and WNLT for each task.
The survey asked the respondents: *"What was your main activity last [DAY D] in the [MORNING/AFTERNOON]? "* Other Tasks include: Ridging and Fertilizing, Irrigation, and other non-harvesting activities.

Table 2.B.4 in the Appendix presents a regression on the probability of being hired by agricultural task between WLT and WLNT, controlling for observables. The results confirm the previous findings: women in labor teams are more likely to be hired for tasks that require more supervision by the landowners (i.e., sowing and planting).

2.5 Validity tests

One threat to the validity of our empirical analysis is the endogeneity of the labor-sharing participation. Indeed, we can think of many omitted variables that could explain both participation in the informal arrangement and the number of paid jobs the woman can obtain. For instance, if the woman has a limited amount of time available (because she has limited autonomy, or because she has many household chores), then she is less likely to allocate time to a team and also work for someone else. Another potential problem is if the woman has a low productivity and is therefore not accepted in a team or hired by a landowner. In this section, we provide a series of robustness tests to assert the validity of our estimation. First, we include additional covariates to limit the potential bias. Second, we follow Cinelli and Hazlett (2019) and assess the risk that our estimate is so biased that it is actually zero.[14] Finally, we implement a matching strategy.

2.5.1 Controlling for observables

To address the risk of omitted variable bias, we include additional covariates that reflect the woman's willingness to provide work outside her farm. The results are shown in Table 2.B.6. We use the proportion of half-days spent on housework during the survey (column 1). We also use an index of woman empowerment based on several variables (column 2). These variables reflect the power of the woman in the household to make a number of decisions. We then use whether the woman was willing to take on a paid job the next day (column 3), as well as her "reservation wage" for taking that job (column 4). We also include an estimate of the (log) household income (column 5). A potential threat is that the woman has a productivity level that is observed by third parties but not by us. In the main specification, her health is a covariate that is systematically included. In addition, we introduce a measure of grip strength, which is an objective additional measure of the person's strength (column 6).The last column includes all variables together. The estimates are strikingly similar with and without these additional covariates.

2.5.2 Sensitivity Analysis

We then follow Cinelli and Hazlett (2019).[15] The method consists of assessing the extent to which an omitted variable would have to be correlated with both the outcome and the WLT variable to fully explain the WLT coefficient. First, we assess the sensitivity of the extensive margin analysis (Table 2.B.7, Panel A).[16] An extreme confounder (orthogonal

[14]This method is similar in spirit to Oster (2019), but does not arbitrarily set the maximum amount of variance that can be explained in the model.
[15]We use the sensemakr Stata package they provide, see Cinelli et al. (2019).
[16]Here, we run all estimations as linear regressions.

to the covariates) that explains 100 percent of the residual outcome variance would need to explain at least 23.66 percent of the residual variance of the treatment to fully account for the observed WLT effect. Since this is an extreme scenario, we also do the reverse exercise and compute the robustness value. In its notation, $RV_{q0.05} = 33.5\%$. Unobserved confounders (orthogonal to the covariates) that explain more than 33.55 percent of the residual variance of both WLT and the probability of obtaining paid group work are strong enough to bring the WLT estimate into a range where it is no longer statistically different from 0 at the 5% level. This is extremely unlikely to happen, especially in this case, since there is no other variable that explains the fact of obtaining group work.

The sensitivity analysis is quite similar when we study the intensive margin (Panel B). For this estimation, the housing score variable is significant at the 10% level (coefficient 0.35), and we can use it as a benchmark for the size of the omitted variable that could turn the results. If the omitted variable had up to three times the observed explanatory power of the housing variable, our estimate would still be in the [0.68; 1.65] 95% confidence interval. In sum, we cannot claim that our estimate is fully causal but we can show that the causal effect is indeed positive.

2.5.3 Propensity Score Matching

To account for the fact that women who participate in a labor-sharing arrangement differ from those who do not, we assess whether implementing a matching strategy between the two groups yields a similar result. Table 2.B.10 estimates the effect of WLT on labor market outcomes, using propensity score matching. The results are similar in magnitude and statistical significance after matching on observables. Table 2.B.9 shows that the balancing on observable characteristics is satisfactory and Graph 2.B.1 shows the common support.

2.5.4 Effect on other working time variables

We finally assess whether we observe other associations between working in a labor exchange team and working activities. Working in a team and working in a group could displace other activities, leading us to wrongly attribute economic returns to the labor exchange practice. Table 2.5.1 shows that being in a labor team is positively associated with the likelihood of obtaining non farm paid work (Col. 1, significant at the 10% level). However, we do not find such a positive association with the number of times where women obtain such non farm paid work in Col. 2 (neither in the OLS specification, nor in the negative binomial regression specification). Next, we assess whether being in a labor exchange team affects how much work is provided on farm. Given that all sampled women work on their own farm, we do not look at the extensive margin and focus on the intensive margin (Col 3). We do it in the following way: we compute the number of person-half-days of work have been provided on own farm. This includes the woman won labor but also, if applicable, the work of the other team members. We do not see a decrease in the intensity of farming one's own plots. Last, we look at household chores in Col. 4 (again, on the intensive margin) and do not find that working in labor teams displaces household domestic activities.

Table 2.5.1: Women: activities besides paid farm work

	Non-farm paid work		Own farm prod.	Chores
	Prob.	No. of times	No. of times	No. of times
	(1)	(2)	(3)	(4)
Panel A				
Woman in Labor Team	0.12*			
	(0.06)			
Panel B				
Woman in Labor Team		0.55	6.83	2.90
		(0.95)	(9.16)	(2.58)
Panel C				
Woman in Labor Team		0.33	0.06	0.06
		(0.20)	(0.14)	(0.04)
Panel D				
Woman in Labor Team		1.69	3.16	3.14
		(1.10)	(7.37)	(2.54)
Observations	200	200	200	200
Sample mean of Y	0.37	4.91	52.91	56.66

Sample: all women surveyed during the eight rounds of follow-up survey. Data aggregated across the eight rounds. Panel A: Logistic regression (coefficient reports the Average Marginal Effect). Panel B: OLS regression. Panel C: Negative Binomial regression (nbreg). Panel D: Average Marginal Effects after nbreg. All estimations include the controls used in Table 2.4.1 (coefficients not shown). Robust standard errors are reported in parenthesis. Significance levels: $*p < 0.10 **p < 0.05 *** p < 0.01$.

2.6 Mechanisms: more

Liquidity constraints

A natural question is why groups are not hired more often by landlords if they do indeed provide benefits to employers. We now show results suggesting that the liquidity constraints faced by employers prevent them from using this efficient system more often. We construct a variable that reflects whether an employer faced liquidity constraints in a given week and then average this information across all employers in a village. We use information on whether the employer had to cancel a planned activity; if so, and if this was due to lack of liquidity, then we code that the employer faced liquidity constraints in that particular week. We show that the share of group hiring decreases when local landlords have faced liquidity constraints in the previous week (Table 2.B.5), while this is not the case for individual hiring. Interestingly, in Table 2.B.11, we also test whether the benefits in terms of additional paid jobs depend on the liquidity constraints faced by employers in the village.[17] We find that, for the average level of constraints, participation in the labor-sharing arrangement is beneficial in the sense that it increases the probability of being hired for group work by 40% . However, for the observed maximum value of liquidity constraints, the effect drops to 21%.

Information asymmetries: monitoring versus signalling

An alternative explanation for the increased hiring associated with labor-sharing arrangements could be that labor-sharing arrangements are used by women as a signalling device to employers. If this were the case, however, we would expect to observe positive effects also on the *individual* hiring of group members because then, women would be perceived by employers as more productive even when working alone. The fact that we only observe an effect for group hiring is thus better explained by the team self-monitoring mechanism.

Transaction costs

Teams can also benefit employers by reducing transaction costs. If the employer needs to hire several people, he could simply contact the leader of a team and secure and instruct 5-10 workers with just one phone call. The instructions that need to be given to the group can then be passed on by the leader, saving the employer time. While this added benefit of teams may be considered by the employer, it certainly cannot explain all of our findings. In particular, it cannot explain why women are more likely to be hired for tasks where effort is more difficult to observe.

Networking effects and disutility from work

Additional benefits may come from forming labor exchange teams: women strengthen their ties and they may have a lower disutility from working together than working alone, as in Bandiera et al. (2010). This could drive some of our results. For instance, women in a labor team may be more prone to share paid jobs with their fellow workers. However, there are several reasons why we think this mechanism is unlikely to explain the results. First, we have seen that labor demand is binding. Therefore, employers

[17] In this specification, liquidity constraints are averaged over the 8 weeks of the survey.

will hire a group only if this is beneficial to them, and it is not clear how women would have sufficient leverage to make their teammates employed. We have seen that liquidity constraints on the employers' side is decisive in the hiring of groups. Second, if women in a labor team were able to negotiate to turn an individual work opportunity into a group work opportunity, then we would observe a reduction in their likelihood to obtain individual paid work along with the increase in the likelihood to do group work. While the OLS estimate for individual paid work is negative, it is far from significance and, in the other specifications, the coefficient is positive (and not significant).

2.7 Conclusion

Informal institutions that reduce imperfections in credit and insurance markets have been widely studied in development economics. In contrast, we know little about how informal arrangements between farmers can help overcome labor market imperfections. In this chapter, we show that non-market labor sharing arrangements help reduce information asymmetries in the labor market in the context of rural Tanzania. We develop a model that analyzes the interactions between agents who form a labor sharing team in the form of a relational contract, and a principal who can hire the agents to do paid work. We show that the principal has a higher payoff from hiring a labor sharing team because she can outsource monitoring to the team members, who themselves have a higher incentive to cooperate due to their informal labor sharing arrangement.

We tested the predictions of the model using novel data collected weekly in 10 villages in Bukoba Rural District, northwestern Tanzania, during the long rainy season of 2023. Our results confirm the main predictions of the model: (i) women from wealthier and smaller households are less likely to engage in team labor and paid work because their marginal utility of the benefits of cooperation and paid labor is high enough; (ii) team members were 12 percentage points more likely to receive paid work from a landlord than women who did not participate in such labor-sharing teams; and (iii) teams where labor exchange was more frequent were offered more paid work over the eight weeks of the survey. From the employer's perspective, we also show that landowners have more incentives to hire teams for activities that have high monitoring costs, such as sowing and planting. Compared to other agricultural tasks, surveyed landlords reported the lowest supervision time when hiring groups of workers for sowing and planting, and the highest average supervision time when hiring individuals. We find that women involved in labor sharing arrangements are more likely to be hired for these tasks, where supervision is more important. This last result is difficult to explain by mechanisms other than team self-monitoring, ruling out pure effects due to information about the quality of the worker or pure effects due to a reduction in transaction costs.

We also provide evidence that the effects we identify are not (entirely) driven by unobservables that affect both the likelihood of participating in a labor-sharing arrangement and the propensity to take on paid work. We achieve this by showing that our result is robust to the inclusion of a wide range of additional covariates and to the use of propensity score matching, and we also provide a sensitivity analysis of our main results.

Appendix

Chapter 2 Appendix

2.A Definition and construction of variables

Woman in Labor Team Indicator on whether the respondent belongs to a labor exchange team.

Household size Number of people who have meals and sleep in the respondent's dwelling.

Age Age of the respondent. For women, we use the following age categories: 18-31; 32-38; 39-47; 48-55.

Marital status Indicator that takes the value of one (1) if the respondent's marital status is "married, monogamous"; "married, polygamous"; or "living together".

No. of children below age 2 Respondent's number of children who are aged 2 years old or less.

Literate Indicator on whether the respondent is able to read and write (either in Kiswahili, English, or other language).

HH total land (ha) Respondent's self-estimate of the number of hectares (ha) that he household cultivate for the long rainy (masika) season of 2023.

Housing PCA score (std) Principal Component Analysis (PCA) score (standardized with mean 0 and standard deviation of 1) that measures the housing characteristics of the respondent's dwelling using the following criteria: (i) number of household members per rooms in the dwelling is less than 2.5; (ii) major source used for lighting is electricity or lamp oil; (iii) the main fuel used for cooking is not firewood; (iv) the household's main source of drinking water is piped water, private or public outside standpipe/tap, or protected well with pump; (v) the walls of the main dwelling are predominantly made of (mud or baked) bricks, or concrete or cement; (vi) the roof of the main dwelling is predominantly made of concrete, cement, or metal sheets; (vii) the floor of the main dwelling is predominantly made of concrete, cement, or tiles; and, (viii) the main toilet facilities of the household's dwelling are closed pit, ventilated improved pit, pour water toilet, or flush toilet.

Durable goods PCA score (std) Principal Component Analysis (PCA) score (standardized with mean 0 and standard deviation of 1) of asset ownership from a list of 20 non-durable goods.

Health PCA score (std) Principal Component Analysis (PCA) score (standardized with mean 0 and standard deviation of 1) that measures the women's physical functioning and role limitations due to physical health problems using questions 3 to 12 from the RAND's 36-Item Short Form Health Survey (SF-36). See (Hays et al., 1993).

Median wage in the village (log) Log of median wage paid to women who provide paid farm work, measured at the village level.

WLT size (listing) Number of team members in the woman's labor exchange team, as declared during the survey listing phase previous to the baseline data collection.

Avg age WLT members Average age of the woman's labor exchange team members.

WLT members have children 2yo Indicator on whether at least one member of the respondent's labor exchange team has a child aged 2 years or less.

Team interactions > p50 Indicator on whether the woman's labor exchange team number of interactions (to meet and exchange work for free on a rotational basis on each member's plots) were above the median number of interactions of all labor exchange teams during the eight weeks of the follow-up survey.

Liq. Constr. in village (%) Percentage of instances across the eight weeks of the follow-up survey where landlords had to cancel activities for which they had planned to hire workers because the landlord did not have enough money to pay for the workers, measured at the village level.

Indiv. wage work Indicator on whether the woman was hired by an employer to provide farm paid work on an individual basis, rather than as part of a group pf workers.

2.B Additional results

Table 2.B.1: Share of employers who hire for each task

Agricultural Task	(%)
Land Preparation	73
Sowing/Planting	40
Watering	3
Weeding	52
Ridge/Fertilizing	25
Other Non-Harvest	8
Harvesting	26

Sample: All 100 employers in the survey
The survey asked the respondents: *"Please tell me all the tasks for which you sometimes hire external workers"*

Table 2.B.2: Women and paid work - extensive margin

	Prob. of providing paid work Farm labor		
	(1) Individual	(2) Group	(3) Total
Woman in Labor Team	-0.02	0.40***	0.12*
	(0.07)	(0.06)	(0.07)
Age	-0.00	0.02	0.01
	(0.03)	(0.02)	(0.03)
Age sq.	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)
Household size	0.03	-0.00	0.03
	(0.02)	(0.02)	(0.02)
Married	0.01	0.05	-0.01
	(0.08)	(0.07)	(0.08)
No. of children below age 2	-0.31***	-0.01	-0.36***
	(0.11)	(0.07)	(0.10)
Literate	-0.00	0.07	0.06
	(0.09)	(0.06)	(0.08)
HH total land (ha)	-0.13*	-0.01	-0.12*
	(0.07)	(0.04)	(0.07)
Health PCA score (std)	-0.01	0.04	0.03
	(0.04)	(0.03)	(0.03)
Housing PCA score (std)	0.01	0.02	0.01
	(0.05)	(0.04)	(0.05)
Durable goods PCA score (std)	-0.21***	-0.03	-0.22***
	(0.07)	(0.05)	(0.07)
Prod. Assets PCA score (std)	-0.08	-0.05	-0.09
	(0.10)	(0.03)	(0.09)
Median wage in the village (log)	-0.21**	0.11	-0.14
	(0.09)	(0.07)	(0.09)
Observations	200	200	200
Sample mean of Y	.45	.2	.52
Pseudo R2	.117	.284	.158

Sample: all women surveyed during the eight rounds of follow-up survey. Data aggregated across the eight rounds.
Logit estimation; coefficients report the average marginal effects (AME). Robust standard errors are reported in parenthesis. Significance levels: $*p < 0.10 **p < 0.05 ***p < 0.01$.
Note. Col. (3) = Col. (1) + Col. (2)

Table 2.B.3: Pay rate for individual vs group work

	Wage ratio
	(1)
Individual hiring	-0.06
	(0.07)
Household size	-0.05*
	(0.02)
No. of children below age 2	0.14
	(0.09)
Literate	0.10
	(0.07)
HH total land (ha)	0.10
	(0.12)
Health PCA score (std)	-0.01
	(0.03)
Housing PCA score (std)	-0.01
	(0.05)
Durable goods PCA score (std)	0.01
	(0.06)
Prod. Assets PCA score (std)	-0.02
	(0.02)
Constant	1.35**
	(0.52)
Observations	657
Sample mean of Y	1.156
R2	.049

The level of observation is the transaction (measured at the woman-day level). The outcome measures the ratio between the woman's reported wage and the median wage in her village. 'Individual hiring" is an indicator of whether the woman provided paid work as an individual, rather than as part of a group. Regression includes age, age squared, and marital status as controls (coefficients not shown). Robust standard errors are reported in parenthesis. Significance levels: $*p < 0.10 **p < 0.05 ***p < 0.01$.

Table 2.B.4: Hiring by agricultural task

	Probability of being hired for:					
	Land Prep.		Sow/Planting		Weeding	
	(1)	(2)	(3)	(4)	(5)	(6)
Woman in Labor Team	-0.04	-0.04	0.09**	0.11**	-0.09**	-0.11***
	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)
Household size	-0.00	0.00	-0.03**	-0.01	0.04**	0.01
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
No. of children below age 2	0.11***	0.12***	0.04	0.03	-0.22***	-0.21***
	(0.04)	(0.05)	(0.07)	(0.07)	(0.06)	(0.05)
Literate	0.00	-0.01	-0.05	-0.08	0.03	0.05
	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.04)
HH total land (ha)	-0.02	0.00	0.05	0.09	-0.05	-0.09**
	(0.04)	(0.04)	(0.05)	(0.06)	(0.05)	(0.04)
Health PCA score (std)	0.02	0.01	0.00	-0.01	0.00	0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Housing PCA score (std)	-0.00	-0.00	0.07***	0.09***	-0.04	-0.03
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)
Durable goods PCA score (std)	0.03	0.01	0.02	-0.05	-0.05	0.01
	(0.03)	(0.03)	(0.04)	(0.05)	(0.04)	(0.03)
Prod. Assets PCA score (std)	0.05**	0.05**	-0.04	-0.05	-0.05	-0.05*
	(0.02)	(0.02)	(0.05)	(0.05)	(0.04)	(0.03)
Observations	686	579	686	518	686	686
Obs. in task	106	106	215	215	339	339
Sample mean of Y	.17	.17	.26	.26	.571	.57
Pseudo R2	.063	.128	.032	.152	.041	.387
Round FE	No	Yes	No	Yes	No	Yes

The level of observation is the transaction (measured at the woman-day level). The outcome measures the probability of being hired for each agricultural task.

Logit estimation; coefficients report the average marginal effects (AME). Regression includes age, age squared, and marital status as controls (coefficients not shown). Robust standard errors are reported in parenthesis. Significance levels: $*p < 0.10 **p < 0.05 ***p < 0.01$.

Table 2.B.5: Impact of employers' liquidity constraints on paid work

	Wage work: individual vs group Prob. of paid work		
	(1) Total	(2) Indiv.	(3) Group
Liq. Constr. in village-round (%)	-0.08*	-0.04	-0.05**
	(0.04)	(0.04)	(0.03)
Household size	0.02***	0.02***	0.00
	(0.01)	(0.01)	(0.00)
No. of children below age 2	-0.14***	-0.12***	-0.02*
	(0.03)	(0.03)	(0.01)
Literate	0.03	0.02	0.03*
	(0.03)	(0.02)	(0.02)
HH total land (ha)	-0.05**	-0.05**	-0.01
	(0.02)	(0.02)	(0.01)
Health PCA score (std)	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)
Housing PCA score (std)	-0.02	-0.03	0.01
	(0.02)	(0.02)	(0.01)
Durable goods PCA score (std)	-0.07***	-0.04*	-0.04***
	(0.02)	(0.02)	(0.01)
Prod. Assets PCA score (std)	-0.02	-0.01	-0.02
	(0.03)	(0.03)	(0.01)
Round 1 Village wage (log)	-0.03	-0.07**	0.03**
	(0.03)	(0.03)	(0.01)
Observations	1400	1400	1400
Round F.E.	Yes	Yes	Yes
Sample mean of Y	.21	.17	.05
Pseudo R2	.065	.064	.097

Observations are at the woman-round level. The outcome measures whether the woman was hired for paid work in each week of the follow-up survey (Col. 1); and the proportion of instances when she engaged in paid work as part of a group, relative to the total number of times she provided paid work within the week (Col 2). measures the proportion of instances in which landlords were unable to hire workers due to liquidity constraints within each village. Regression includes age, age squared, and marital status as controls (coefficients not shown). Robust standard errors are reported in parenthesis. Significance levels: $*p < 0.10 **p < 0.05 ***p < 0.01$.

Table 2.B.6: Controlling on observables

	Providing paid work (hired as a group)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A : Extensive margin							
WLT	0.402***	0.387***	0.395***	0.388***	0.398***	0.397***	0.385***
	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)	(0.054)
Observations	200	200	200	199	199	200	198
Pseudo R2	.29	.288	.286	.295	.288	.286	.314
Panel B : Intensive margin							
WLT	1.263***	1.174***	1.206***	1.207***	1.245***	1.230***	1.223***
	(0.274)	(0.238)	(0.249)	(0.261)	(0.263)	(0.261)	(0.261)
Observations	200	200	200	199	199	200	198
R2	.183	.169	.173	.171	.192	.172	.232
Control	Chores	Empowerm.	Job next day	Reserv. W.	HH Income	Grip str.	All

Sample: all women surveyed during the eight rounds of follow-up survey. Data aggregated across the eight rounds.
Panel A: Logit estimation. Panel B: OLS estimation. Each column corresponds to a regression where the outcome is providing paid work as a group (probability of being hired in Panel A; number of times of paid work as a group in Panel B). Regressions include all controls as in the main estimation (coefficients not shown) plus the additional control indicated at the bottom.
Robust standard errors are reported in parenthesis. Significance levels: $*p < 0.10 **p < 0.05 *** p < 0.01$.

Table 2.B.7: Sensitivity analysis

Treatment	Coef.	S.E.	$t(H0)$	R2yd.x	RV_q	$RV_{q0.05}$
Panel A: Probability to obtain paid group work						
WLT	0.40	0.05	7.59	0.24	0.42	0.33
Panel B: Number of times with paid group work						
WLT	1.22	0.25	4.85	0.11	0.30	0.19

Sample: all women surveyed during the baseline survey.
OLS estimations.

Figure 2.B.1: Propensity Score Matching: common support

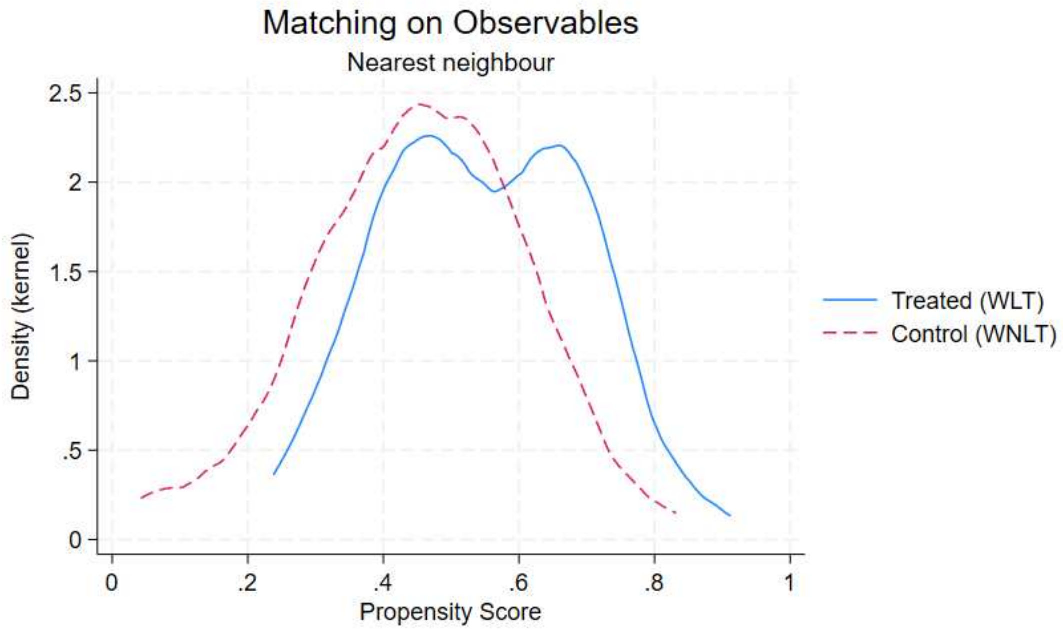


Table 2.B.8: PSM - Common Support

Treatment	Common support		Total
	Off	On	
Untreated	8	92	100
Treated	2	98	100
Total	10	190	200

Table 2.B.9: Propensity Score Matching - Balance test

Variable	Unmatched Matched	Mean Treated	Mean Control	%bias	%reduct bias	t-test t	t-test p-value	V(T)/V(C)
Age	U	38.23	40.1	-18.9		-1.34	0.182	0.81
	M	38.276	37.837	4.4	76.5	0.32	0.748	0.96
Age sq.	U	1548	1715	-21.7		-1.54	0.126	0.79
	M	1553	1523	3.9	82.2	0.28	0.776	0.98
Household size	U	5.060	4.820	12.3		0.87	0.387	0.79
	M	5.041	5.031	0.5	95.7	0.04	0.971	0.74
Married	U	0.710	0.680	6.5		0.46	0.647	.
	M	0.704	0.735	-6.6	-2	-0.47	0.635	.
No. of children below 2	U	0.210	0.210	0		0	1	1.12
	M	0.214	0.214	0	.	0	1	1.12
Literate	U	0.790	0.800	-2.5		-0.17	0.862	.
	M	0.796	0.806	-2.5	-2	-0.18	0.859	.
HH total land (ha)	U	0.635	0.719	-16.4		-1.16	0.249	0.7
	M	0.643	0.668	-4.8	70.5	-0.35	0.728	0.78
Health PCA score (std)	U	-0.099	0.099	-19.9		-1.41	0.161	1.48
	M	-0.040	-0.014	-2.6	87	-0.18	0.861	0.95
Housing PCA score	U	-0.277	-0.140	-16		-1.13	0.26	0.4
	M	-0.288	-0.142	-17	-6.2	-1.37	0.171	0.62
Durable goods PCA score	U	-0.463	-0.208	-35.6		-2.52	0.013	0.45
	M	-0.454	-0.446	-1.1	96.9	-0.11	0.915	1.48
Prod. Assets PCA score	U	-0.137	-0.122	-2.9		-0.2	0.84	1.06
	M	-0.134	-0.128	-1.1	61.9	-0.08	0.935	1.51
Median wage in the village	U	7.439	7.439	0		0	1	1
	M	7.437	7.456	-5.3	.	-0.37	0.71	1.02

Table 2.B.10: Propensity Score Matching Estimations

	Extensive and intensive margins of paid work for WLT					
	Did paid farm work (Y/N)			No. of times of paid farm work		
	(1) Individual	(2) Group	(3) Total	(4) Individual	(5) Group	(6) Total
ATT	-0.02	0.40	0.12	-0.24	1.21	0.97
Std Err	0.08	0.05	0.08	0.89	0.25	0.93
P-value	0.79	0.00	0.12	0.78	0.00	0.30
Observations	200	200	200	200	200	200

Sample: all women surveyed during the eight rounds of follow-up survey. Data aggregated across the eight rounds.
PSM estimations with one neighbor and observations within the common support. The coefficient shows the Average Treatment on the Treated (ATT) effect of being part of a women labor team (WLT) on the probability of providing paid work (Cols. (1) - (3)) and the number of half-days of work provided (Cols. (4) - (6)). The matching estimation includes all determinants used in the main estimation in Table 2.4.1 (coefficients not shown). Reported standard errors are Abadie-Imbens heteroskedasticity-consistent analytical SE with one neighbor. Significance levels: $*p < 0.10 **p < 0.05 *** p < 0.01$.

Table 2.B.11: Paid farm work and landowners' liquidity constraints

	Extensive and intensive margins of paid farm work					
	Did paid farm work (Y/N)			No. of times of paid farm work		
	(1) Individual	(2) Group	(3) Total	(4) Individual	(5) Group	(6) Total
Woman in Labor Team	-0.07	0.68***	0.14	-2.21	2.49***	0.28
	(0.20)	(0.14)	(0.20)	(2.03)	(0.78)	(2.29)
Liq. Constr. in village (%)	-0.17	-0.09	-0.23	-0.33	-0.36	-0.69
	(0.27)	(0.09)	(0.26)	(2.67)	(0.48)	(2.76)
Woman in Labor Team × Liq. Constr.	0.11	-0.61**	-0.05	3.71	-2.67**	1.03
	(0.38)	(0.28)	(0.37)	(4.20)	(1.32)	(4.56)
Observations	200	200	200	200	200	200
Sample mean of Y	.45	.2	.52	2.91	.61	3.52
Coef WLT (at Liq. Const. mean)	-0.02	0.40	0.12	-0.45	1.22	0.77
p-value (at Liq. Const. mean)	0.82	0.00	0.10	0.54	0.00	0.34
Coef WLT (at Liq. Const. max)	0.02	0.21	0.11	0.67	0.41	1.08
p-value (at Liq. Const. max)	0.90	0.03	0.41	0.67	0.23	0.51

Sample: all women surveyed during the eight rounds of the follow-up survey. Data aggregated across the eight rounds. Liq. Constraint in village measures the proportion of instances in which landlords were unable to hire workers due to liquidity constraints within each village. Logit estimation for Cols 1-3 (coefficients report the average marginal effects), and OLS estimation for Cols 4-6. Regressions include all controls used in Table 2.4.1 (coefficients not shown). Mean of Liquidity Constraint in the sample: 0.474. Max of Liquidty Constraint in the sample: 0.778.
Robust standard errors are reported in parenthesis. Significance levels: $*p < 0.10 **p < 0.05 *** p < 0.01$.

2.C Proofs

Proof of Proposition 2.1:

First, we conduct comparative statics for $\bar{\alpha}$, which are

$$\frac{d\bar{\alpha}}{d\delta} = (1-\delta)\,\frac{(1-p)\left[u(W+\gamma\theta)-\alpha-u(W+\theta)\right]+p\left(u_T^E-u_I^E\right)}{(1-\delta p)^2}$$
$$\frac{d\bar{\alpha}}{dW} = \delta\frac{(1-p)\left[u'(W+\gamma\theta)-u'(W+\theta)\right]+p\left(\frac{du_T^E}{dW}-\frac{du_I^E}{dW}\right)}{1-\delta p}.$$

$d\bar{\alpha}/d\delta > 0$ follows from $\bar{\alpha} > 0$. For $d\bar{\alpha}/dW$, note that $u'(W+\gamma\theta)-u'(W+\theta) < 0$; therefore, a sufficient condition for the term to be negative is that p is sufficiently small.

Comparative statics for Δ are

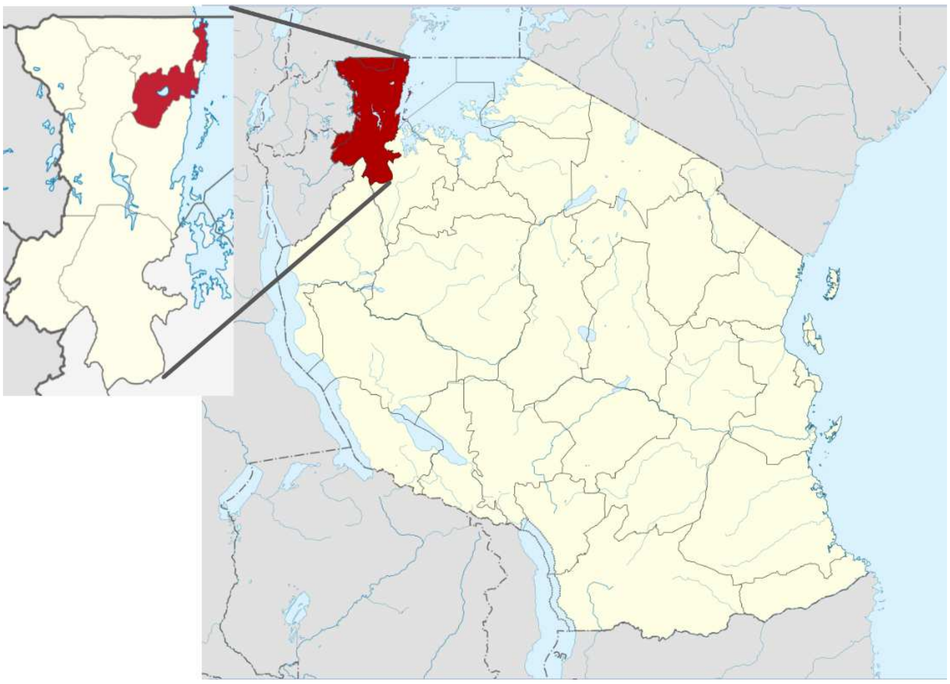
$$\frac{d\Delta}{d\delta} = \frac{(1-p)\left[u(W+\gamma\theta)-\alpha-u(W+\theta)\right]+p\left(u_T^E-u_I^E\right)}{(1-\delta)^2}$$
$$\frac{d\Delta}{dW} = \frac{(1-p)\left[u'(W+\gamma\theta)-u'(W+\theta)\right]+p\left(\frac{du_T^E}{dW}-\frac{du_I^E}{dW}\right)}{1-\delta}.$$

$d\bar{\alpha}/d\Delta > 0$ follows from $\Delta > 0$. The conditions for $d\Delta/dW < 0$ are equivalent to the conditions for $d\bar{\alpha}/dW < 0$.

■

2.D Additional tables and figures

Figure 2.D.1: Map: Bukoba rural district



Chapter 3

Rainfall, remoteness, labor exchange, and farm labor allocation in Sub-Saharan Africa

3.1 Introduction

Agriculture is the main livelihood of a large proportion of households in Sub-Saharan Africa (SSA). The majority of rural African households specialize in on-farm activities, and only one in ten are specialized in non-farming business or self-employment (Christiaensen and Maertens, 2022). Agriculture accounts for around 20% of Africa's GDP and employs half of the continent's labor force (FAO, 2022). Understanding how farmers allocate labor to farming activities is crucial to addressing the challenges of poverty and livelihood diversification in SSA. This is particularly relevant in a continent that is expected to host 80% of the world's poor by 2030 (United Nations, 2024; The Economist, 2025).

In this chapter, I take a deep look at labor utilization at the farm level in four Sub-Saharan countries and study how farmers adjust the use of different types of labor to precipitation deviations. Rainfed agriculture is dominant in Africa, with more than 90% of total cropland being dependent on rainfall (Calzadilla et al., 2013; Abrams, 2018). Therefore, deviations in precipitation can vastly affect agricultural output and labor utilization, more so in contexts where climate anomalies are more prone to affect farmer's livelihoods. Indeed, SSA concentrates the majority of countries most vulnerable to climate change (United Nations Economic Commission for Africa, 2023).

Traditionally, studies of agricultural labor consider only the use of family labor and hired workers as labor inputs. Development economists have largely neglected labor exchange, a non-market institution that is still prevalent across SSA and other countries in the developing world.[1] Although this informal institution has been documented

Special thanks to Christelle Dumas, Clément Imbert, and Conny Wunsch for their thoughtful comments and suggestions. Alexandre Darbellay provided helpful research assistance.

[1]Depending on the context and local practices, this form of labor is also known as labor-sharing, cooperative labor, reciprocal labor, or work party (Suehara, 2006; Takasaki et al., 2014).

by scholars in other social sciences at least since the 1950s (e.g. Erasmus (1956)), agricultural household models in economics have not systematically been extended to incorporate non-family and non-market labor force (Takasaki et al., 2014).[2] Compared to other nonmarket institutions that exist in the agrarian economy and that have been largely studied by economists such as sharecropping (Braverman and Stiglitz, 1982) and Roscas (Besley, 1995), development economists have produced little evidence on the existence, determinants, and benefits of using this form of labor by agricultural households (Takasaki et al., 2014).

Labor exchange is a mechanism employed by farmers to deal with the shortage of family and/or hired workers, specially around the rainy season (Jaimovich, 2015). Farmers that exchange labor help each other in farming tasks by reciprocating labor, or in exchange for food and drinks (Suehara, 2006; Krishnan and Sciubba, 2009). Some of the reasons of why farmers participate in labor exchange include greater efficiency in completing time sensitive tasks (Kang, 2020), increased motivation and productivity of working with others (Mekonnen and Dorfman, 2017), or the possibility to access labor force when liquidity constraints limit access to paid laborers (Moore, 1975; Gilligan, 2004). Social norms concerning mutual help and cooperation can also explain the persistence of this nonmarket institution (Geschiere, 1995).

In this chapter, I explicitly introduce labor exchange as part of the labor demand and labor allocation decisions of rural households. Based on Gilligan (2004) and Chang et al. (2012), I build a simple model of agricultural production that explicitly includes, besides family labor and hired workers as labor inputs, labor exchange in the farmer's production technology. The model also considers transaction costs in the agrarian and off-farm labor markets, and non-monetary costs associated to labor-sharing. I derive predictions on how the farmer allocates each type of labor after experiencing exogenous productivity shocks in the form of rainfall deviations, and further analyze farm-level labor utilization by considering the role of remoteness in the farmers' labor allocation decisions, as it is well known that economic isolation is an important barrier to development (Khandker et al., 2009; Qin and Zhang, 2016; Donaldson, 2018; Shamdasani, 2021; Djemaï et al., 2024). When landholdings are widespread and population centers distant, wage workers are more difficult to find. In these contexts, labor exchange may be an alternative to access labor beyond the family members' labor force (Gilligan, 2004).[3]

I test the predictions of the model using national representative data from the World Bank's Living Standards Measurement Study (LSMS-ISA). Specifically, I use data from

[2]For example, in a recent review on farm labor and agricultural labor supply, Hill et al. (2021) consider a conceptual model of an agricultural household that allocates farm labor using only family and hired labor, without considering labor exchange as a third labor input.

[3]I do not seek to extend the theory of agricultural household model per sé -which is something beyond the scope and motivations of this article- but rather analyze how labor exchange enters the labor utilization decisions of farmers in SSA and how this decision varies with rainfall deviations and remoteness.

more than 9,500 households in Ethiopia, Niger, Nigeria, and Malawi. Together, these countries account for a third of the total population of SSA and provide a wide geographic coverage. Including countries from both East and West Africa also allows me to capture differences in the intensity of rural employment across economies in different stages of development.[4]

The empirical analysis exploits spatiotemporal variation in household's exposure to rainfall shocks, defined as standardized deviations from the historical precipitation mean in their location. The longitudinal component of the LSMS-ISA surveys allows me to control for time-invariant household-specific characteristics that may be correlated with farm labor allocation decisions. Additionally, a set of year-by-country and wave fixed effects allows me to account for changes over time and time-varying country-specific unobservable factors that could correlate with climate or economic patterns both temporally and across countries. I also control for time-varying household-specific factors, such as household composition and cultivated land, as well as locality-level characteristics, such as the percentage of agricultural activity and the agro-climatic zone. Finally, I include tensor products of Legendre polynomials of latitude and longitude to control for spurious correlations and spatiotemporal patterns of weather data (Lind, 2019), an approach that has been poorly utilized in studies exploiting precipitation as an exogenous shock. The identification relies on the assumption that, conditional on the controls and the fixed effects, any remaining variation in rainfall is effectively random (Liu et al., 2023).

The empirical findings validate most of the predictions of the model. In line with the model, results show that (i) households in more remote locations reduce their demand for labor exchange by 7% when there is a one standard deviation decrease in rainfall; and (ii) farmers living close to population centers and markets reduce the use of family labor in on-farm tasks by 13.8%, equivalent to up 10 person-days across the agricultural season. Surprisingly, and at odds with the model predictions, I find that farmers increase the use of hired workers in years where they experience negative rainfall. Heterogeneity tests reveal that large landholders are the ones driving this result on hired workers, and that all the aforementioned adjustments in labor utilization are strongly gendered: the responses affect only the allocation and use of male labor force (Afridi et al., 2022; Maitra and Tagat, 2024). Moreover, I find no effect of positive rainfall deviations on the utilization of any type of labor, raising the question of why farmers in this setting do not react to positive shocks.

This chapter builds on several active strands of literature on rural labor markets and agriculture in SubSaharan Africa by explicitly incorporating labor exchange in the labor

[4] Christiaensen and Maertens (2022) show that these regions present divergent trends in agricultural and rural transformation, with East Africa relying on more than 80% of rural employment in agriculture, whereas this share is close to 50% in the West.

allocation decisions of rural households, thus extending our overall understanding and functioning of rural labor markets.

First, I extend the scarce literature on the economics of labor exchange. I document the use of labor exchange across several countries in SSA and shed light on how farmers adapt the use of this non-market type of labor to exogenous productivity shocks. A few recent studies have found positive effects across farmers who engage in labor-sharing. In the context of Ethiopia, Mekonnen and Dorfman (2017) find that labor-sharing among subsistence farmers leads to important productivity gains of around 30% due to synergy effects that increase labor productivity in years when farmers exchange labor. Fumagalli and Martin (2023) find that reciprocal labor among adult farmers in Mozambique leads to a reduction in child labor and an increase in cultivated area, as labor exchange allows farmers to circumvent market imperfections in accessing labor force. More recently, Arciniegas et al. (2025) find that women that participate in labor exchange teams in Tanzania have a higher likelihood of being hired by a landowner and obtain paid work by being hired for group tasks. Incorporating labor exchange in the household's production decisions seems naturally relevant to better understand the role of this non-market institution in the agrarian economy.

I also contribute to the literature that studies labor market imperfections in Sub-Saharan Africa (Dillon and Barrett, 2017; Dillon et al., 2019; Lam and Elsayed, 2021; de Janvry et al., 2022; Kebede, 2022). If labor exchange is the consequence of malfunctioning credit and/or labor markets, where farmers cannot hire paid workers due to liquidity constraints or few available laborers, then the recurrence and intensity of labor exchange could be a potential indicator of the state of imperfections in rural markets (Gilligan, 2004). Therefore, explicitly modeling and empirically accounting for labor exchange in the farmer's labor allocation decision provides a more complete view of the functioning of rural labor markets in SSA, opening avenues for future research.

Finally, I provide a comprehensive overview of how rural labor in Sub-Saharan Africa adjust to weather anomalies and add to the large body of research that studies off-farm labor as one of the strategies used by rural households to cope with idiosyncratic or covariate shocks (Kochar, 1999; Rose, 2001; Jayachandran, 2006; Ito and Kurosaki, 2009; Mathenge and Tschirley, 2015; Gao and Mills, 2018; Call et al., 2019; Musungu et al., 2024). When households face a negative shock, they look for job opportunities outside of the farm as one strategy to smooth consumption. However, most articles that study labor supply in off-farm activities do not disentangle whether the activities take place in agriculture or in the non-agricultural economy, as *off-farm* employment can still take place in farming activities by providing wage work to a landlord.[5] By focusing on how

[5] For instance, in the set of countries that I cover in this chapter, the share of people who are continuously employed in the non-farm economy is low, ranging from 16% in Ethiopia to 33% in Malawi (van den Broeck and Kilic, 2019).

farmers demand and allocate different types of labor to on-farm activities -instead of analyzing labor supply decisions-, I am able to shed light on the capacity of agricultural labor markets in SSA to absorb -at least partly- the shocks created by rainfall deviations.

The rest of the chapter is organized as follows: Section 3.2 presents the conceptual framework and a theoretical model that includes labor exchange as an input in the production function of an agricultural household. Section 3.3 describes the data and empirical strategy to test the predictions of the model. Section 3.4 presents the results of the empirical estimation, together with heterogeneity analysis by landholdings and gender, and a battery of robustness checks. Section 3.5 discusses limitations of this chapter and suggests extensions and avenues for future research, and finally Section 3.6 concludes.

3.2 Conceptual Framework and Model

Labor exchange, or labor-sharing, is a non-market institution that remains underexplored in the literature on rural labor markets, despite its continued importance in many developing countries (Takasaki et al., 2014). Labor-sharing consists on farmers helping each other on farming tasks without any monetary payment involved. The use of labor exchange seems to be common practice across households in the four SubSaharan countries I study in this chapter. On average, 55% of households used exchange laborers on their plots at least once during the survey waves. The share of households using this type of labor ranges from 31% in Nigeria and up to 88% in Ethiopia (See Table 3.B.2 in the Appendix).

Although it seems to be common practice for households to make use of this non-market institution, labor exchange does not represent a large share of the total labor force used by farmers on their plots. Labor exchange corresponds to less than 5% of the average number of person-days employed on-farm (around 3 person-days per season), which is half of what is employed from hired workers.[6] However, it is important to note that more than 85% of the total labor employed on farms comes from the household's own labor force (see Table 3.B.3).

This widespread yet low-intense use of labor exchange could be explained by the nature and benefits of this type of activity. Researchers from social sciences and economics have proposed various reasons and motivations to explain farmers' participation in labor exchange. These motivations can be broadly categorized under three hypotheses: (1) coordination, (2) imperfect labor markets, and (3) social and cultural norms.[7]

[6] Arciniegas et al. (2025) find as well a low use of labor exchange in Tanzania.

[7] See Gilligan (2004) and Kang (2020) for detailed discussion on these hypotheses and other reasons for labor exchange.

The coordination argument posits that farmers engage in labor exchange because it enables them to perform time-sensitive agricultural tasks more efficiently, ensuring the timely completion of critical activities within the farming season. This is particularly relevant for tasks such as land preparation and sowing, which must be completed before the first rains arrive. For example, de Janvry et al. (2022) note that labor exchange helps households in Malawi to "spread each household's work over a longer period of time if there is some heterogeneity in the exact timing of the task, or if the task is for technical reason difficult to spread over more days" (p. 14). Furthermore, the psychological benefits of working with others, such as increased motivation and productivity synergies (Mekonnen and Dorfman, 2017), can also explain why farmers participate in labor-sharing.

The imperfect markets hypothesis suggests that labor exchange serves as a substitute for wage workers in regions where the supply of labor is limited or difficult to access, especially during peak agricultural periods and in geographically isolated areas. When wage labor is unavailable or expensive, labor exchange offers a way for farmers to access a labor force on top of own's household labor supply. Additionally, labor exchange can also be an alternative for households that face liquidity constraints. If for example, imperfect or missing credit markets limit the possibilities of farmers to hire wage labor, free labor exchange offers them a way to overcome financial constraints that would otherwise prevent them from securing labor.

Finally, the social and cultural norms hypothesis provide non-economic reasons of why labor exchange is still persistent. In communities with strong social networks and where values such as mutual assistance and cooperation are prevalent, labor exchange remains common even when formal labor markets exist and farmers could hire workers.[8]

Gilligan (2004) is the first documented attempt in economics to formally analyze labor exchange in agricultural production. He shows that participation in labor-sharing requires that the marginal return of exchanging labor equals its marginal cost: the shadow value of time spent on teammates' farms + the marginal disutility of time spent supervising and coordinating exchange workers should equal the marginal benefits of exchanging labor. He also shows that, if the (time) cost of organizing labor exchange (c_e) is equal to the combined cost of hiring-in labor (c_h) and of searching off-farm work employment (c_o), a household may engage in labor-sharing activities, on top of family and hired labor. Put differently, if $c_e \leq c_h + c_o$, the household may engage in labor exchange. Gilligan also points out that the reciprocal nature of exchange of labor requires

[8] In a general setting beyond labor markets, Kranton (1996) examines the interaction between personalized, long-term exchange relationships and anonymous market exchange. She develops the conditions in which both market and reciprocal exchange can lead to socially efficient outcomes, or even co-exist under certain circumstances. In particular, she shows that personalized exchange is more likely to take place when goods and services are homogeneous and people (expect to) interact on a frequent basis, and also if the cost of searching for trading partners in the market is higher.

a more homogeneous distribution of land size, crop types, irrigation technology and human capital among members for labor exchange to be more beneficial.[9]

Which combination of labor inputs a household choose will depend on the relative size of transaction costs for each type of labor, plus the household's working capital constraint, production technology, and other covariate and household-specific factors. Of these, one factor that can affect how farmers make use of different types of labor is the remoteness of their location.

In more isolated areas, search costs for hiring-in labor through the market are likely to be high, as well as the costs of finding off-farm job opportunities. Therefore, one could expect to find more labor exchange (and potentially more household labor) in more isolated areas as its relative cost is lower. Conversely, where remoteness is less of a problem, the costs of hiring in and hiring out labor are lower, and labor exchange will be relatively less attractive. Therefore, in non-remote areas, households might prefer to hire workers over labor-sharing, whereas in more isolated locations labor exchange might be more prevalent. Consequently, the demand for different types of labor will depend, among other factors, on the remoteness of the household's farm.

In the sample of households I will study in this chapter, I observe that labor exchange is more common in more remote/isolated regions, where the use of hired labor tends to decrease as well. Figure 3.2.1 below plots a local polynomial regression of the probability that households employ labor exchange workers on a measure of remoteness using an Epanechnikov kernel.[10] Figures 3.B.1 and 3.B.2 in the Appendix section 3.B present the same local polynomial regression graph for the probability of using family and hired labor, respectively, as a function of remoteness.

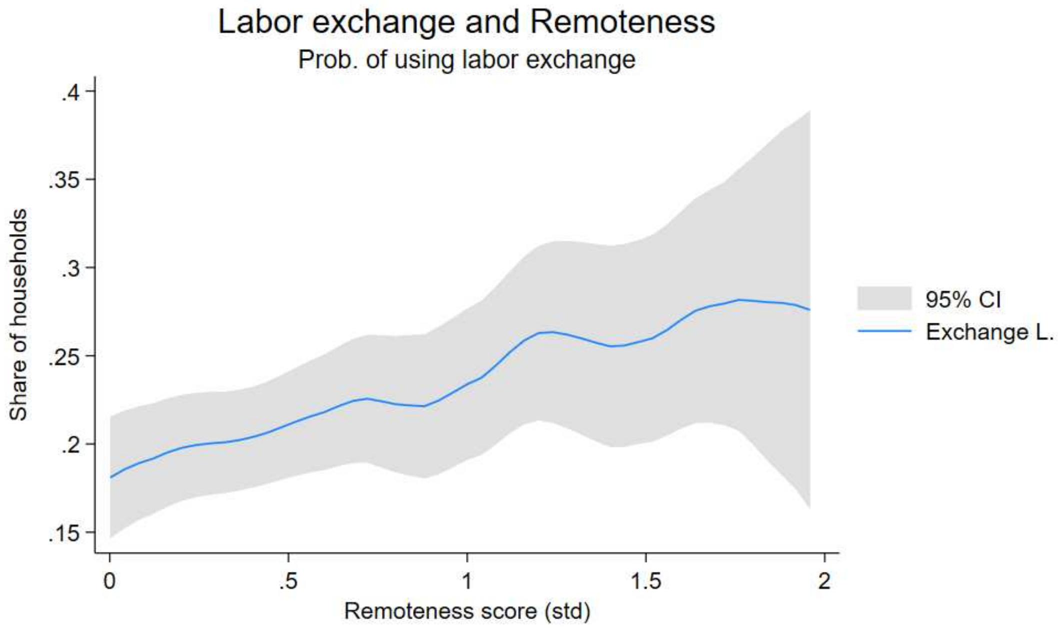
This observation is in line with Gilligan (2004) who finds, in a sample of 1494 Indonesian households, that labor exchange was common in the more remote regions of South Sulawesi and West Nusa Tenggara. Jaimovich (2015) also finds that, across 60 villages in The Gambia, households that have more (less) economic links outside of their village are less (more) likely to participate in reciprocal exchanges (of labor and other inputs) with farmers in their own village.

In what follows, I draw from Gilligan (2004) and Chang et al. (2012) to develop a utility maximization problem of a rural household that incorporates labor exchange in the production function. In the model, the household cultivates land using different

[9] Krishnan and Sciubba (2009) study labor-sharing arrangements in Ethiopia and provide theoretical evidence on the necessary conditions of endogenous network formation for exchanging labor. The authors show that a stable network of farmers who exchange labor requires them to be of similar quality and homogeneous in endowments. When farmers differ in their quality and endowments, asymmetric labor-sharing networks are stable, where a better endowed farmer has more links that a less endowed one.

[10] I construct a PCA index based on distances to a major road, the nearest market, and a large population center. See section 3.3 for details on the remoteness measure.

Figure 3.2.1: Probability of using Exchange Labor as a function of remoteness



types of labor (family labor, hired workers, or exchange laborers) and can also sell labor in the off-farm economy. As in Gilligan (2004), the model includes transaction costs for hiring in workers and supplying labor in the off-farm economy, which can be thought as proxies for the spatial and economic isolation of a household.

I first build a basic model in which the farmer only uses family and exchange labor to cultivate land (Section 3.2.1), and then extend it to include hired workers as well (Section 3.2.2). Since rainfed agriculture is dominant in Africa (Calzadilla et al., 2013; Abrams, 2018), deviations in precipitation can vastly affect agricultural output and inputs utilization, including the optimal allocation of labor to farming activities and the use of the off-farm economy as a coping mechanism. Therefore, from the model I seek to determine how a farmer adjusts the use of each type of labor in the presence of rainfall deviations.

3.2.1 Basic Model with family and exchange labor

A farmer seeks to maximize his household's utility, which depends on consumption and leisure:

$$U(C, R) = \Phi(C, R) \tag{3.1}$$

where $\Phi(\cdot)$ is a strictly quasi-concave and twice continuously differentiable function ($\Phi' > 0$ and $\Phi'' < 0$). The farmer cultivates land to produce output Q using labor L.[11] The farmer can make use of two types of labor to cultivate land: family labor (F) and exchange laborers (E). The production function is thus given by $Q = \theta G(F, E)$, where θ captures unobserved random productivity shocks, which can include rainfall deviations. G is a non-negative, twice continuously differentiable, and strictly concave function, i.e.:

$$G_i > 0; G_{ii} < 0; G_{ij} = G_{ji}; G_{ii}G_{jj} - G_{ij}^2 > 0; \forall_{i,j} \in \{F, E\}$$

The farmer allocates time to different activities. Family time endowment $\overline{T}$ can be split into leisure time (R), on-farm family labor (F), and off-farm employment (N_o). On top of the time spent working off-farm, N_o requires a per-unit cost c_o of searching for off-farm jobs. Finally, the farmer must allocate time to reciprocate labor exchange with his partners when required. Exchanging labor implies a cost c_e of organizing and coordinating a labor exchange task. The farmer's time constraint can be written as:

$$\overline{T} - R - F - (1 + c_e)E - (1 + c_o)N_o \geq 0 \tag{3.2}$$

With on-farm and off-farm work, the household has two sources of income: (i) farming income, defined as farm revenue $y_f \equiv pQ = p\theta G(F, E)$; and (ii) off-farm labor income, which can be obtained by selling N_o labor days in off-farm employment for a wage w_o. Assuming p as the numéraire ($p = 1$), household's total income (I) is given by:

$$I = \theta G(F, E) + w_o N_o \tag{3.3}$$

For simplification, I assume that the household consumes all their income, i.e. $C = I$

The farmer's optimization problem consists in maximizing household utility (3.1) subject to the time constraint (3.2), income equation (3.3), and the non-negative constraints of the choice variables F, E, N_o and R. Integrating the income equation and the time constraint into the utility function we obtain:

$$\max_{F,E,R} U(C, R) = U\left(\theta G(F, E) + w_o \frac{T - R - F - (1 + c_e)E}{1 + c_o}, R\right)$$

The First Order Conditions are given by:

$$\frac{\partial U}{\partial F} : \theta G_F - \frac{w_o}{1 + c_o} = 0 \tag{3.4}$$

[11] To simplify the analysis, I use a very basic model with only one input -labor-. It could be easily expanded to included other types of inputs such as tools, land, etc.

$$\frac{\partial U}{\partial E} : \theta G_E - \frac{w_o}{1+c_o} \cdot (1+c_e) = 0 \tag{3.5}$$

$$\frac{\partial U}{\partial R} : U_C \left(-\frac{w_o}{1+c_o} \right) + U_R = 0 \tag{3.6}$$

Equation 3.4 shows that the household allocates family labor (H) to the level where the marginal return to on-farm labor (θG_F) equals the net return from off-farm employment, measured as the off-farm wage adjusted for transaction costs $\left(\frac{w_o}{1+c_o}\right)$. In this case, the shadow wage of on-farm family labor is measured as the off-farm wage. Similarly, equation 3.5 shows that the household uses labor exchange up to the point where the value of its net marginal product $(\frac{\theta G_E}{(1+c_e)})$ equals the net marginal return of off-farm employment. Finally, equation 3.6 states that the household maximizes utility at the point where the marginal rate of substitution of leisure for income $(\frac{U_R}{U_C})$ is equal to the net income obtained by working off-farm.

Given the prevalence of rainfed agriculture in Africa, variations in rainfall can significantly alter agricultural productivity and the distribution of labor across farming and non-farming activities. In order to conduct a comparative static analysis and determine the effect of rainfall deviations on the utilization of family and exchange labor, I take the total differential of the FOCs in equations (3.4)-(3.6) and obtain the following:[12]

$$\begin{pmatrix} \theta G_{FF} & \theta G_{FE} & 0 \\ \theta G_{EF} & \theta G_{EE} & 0 \\ 0 & 0 & J \end{pmatrix} \cdot \begin{pmatrix} dF^* \\ dE^* \\ dR^* \end{pmatrix} = \begin{pmatrix} -G_F d\theta + \frac{1}{1+c_o} dw_o \\ -G_E d\theta + \frac{1+c_e}{1+c_o} dw_o \\ K \end{pmatrix} \tag{3.7}$$

The effects of rainfall deviations (θ) on family labor (F) and exchange labor (E) are given by solving $\frac{\partial i}{\partial \theta}, i \in \{F, E\}$ from the system of equations in (3.7). See the details in the Appendix section 3.C.1.

Family Labor F

Solving the system of equations for $\frac{\partial F^*}{\partial \theta}$, it can be easily shown that:

$$\frac{\partial F^*}{\partial \theta} = \frac{\gamma}{|D_2|} (G_{EE} - G_{FE}) \tag{3.8}$$

[12] This exercise assumes an interior solution to the maximization model. For this to be the case, the second order conditions must guarantee a negative definite Hessian matrix, See details in the Appendix.

where $\gamma = \frac{(-w_o)(1-\epsilon_{w_o})}{1+c_o}$ and ϵ_{w_o} corresponds to the elasticity of the off-farm wage w_o with respect to the rainfall deviation ($\epsilon_{w_o} = \frac{\partial w_o}{w_o} / \frac{\partial \theta}{\theta}$). $|D_2|$ is the determinant of the 2×2 matrix of second order conditions of the production function $Q = \theta G(F, E)$, i.e., $|D_2| = \theta^2 (G_{FF}G_{EE} - G_{FE}G_{EF})$.[13]

Under the assumptions that $\epsilon_{w_o} < 1$ (i.e. the off-farm economy wage is rather inelastic to rainfall deviations) and that family and exchange labor are q-complements ($G_{FE} > 0$) then it is the case that $\frac{\partial F^*}{\partial \theta} > 0$.[14]

Let's consider the case of negative rainfall deviations (e.g. droughts). A large literature has shown that households in rural areas reduce time in on-farm tasks and increase their supply to off-farm activities as a coping mechanism to negative shocks (Kochar, 1999; Rose, 2001; Ito and Kurosaki, 2009; Liu et al., 2023). Equation 3.8 shows indeed that family labor allocated to on-farm activities (F) decreases after a negative rainfall deviation, and that it depends negatively on the off-farm wage w_o. That is, better conditions in the off-farm economy will induce households to supply less on-farm family labor F and will make off-farm activities more attractive. Importantly, equation 3.8 also shows how the effect varies depending on the costs associated to find a job in the off-farm economy.

With no or low costs ($c_o = 0$), as it would be the case of households that live close to population centers or markets, the effect of a negative rainfall deviation on family labor time allocated to on-farm activities will depend entirely on the off-farm wage w_o. When transaction costs for finding off-farm jobs ($c_o > 0$) are high, the effect of a negative rainfall deviation is diminished. Farmers who face greater difficulty finding off-farm employment will adjust family labor less in response to changes in θ. That is, the amount of family labor F allocated to on-farm activities by households living in more remote areas -where off-farm opportunities are scarcer or costlier- will adjust less to rainfall deviations, because they cannot easily switch between on-farm and off-farm activities.

Prediction 3.1. *Family labor time (F) allocated to on-farm activities decreases when the household experiences a negative rainfall deviation (θ^-). In the presence of high transaction costs in the off-farm economy ($c_o > 0$), the effect of the rainfall deviations on on-farm family labor is weaken: the larger the cost, the lower the effect of rainfall on F.*

[13] This determinant is positive from the assumptions of a concave production function. For the function to be concave, the Hessian matrix must be negative semi-definite, implying $|D_2| > 0$.

[14] These two assumptions have support in the literature. Balachandran et al. (2023) conduct a meta-analysis on more than one hundred papers and estimate an off-farm labor supply elasticity of approximately 0.64-0.77, using studies from both developed and developing countries. Regarding the complementarity of F and E, Mekonnen and Dorfman (2017) find that labor-sharing arrangements among farmers in Ethiopia lead to productivity gains of more than 30% due to synergy effects that boost labor productivity. Indeed, some degree of complementarity between family and exchange labor must exist for the household to engage in labor exchange, since E incurs the cost c_e.

By the symmetry of the model, a positive rainfall deviation (θ^+) should have the opposite effect.

Exchange Labor E

Similar to the family labor expression, the effect of rainfall deviations on the use of labor exchange is given by:

$$\frac{\partial E^*}{\partial \theta} = \frac{\gamma}{|D_2|}\left[(1+c_e)G_{FF} - G_{EF}\right] \tag{3.9}$$

where $\gamma = \frac{(-w_o)(1-\epsilon_{w_o})}{1+c_o}$. Again, if $\epsilon_{w_o} < 1$ and family and exchange labor are q-complements ($G_{EF} > 0$), then $\frac{\partial E^*}{\partial \theta} > 0$.

Equation 3.9 is very similar to equation 3.8, but now there is also the cost associated to organize and coordinate a labor exchange task on own's farm (c_e). With no costs associated to exchanging labor with neighbors or friends ($c_e = 0$), labor exchange reacts to rainfall deviations similarly to family labor. However, in the presence of labor-sharing costs ($c_e > 0$), labor exchange will adjust even further to negative rainfall deviations. This is especially true for households that rely more on labor exchange, as negative rainfall reduces the marginal benefit of exchanging labor (see FOC in equation 3.5), but the cost associated to it remain the same. Since labor exchange is more common in remote or isolated areas (as shown in Figure 3.2.1), negative rainfall deviations will reduce labor-sharing even further in those regions.[15]

Prediction 3.2. *The use of exchange labor (E) decreases when the household experiences a negative rainfall deviation. With high costs associated to labor exchange, E will adjust more to negative rainfall.*

In summary, predictions 3.1 and 3.2 establish that negative rainfall deviations (θ^-) will reduce the use of family labor (F) and exchange laborers (E) for own-farm agricultural tasks, and that this effect is mediated by the costs associated to finding off-farm jobs (c_o) to cope with the shock, and organizing a labor-sharing task (c_e). By the symmetry of the model, a positive rainfall deviation (θ^+) should have the opposite effect.

3.2.2 Extended Model with family, hired, and exchange labor

Now, let's assume that the farmer uses three different types of labor inputs to cultivate his land: family labor (F), hired workers (H), and exchange laborers (E). In this new

[15] For example, in more remote areas, neighbors live farther apart, or communication systems are less reliable, increasing the cost of calling and setting a labor exchange task.

setting, the production function becomes $Q = \theta G(F, H, E)$ and the time constraint expands to

$$\overline{T} - R - F - (1 + c_e)E - c_h H - (1 + c_o)N_o \geq 0 \tag{3.10}$$

where c_h captures a transaction cost of finding and recruiting external workers that the farmer incurs if he decides to hire-in. Total income equation also changes, as the farmer now needs to pay for hiring-in workers a wage w_h. The new net income equation is:

$$I = \theta G(F, H, E) + w_o N_o - w_h H \geq 0 \tag{3.11}$$

The farmer's new optimization problem consists in maximizing household utility (3.1) subject to the extended time constraint (3.10) and the net income expression (3.11). Integrating these equations into the utility function we obtain:

$$\max_{F,H,E,R} U(C, R) = U\left(\theta G(F, H, E) - w_h H + w_o \frac{T - R - F - (1 + c_e)E - c_h H}{1 + c_o}, R\right)$$

The First Order Conditions in this new setting are:

$$\frac{\partial U}{\partial F} : \theta G_F - \frac{w_o}{1 + c_o} = 0 \tag{3.12}$$

$$\frac{\partial U}{\partial H} : \theta G_H - w_h - \frac{w_o}{1 + c_o} \cdot c_h = 0 \tag{3.13}$$

$$\frac{\partial U}{\partial E} : \theta G_E - \frac{w_o}{1 + c_o} \cdot (1 + c_e) = 0 \tag{3.14}$$

$$\frac{\partial U}{\partial R} : U_C \left(-\frac{w_o}{1 + c_o}\right) + U_R = 0 \tag{3.15}$$

The FOCs for F, E and R are similar as those in the two-input model. The FOC for hired labor (H) in equation 3.13 shows that the household hires in external workers up to the level where the value of hired labor's marginal product (θG_H) equals its marginal cost, measured as the wage w_h to be paid to workers, plus the cost in terms of time of finding and recruiting those workers (c_h) -which reduces the household's available time to work off-farm and earn w_o.

As in the case of to the two-inputs model, to determine the effect of rainfall deviations on the utilization of family, hired, and exchange labor, I take the total differential of the FOCs (equations 3.12-3.15) and obtain the following:

$$\begin{pmatrix} \theta G_{FF} & \theta G_{FH} & \theta G_{FE} & 0 \\ \theta G_{HF} & \theta G_{HH} & \theta G_{HE} & 0 \\ \theta G_{EF} & \theta G_{EH} & \theta G_{EE} & 0 \\ 0 & 0 & 0 & U_{RR} \end{pmatrix} \cdot \begin{pmatrix} dF^* \\ dH^* \\ dE^* \\ dR^* \end{pmatrix} = \begin{pmatrix} -G_F d\theta + \frac{1}{1+c_o} dw_o \\ -G_H d\theta + dw_h + \frac{c_h}{1+c_o} dw_o \\ -G_E d\theta + \frac{1+c_e}{1+c_o} dw_o \\ \tilde{K} \end{pmatrix} \tag{3.16}$$

Again, the effects of rainfall deviations (θ) on family labor (F), hired labor (H), and exchange labor (E) are given by solving $\frac{\partial i}{\partial \theta}, i \in \{F, H, E\}$ from the system of equations in (3.16). The solutions are: [16]

Family labor

$$\begin{aligned} \frac{\partial F^*}{\partial \theta} = \frac{\theta}{|D_3|} \cdot \frac{1}{1+c_o} \Big[& \gamma_o \left[(G_{HH}G_{EE} - G_{HE}G_{EH}) + (1+c_e)\left(G_{HF}G_{EH} - G_{HH}G_{EF}\right) - c_h \left(G_{HF}G_{EE} - G_{HE}G_{EF}\right) \right] \\ & + (1+c_o)\gamma_h \left(G_{HF}G_{EE} - G_{HE}G_{EF}\right) \Big] \end{aligned} \tag{3.17}$$

Hired labor

$$\begin{aligned} \frac{\partial H}{\partial \theta} = \frac{\theta}{|D_3|} \cdot \frac{1}{1+c_o} \Big[& \gamma_o \left[(G_{FE}G_{EH} - G_{FH}G_{EE}) - (1+c_e)\left(G_{FF}G_{EH} - G_{FH}G_{EF}\right) + c_h \left(G_{FF}G_{EE} - G_{FE}G_{EF}\right) \right] \\ & - \left[(1+c_o)\gamma_h \left(G_{FF}G_{EE} - G_{FE}G_{EF}\right) \right] \Big] \end{aligned} \tag{3.18}$$

Exchange labor

$$\begin{aligned} \frac{\partial E}{\partial \theta} = \frac{\theta}{|D_3|} \cdot \frac{1}{1+c_o} \Big[& \gamma_o \left[(G_{FH}G_{HE} - G_{FE}G_{HH}) + (1+c_e)\left(G_{FF}G_{HH} - G_{FH}G_{HF}\right) - c_h \left(G_{FF}G_{HE} - G_{FE}G_{HF}\right) \right] \\ & + \left[(1+c_o)\gamma_h \left(G_{FF}G_{HE} - G_{FE}G_{HF}\right) \right] \Big] \end{aligned} \tag{3.19}$$

where $\gamma_o = (-w_o(1-\epsilon_{w_o}))$; $\gamma_h = (w_h(1-\epsilon_{w_h}))$; $\epsilon_{w_o} = \frac{\partial w_o}{w_o} / \frac{\partial \theta}{\theta}$; $\epsilon_{w_h} = \frac{\partial w_h}{w_h} / \frac{\partial \theta}{\theta}$ and $|D_3|$ is the determinant of the Hessian matrix of second order derivatives of the production function $\theta G(F, H, E)$.

$$|D_3| = \theta^3 \left[G_{FF}(G_{HH}G_{EE} - G_{HE}G_{EH}) - G_{FH}(G_{HF}G_{EE} - G_{HE}G_{EF}) + G_{FE}(G_{HF}G_{EH} - G_{HH}G_{EF}) \right]$$

Whether F, H, and E react positively or negatively to rainfall deviations depends on two main factors: (i) the degree of complementarity or substitutability between labor inputs (i.e., $G_{ij} > 0$ or $G_{ij} < 0$, indicating q-complements or q-substitutes); and (ii) whether the off-farm economy wage (w_o) or the hiring-in wage (w_h) reacts more strongly to the rainfall deviation and dominates the other—net of costs associated with searching

[16] see details in Appendix 3.C.2

for off-farm jobs, hiring external workers, and organizing labor-sharing tasks. Therefore, the effects of rainfall deviations (θ) on the use of family (F), hired (H), and exchange (E) labor, as presented in Eqs. (3.17)–(3.19), are, in general, indeterminate.

Although it does not seem possible to analytically predict how the farmer will allocate family, hired, and exchange labor in response to rainfall deviations, based on the predictions of the model in Section 3.2.1 and the discussion in the conceptual framework, I attempt to intuit how the three types of labor react to rainfall deviations and how the effect varies according to the remoteness of the household's location. I later test these hypotheses using data.

In the case of labor exchange, the benefits of using this type of labor can be thought of as decreasing with rainfall. The benefits of labor exchange decline during low-rainfall periods because the need to undertake time-sensitive tasks in a short period is less urgent. As labor exchange is more likely to occur in remote areas, negative rainfall deviations likely reduce the demand for this type of labor even further in such isolated localities. One should also expect to find less use of family labor on on-farm tasks after negative rainfall deviations, as agricultural productivity declines. However, as noted in Prediction 3.1 in the simple two-input model, higher transaction costs for finding jobs in the off-farm economy (as is typical in more remote locations) will attenuate the effect of rainfall on family labor. This attenuation also seems to hold in the three-input model, as shown in Eq. (3.17). Regarding hired workers, their use should also decrease when agricultural productivity declines. Nevertheless, in more isolated areas, the already low reliance on hired labor further limits its adjustment to rainfall deviations.

In less remote areas, where the costs of hiring in and hiring out labor are lower relative to labor exchange, precipitation should have a relatively more pronounced effect on family (F) and hired (H) labor than on labor exchange (E). Since negative rainfall reduces overall farming productivity, household members will allocate less labor to on-farm activities and instead seek off-farm opportunities to cope with the shock (as predicted in Prediction 3.1). The use of hired workers should also decline with negative rainfall, as the marginal productivity of agriculture diminishes.

Below, I summarize the hypotheses of how negative rainfall deviations affect each type of labor, differentiated by non-remote and remote locations:

Hypothesis 3.1. *In less remote locations, negative rainfall deviations:*

- *reduce the allocation of family labor (F) to on-farm tasks;*
- *reduce the use of hired workers (H);*
- *not affect labor exchange (E), as labor-sharing is not common in these locations.*

Hypothesis 3.2. *In more remote locations, negative rainfall deviations:*

- *do not affect the allocation of family labor (F) to on-farm tasks, as households face higher costs for finding off-farm job opportunities and cannot easily switch between F and N_o;*

- *do not affect the use of hired workers;*

- *reduce the use of labor exchange (E), as there is less need to employ this type of labor.*

In the next section, I present the data and estimation strategy I will use to test Predictions 3.1 – 3.2 and Hypotheses 3.1 - 3.2

3.3 Data and Empirical Estimation

In this section, I present the data and empirical estimation to test the predictions of the previous models and analyze how farmers in Ethiopia, Niger, Nigeria, and Malawi adjust family, hired, and exchange labor to rainfall deviations.

3.3.1 Data

I use two main sources of data to estimate the responses of labor allocation to rainfall and remoteness: (i) the World Bank's Living Standards Measurement Study - Integrated Surveys on Agriculture (LSMS-ISA), and (ii) NOAA African Rainfall Climatology ARC2 precipitation estimates.

The LSMS-ISA surveys are conducted by the World Bank in collaboration with national statistical offices across several African countries, assuring a high degree of homogeneity and comparability across countries. These surveys are designed to collect detailed, multi-topic, and nationally representative surveys with a strong focus on agriculture. The survey covers modules on agricultural activities, household characteristics, non-farm income, and living conditions in rural and urban areas, among several other modules. The surveys have been designed as a panel study, allowing for the analysis of the dynamics of poverty, agricultural productivity, and household welfare. Relevant for my estimation, the longitudinal component of the survey allows me to control for household's time-invariant characteristics that can be potentially correlated with the household's farm-level labor demand.

Out of the eight Sub Saharan countries where the LSMS-ISA surveys have been conducted, I focus on four of them: Ethiopia, Niger, Nigeria, and Malawi.[17] These four

[17] The other countries are: Burkina Faso, Mali, Tanzania, and Uganda. Mali's survey is cross-sectional and not panel. Tanzania does not collect data on agricultural labor exchange and Uganda only started to collect it as a separate category in the last survey. Burkina Faso's second wave of the panel was released in March 2024, when all other countries' data have been already gathered and structured for

countries represent more than 30% of the total population in Sub-Saharan Africa, and the sample expands across economies in different stages of development, and ensures a wide geographic coverage. The sample I use in the analysis corresponds to a total of 9,631 households, split across the four countries and along different survey waves. Table 3.B.1 in the Appendix present the details of the sample sizes by country and survey wave.

For each household in each country, the agricultural module of the survey contains information disaggregated up to the season-field-crop level. For the estimation in the empirical part, I collapse the information at the household level, separately by season (pre-harvesting -land preparation, sowing, etc.- and harvest). The main dependent variable corresponds to the number of person-days employed by the household in farming activities during planting and harvesting seasons. These person-days supply can come from household members (F), hired laborers (H), and/or exchange workers (E).[18] The unit of observation in my analysis is at the household-by-season level. Thus, for the four countries, I have a total of 74,867 observations.[19] Tables 3.B.2 and 3.B.3 in the Appendix present, respectively, the proportion of households that used each type of labor, and the average number of person-days of each type of labor across the surveys.

The surveys collect household-level geo-referenced data that allows me to estimate the remoteness of each household, based on a series of different measures.[20] Specifically, the data contains information on the household's distance to the nearest major road, nearest town of >20,000 pop., nearest major market, and distance to the capital of the region of residence. I use this information to create an index of the "isolation" or "remoteness" of the household. Specifically, I construct a standardized index using Principal Component Analysis (PCA) to have a continuous variable with mean 0 and a standard deviation of 1. Larger values in the index represent households living in more spatially and economically isolated locations.

The surveys also contain climatology, landscape typology, and agro-ecological information for each household that I use to improve the precision of the estimates. Finally, the LSMS-ISA surveys collect household socio-economic characteristics, that I use as controls for the empirical estimation. Section 3.A in the Appendix presents the defini-

the analysis and when the first draft of the chapter was already in construction. It is let for future research to integrate Burkina Faso to the analysis.

[18]I follow Dillon et al. (2019) to construct the number of person-days for each type of labor. The only difference with those authors is that I exclude child labor from the main estimation, due to its very low contribution to the total labor demand.

[19]The number of observations used in the empirical analysis could be different if, for example, one household has missing in one control variable; or if there are singletones observations for the estimation of high-dimensional fixed effects. As in Dillon et al. (2019), I estimate regressions on the sample of households that cultivated land in at least 50% of the survey waves (i.e. two different agricultural seasons at least).

[20]The Information Document that accompanies each of the surveys details the specific sources used for each variable and for each country.

tion of the main variables used in the empirical estimation. Table 3.B.4 in the Appendix presents some descriptive statistics on the main control variables.

To measure the rainfall deviations, I use gridded monthly precipitation estimates at 0.1° spatial resolution from the National Oceanic and Atmospheric Administration's African Rainfall Climatology v2 (NOAA-ARC2) data.[21] I use data for the period 1985-2021 to calculate the rainfall deviation, which corresponds to the standardized deviation of rainfall in year t with respect to the long-term precipitation levels (1985 - 2021) in location l $\left(\frac{Rain_{tl}-\bar{X}_l}{\sigma_l}\right)$. I focus on the months of the main rainfall season in each country to construct the precipitation deviations.

3.3.2 Empirical estimation

The conceptual framework and the two-input model presented in section 3.2.1 predict that negative rainfall deviations reduce the use of family labor (in non-remote areas) and of labor exchange (in remote locations). Although the extended model that includes hired labor presented in Section 3.2.2 does not allow to analytically predict the effect of rainfall deviations on the use of each type of labor, one could expect to find the same effects for family and exchange labor as described below, and the same direction of the effect for hired labor.

To empirically validate these hypotheses, I analyze how farm labor allocation of family, hired, and exchange labor reacts to productivity shocks, measured as contemporaneous rainfall deviations from historical precipitation levels. I further investigate if farm labor utilization responds differently depending on the remoteness of the household's location. I investigate the responses at the extensive margin -the probability of using each type of labor- and the intensive margin -the number of person-days of each type of labor that the household allocated in all of their land. The equation below presents the main empirical estimation.

$$Y_{hflct} = \alpha_0+\beta_1 Shock_{lt}+\beta_2 Remoteness_{hlc}+\beta_3\left(Shock_{lt} \times Remoteness_{hlc}\right)+\mathbf{X}_{hflct}\zeta+\delta_h+\tau_t+\nu_{ct}+\theta_{hlct} \tag{3.20}$$

where Y_{hlct} measures the on-farm labor allocation of household h during cultivation phase f (pre-harvesting or harvesting) in location l of country c in year t. The labor allocation is split into family labor (F), hired labor (H), or exchange labor (E) and is

[21]The African Rainfall Climatology (ARC) dataset is developed by the National Oceanic and Atmospheric Administration as part of the Famine Early Warning Systems Network (FEWS NET). See Novella and Thiaw (2013) for a description. The data can be accessed through the IRI/LDEO Climate Data Library of the University of Columbia.

measured at the extensive (probability of using) and intensive margin ((log of) number of person-days).[22]

$Shock_{lt}$ measures the continuous standardized rainfall deviation during the months of the main raining season in location l. This variable takes on positive and negative values and it is standardized at mean zero. Positive values capture rainfall deviations above the average precipitation level during the main raining season between 1985 and 2021 in location l, while negative values capture deviations below the average (e.g. droughts).[23]

$Remoteness_{hlc}$ is the standardized remoteness index of household h, measured at baseline (i.e. first survey wave) to reduce potential concerns of endogeneity (i.e. if the household moved to another location due to bad weather realizations, or if a road construction/extension program targeted specific remote or non-remote localities). Therefore, the coefficient β_2 in equation (3.20) is absorbed by the household fixed effect δ_h.

The vector $\mathbf{X}_{hlct}$ is a set of control variables that includes the household size, the cultivated area (ha), the percentage of land under agriculture within 1 km buffer, the average rainfall in the wettest quarter of the year, the agro-ecological zone, and the season (planting or harvesting). I also include wave (τ_t) and household-level (δ_h) fixed effects, and a specific country-by-year fixed effect (ν_{ct}) to capture unobserved heterogeneity at the country level that could affect labor allocation across households in different years.[24] Standard errors are clustered at the cell level (0.1° Latitude x 0.1° Longitude) to account for correlation across space over time.

To control for potential spurious weather correlations with spatiotemporal patterns in the outcomes of interest, I include $P_{l,t}$, the tensor product of first-order Legendre polynomials of latitude and longitude.[25] Controlling for this type of correlations is not systematically done in studies that exploit rainfall or other weather shocks as an

[22] For the main estimation, I measure outcomes at the intensive margin as log(1+y). Since most households employ one or more household members to work on the household's plots,the log transformation is not affected by the presence of zeros in the number of person-days of family labor. However, for hired and exchange labor, the mass of zeros can distort the estimates of a linear regression. As such, a non-linear method such as a Poisson regression would be more appropriate for the estimation. However, due to the panel component of the data that can lead to statistical separation or dropping singleton observations, plus the presence of high-dimensional fixed effects, maximum likelihood estimates are not guaranteed to exist (Correia et al., 2020) or an important number of estimations can be excluded. Therefore, I use the log-transformation of the outcome in the main specification, but I show that results are robust to untransformed OLS estimation as well as to a non-linear Poisson pseudo-likelihood regression.

[23] Jayachandran (2006) and Kaur (2019) use rainfall shocks to study patterns of labor allocation in rural India. They define a negative shock as rainfall below the twentieth percentile of the district's usual distribution, and a positive shock as above the eightieth percentile (in the first month of the monsoon season). This way of measuring the shock as an indicator variable does not allow to exploit the full distribution of the rainfall deviation, and therefore I prefer to use the z-score measure in my main specification. In section 3.4.3 I use the indicator variable as measure of the shock as a robustness test.

[24] This would account for factors such as macroeconomic conditions, national policy changes, or other country-specific events that might influence labor markets or household decisions within a given year.

[25] $P_{l,t} \equiv P(x,y,t) = t\sum_{j=0}^{J}\sum_{k=0}^{K}\theta_{jk}P(x)P(y)$, where $P_i(\cdot)$ is the ith-order Legendre polynomial over dimensions x and y which, in this case, correspond to longitude and latitude.

exogenous variation, and can lead to biased or inconsistent estimated parameters, even if spatial trends can be controlled for with the inclusion of fixed effects (Lind, 2019). To determine if positive and negative rainfall deviations have asymmetric effects on labor utilization, I split rainfall deviations between above and below zero. Equation (3.21) below shows the final empirical estimation to assess the effect of rainfall shocks and remoteness on farm labor allocation at the household level.[26]

$$\begin{aligned} Y_{hflct} = \alpha_0 + \beta_1 Shock^{+}_{lt} + \beta_2 \left(Shock^{+}_{lt} \times Remot._{hlc}\right) + \beta_3 Shock^{-}_{lt} + \beta_4 \left(Shock^{-}_{lt} \times Remot._{hlc}\right) \\ + \mathbf{X}_{hflct}\zeta + \varphi P_{lt} + \delta_h + \tau_t + \nu_{ct} + \theta_{hlct} \end{aligned} \tag{3.21}$$

The main coefficients of interest are β_1 - β_4, which measure the effect of positive and negative rainfall deviations on the household's labor allocation decisions, and how this effect evolves with the remoteness of the household's location l.

3.4 Results

In this section, I test predictions 3.1-3.2 and Hypotheses 3.1-3.2 and present the results of estimating equation (3.21) with the LSMS-ISA data to determine how households in Ethiopia, Malawi, Niger, and Nigeria adjust their use of different types of labor inputs to rainfall deviations. I first present the results of a regression where the outcome variable is the (log. of) number of person-days of each type of labor (i.e. the intensive margin) in Section 3.4.1.[27] I then present heterogeneity analysis by cultivated land size and gender in Section 3.4.2 to better disentangle the general results. Finally, I present and discuss a battery of robustness checks to validate the main findings in Section 3.4.3.

3.4.1 Main results: intensive margin

Table 3.4.1 presents the results of the effect of rainfall deviations on the (log of) number of person-days of family (F), hired (H), and exchange (E) labor across the four countries in the sample. The first key result emerging from Table 3.4.1 is that positive rainfall deviations do not significantly impact the demand and allocation of any type of labor at the farm level. Only negative deviations (i.e., droughts) affect how farmers allocate

[26] To facilitate the interpretation of the results -particularly for negative rainfall-, I take the absolute value of the deviation when estimating equation (3.21).

[27] I also estimate the probability of using each type of labor. Nevertheless, due to the large number of observations and the presence of high-dimensional fixed effects, non-linear models such as logit fail to converge. Therefore I estimate equation 3.21 using a Linear Probability Model. Table 3.D.1 in the Appendix presents the results of estimating the probability that the household uses each type of labor when facing a contemporaneous rainfall deviation. The results for the intensive margin (log. of number of person-days) follow the same patter as the probability of using each type of labor, so I prefer to discuss the intensive margin results in detail.

labor to their plots. Therefore, in what follows I focus the discussion on the effects of negative rainfall on farm-level usage, and in section 3.5, I discuss the absence of effects of positive rainfall deviations. As a complement to the results of Table 3.4.1, in Appendix section 3.E I present plots of the average marginal effects of negative rainfall deviations on each type of labor by levels of remoteness.

Table 3.4.1: Labor demand by the household-farm - Pos. and Neg. Rainfall shock

	Number of person-days (Log.)			
	Total Labor	Household Labor	Hired Labor	Exchange Labor
	(1)	(2)	(3)	(4)
Pos. Rainfall	0.03	0.04	0.02	-0.02
	(0.03)	(0.04)	(0.02)	(0.02)
Pos. Rainfall × Remoteness index	0.01	0.02	0.02	-0.02
	(0.02)	(0.03)	(0.02)	(0.02)
Neg. Rainfall	-0.06	-0.10*	0.13***	-0.01
	(0.05)	(0.06)	(0.04)	(0.04)
Neg. Rainfall × Remoteness index	-0.02	0.03	0.01	-0.08**
	(0.05)	(0.05)	(0.04)	(0.04)
Observations	60186	60186	60186	60186
Mean of Dep. Variable	3.66	3.47	.764	.461
Adjusted R2	.371	.359	.393	.419
F-stat	20.8	23.3	7.89	6.59
Controls	Yes	Yes	Yes	Yes
Legendre Pol.	Deg. 1	Deg. 1	Deg. 1	Deg. 1
Fixed Effects	Yes	Yes	Yes	Yes
β Pos. + γ Pos. × Remot. (p-value)	.134	.114	.311	.237
β Neg. + γ Neg. × Remot. (p-value)	.237	.345	.007	.065

Observations are at the household-wave-season level. Method of estimation: OLS regression with high-dimensional fixed effects. Robust standard errors clustered at the Cell level (0.1° Latitude x 0.1° Longitude) are reported in parenthesis. Controls (coefficients not shown): Log. of household size, Log. of cultivated area (ha), Percentage of land under agriculture within approx 1 km buffer, Average total rainfall in wettest quarter (mm) within 12 months, Agro-Ecological Zone, and Season (non-harvesting or harvesting). Fixed Effects: household, year, and country-by-year. Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

The results in Table 3.4.1 show that negative rainfall deviations have different impacts on labor allocation, depending on the type of labor. First, the number of family labor person-days (Col. 2) allocated to on-farm activities decreases with negative rainfall deviations, and this effect varies with household remoteness, as predicted by the model. Although the coefficient β_4 is not statistically significant, computing the average marginal effect for negative rainfall shows that one standard deviation decrease in rainfall with respect to the historical mean make households living close to markets and population centers (i.e. one std. dev. below the average remoteness index) to reduce the use of family labor person-days allocated to on-farm tasks by 13.8%, equivalent to 11.8 person-days. Households living in isolated areas (i.e. one std. dev. above the average remoteness index) do not adjust the use of family labor to negative rainfall deviations.[28]

[28]The last two columns of Table 3.4.1 show the linear combination test of $\beta_1 + \beta_2$ and $\beta_3 + \beta_4$ evaluated at *Remoteness* = 1 (one std. dev. above the average remoteness index). For all columns in Table 3.4.1, and for the rest of Tables in this Section, I estimate the marginal effect at different levels of

Figure 3.E.1 illustrates the average marginal effects of negative rainfall on family labor usage across levels of remoteness. As stated in predictions 3.1 and 3.1, households near markets and population centers reduce their allocation of family labor (F) to on-farm activities, likely compensating with off-farm employment opportunities. In contrast, households in more isolated locations do not adjust their use of family labor after experiencing a negative rainfall deviation, likely due to limited off-farm labor opportunities to cope with the shock.

For hired labor (Col. 3), a one standard deviation decrease in rainfall leads to an average increase in the use of person-days of hired workers by almost 14%, or 1.02 person-days. This result contradicts the model's predictions in section 3.2.2 and can be counterintuitive, as decreased agricultural productivity is often associated with reduced labor input demand. Moreover, this effect is independent of remoteness (see Figure 3.E.2).

If hired labor is increasing despite a negative productivity shock in the form of negative rainfall, one would think that the agricultural wage w_h is adjusting to allow farmers to hire-in more workers. Indeed, if negative rainfall leads households to allocate less family labor (and possibly allocating this time to off-farm labor), then there is an increase in the available labor supply for landlords to hire from. One would therefore expect the wage to decrease in such a case. Table 3.4.2 below presents the estimation where the outcome variable is the log. of wages.

Results show that negative rainfall deviations have no effect on wages paid to hire workers. This is consistent with downward nominal rigidities in rural villages (Kaur, 2019), but does not allow to explain why farmers are demanding more use of external hired workers. In section 3.4.2.1, I show that the increase in the use of hired workers is driven by large landowners that are closer to population centers and markets, which could partially explain the increase in demand for hired workers despite the negative rainfall deviation.

Back to Table 3.4.1, Col. (4) shows that farmers reduce the number of person-days of exchange laborers after negative rainfall deviations, consistent with predictions 3.2 and 3.2 in the model. This effect occurs primarily in more remote locations, where households living beyond one standard deviation above the average remoteness index reduce labor exchange use by 9.4% -equivalent to 0.4 person-days with respect to the sample mean- following a one std. dev. reduction in rainfall. Figure 3.E.3 shows that households near markets and population centers (i.e., one standard deviation below the average remoteness index) do not significantly adjust their use of exchange labor in response to

remoteness (e.g. one std. dev. below) to determine the effect of remoteness on labor utilization. See Appendix section 3.E.

Table 3.4.2: Log. of daily wage paid to hired workers

	Daily wage (Log.)
	(1)
Pos. Rainfall	0.00
	(0.03)
Pos. Rainfall × Remoteness index	0.07**
	(0.03)
Neg. Rainfall	0.01
	(0.05)
Neg. Rainfall × Remoteness index	0.01
	(0.04)
Observations	14375
Mean of Dep. Variable	6
Adjusted R2	.83
F-stat	.93
Controls	Yes
Legendre Pol.	Deg. 1
Fixed Effects	Yes
β Pos. + γ Pos. × Remot. (p-value)	.0724
β Neg. + γ Neg. × Remot. (p-value)	.656

Observations are at the household-wave-season level. Method of estimation: OLS regression with high-dimensional fixed effects. Robust standard errors clustered at the Cell level (0.1° Latitude x 0.1° Longitude) are reported in parenthesis. Controls (coefficients not shown): Log. of household size, Log. of cultivated area (ha), Percentage of land under agriculture within approx 1 km buffer, Average total rainfall in wettest quarter (mm) within 12 months, Agro-Ecological Zone, and Season (non-harvesting or harvesting). Fixed Effects: household, year, and country-by-year. Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

rainfall deviations. Finally, total labor allocation (Col. 1) remains unaffected by rainfall deviations due to counterbalancing effects across family, hired, and exchange labor.

The results in Table 3.4.1 validate the model's predictions of an effect of negative rainfall deviations on: (i) reducing family labor utilization in locations close to markets and population centers (predictions 3.1 and 3.1), and (ii) decreasing labor exchange usage in more remote locations (predictions 3.2 and 3.2). However, the results for hired labor are at odds with Hypotheses in the three-input model (more on this later).

The results for a reduction in the use of family labor are in line with the literature that studies how agricultural households allocate their labor supply when they experience negative shocks: they reduce time in on-farm tasks and increase their supply to off-farm activities as a coping mechanism (Kochar, 1999; Rose, 2001; Ito and Kurosaki, 2009; Liu et al., 2023). The fact that this adjustment in the use of family labor occurs only among households located near population centers and markets suggests that access to off-farm opportunities is crucial for households to efficiently adjust labor utilization in response to negative shocks (Merfeld, 2023).

The result for labor exchange also provides evidence on the relevance of this non-market institution for households that live in more isolated regions, where paid labor can be scarce. The fact that the adjustment in E takes place in more remote locations is indicative of the importance of this collaborative form of labor for households that are far away from markets and urban centers, providing support for the "imperfect markets hypothesis" that seeks to explain why farmers engage in labor-sharing. Additionally, this result points towards the idea that labor exchange is particularly relevant for time-specific activities where exchanging labor is most valuable, for example the timely planting of seeds when the first rains arrive. When there is a decrease in rainfall, the urgency of such tasks diminishes. Although exchanging labor does not require cash payments, there are time and in-kind costs associated to it, and so by reducing the amount of labor exchange the household can save on these costs.

To better disentangle the results presented in Table 3.4.1, below I conduct heterogeneity analysis by land size and gender.

3.4.2 Heterogeneity analysis

3.4.2.1 Land size

The unexpected increase in the use of hired labor when farmers experience negative rainfall deviations could be driven by large landowners, who are usually net buyers of labor. If negative rainfall deviations cause farmers to allocate less family labor to on-farm activities (potentially sending some members to off-farm work), as shown earlier, a larger pool of workers might become available, especially near large population centers and markets. Thus, large cultivators could be driving the increase in the use of hired labor, despite the negative rainfall deviation that lowers agricultural productivity.

To evaluate this hypothesis and explore how rainfall deviations differentially affect labor allocation among small and large land cultivators, I classify households based on cultivated land size relative to the country median in each survey. Table 3.4.3 presents the results of estimating equation (3.21) for households categorized by their landholdings.

Results in Table 3.4.3 support the hypothesis that large landowners are the ones that increase the demand for hired workers when they experience a negative rainfall shock.[29] The results also reveal interesting patterns in how households allocate different types of labor based on their cultivated land size.

Small landowners, those with cultivated land below the median size in their country, appear to be the ones reducing the use of exchange workers in more remote areas after a negative rainfall deviation (Col. 4). Although the effect of the interaction between negative rainfall deviation and remoteness is not statistically significant at conventional

[29] However, the analysis of wages does not show any different pattern as the set of result in Table 3.4.2. Negative rainfall deviations do not have any impact on wages paid either small or large landowners, which remains a puzzling question. Results available on demand.

Table 3.4.3: Labor demand by the household-farm - Pos. and Neg. Rainfall shock (by land size)

	Number of person-days (Log.)							
	Land size < p50				Land size > p50			
	(1) Total Labor	(2) Household L.	(3) Hired L.	(4) Exchange L.	(5) Total Labor	(6) Household L.	(7) Hired L.	(8) Exchange L.
Pos. Rainfall	-0.00	-0.03	0.03	-0.00	0.04	0.07	0.01	-0.05
	(0.05)	(0.06)	(0.03)	(0.03)	(0.04)	(0.05)	(0.04)	(0.04)
Pos. Rainfall × Remoteness index	-0.00	0.01	0.03	-0.01	0.01	-0.00	0.02	-0.02
	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.02)
Neg. Rainfall	-0.09	-0.13	0.00	-0.03	-0.06	-0.10*	0.16***	0.00
	(0.09)	(0.11)	(0.05)	(0.04)	(0.05)	(0.06)	(0.05)	(0.05)
Neg. Rainfall × Remoteness index	-0.12	-0.07	0.03	-0.08**	0.03	0.08	-0.02	-0.05
	(0.08)	(0.08)	(0.04)	(0.04)	(0.05)	(0.06)	(0.06)	(0.06)
Observations	29050	29050	29050	29050	30940	30940	30940	30940
Mean of Dep. Variable	3.25	3.07	.593	.34	4.06	3.85	.926	.576
Adjusted R2	.331	.322	.396	.384	.324	.332	.399	.458
F-stat	8.47	8.84	2.9	4.9	10.1	12.3	5.42	3.6
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Legendre Pol.	Deg. 1	Deg. 1	Deg. 1	Deg. 1	Deg. 1	Deg. 1	Deg. 1	Deg. 1
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
β Pos. + γ Pos. × Remot. (p-value)	.869	.681	.101	.827	.272	.175	.587	.055
β Neg. + γ Neg. × Remot. (p-value)	.073	.11	.619	.111	.649	.831	.053	.454

Observations are at the household-wave-season level. Method of estimation: OLS regression with high-dimensional fixed effects. Robust standard errors clustered at the Cell level (0.1° Latitude x 0.1° Longitude) are reported in parenthesis. Controls (coefficients not shown): Log. of household size, Log. of cultivated area (ha), Percentage of land under agriculture within approx 1 km buffer, Average total rainfall in wettest quarter (mm) within 12 months, Agro-Ecological Zone, and Season (non-harvesting or harvesting). Fixed Effects: household, year, and country-by-year. Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

levels (p-value of 0.111), the result in Col. (4) suggests that small cultivators in more remote locations adjust their use of labor exchange in response to reduced rainfall (see Figure 3.E.6 in the Appendix). This result is unsurprising given that small landholders are likely more cash-constrained and depend more on free labor exchange to overcome these constraints. Gilligan (2004) notes that labor exchange typically requires participants to have relatively homogeneous land sizes, a condition more likely to be met by small to medium farmers. Moreover, Table 3.4.3 shows that small landowners do not adjust their utilization of hired labor (Col. 3) or family labor (Col. 2) for on-farm activities.

In contrast, large cultivators do not adjust their use of labor exchange, but they are the ones increasing demand for hired labor while simultaneously reducing the allocation of family labor to on-farm work. Column 6 and Figure 3.E.4 show that households near markets and population centers (i.e., one standard deviation or more below the average remoteness index) reduce the number of family labor person-days by 9.3% on average after a one standard deviation decrease in rainfall. However, households in more isolated areas do not adjust their family labor usage after experiencing a similar shock.

For hired labor, Column 7 reveals that large landowners are the ones increasing its use after experiencing negative rainfall deviations (see Figure 3.E.5). For instance, farmers near population centers and markets (one standard deviation below the average remoteness index) increase their demand for hired workers by 19.7% (or 0.5 person-days) following a contemporaneous one standard deviation decrease in rainfall.

Taken together, these results suggest that different opportunity and transaction costs in accessing labor markets influence how farmers in Ethiopia, Malawi, Niger, and Nigeria allocate family and hired labor to their plots. This corresponds with recent findings showing that failures in agricultural (labor) markets are often household-specific rather than a market-wide phenomena (LaFave et al., 2020; Merfeld, 2023).

Merfeld (2023) argues that landholdings and limited off-farm labor opportunities explain why small landholders in India overallocate labor to agricultural production. Consistent with this evidence, I find that small cultivators in my sample are unable to reallocate labor even when doing so would be more efficient. When they face negative rainfall deviations that lower the marginal productivity of labor, they do not reduce the use of family labor.

Moreover, I find asymmetric responses to negative rainfall deviations even among large cultivators. Largeholders should be able to reallocate labor across different plots more efficiently as land size is not binding (Merfeld, 2023). However, Table 3.4.3 shows that remoteness plays a significant role in labor reallocation, even for large cultivators. Large farmers near population centers and markets are able to reallocate family labor out of on-farm activities, whereas those in more isolated areas do not (see panel (b) of Figure 3.E.4). This suggests that both landholdings and remoteness influence labor (mis)allocation. Consequently, small landowners and those living in isolated regions across Ethiopia, Malawi, Niger, and Nigeria appear to be overallocating labor to agricultural tasks, even when productivity is low.

3.4.2.2 Gender

As a second heterogeneity analysis, I study how the use of different types of labor react differently to rainfall deviations depending on the gender of workers. In her study of how labor markets allow households to shift labor from farm to off-farm employment to cope with negative income shocks in rural India, Kochar (1999) finds that household males increase their market hours of work in response to those shocks while there is little significant effect for females. Recent evidence, as well in the context of India, finds the same result: men increase their time allocated to wage work and diversify to non-farm sector jobs to cope with droughts, while women do not (Afridi et al., 2022; Maitra and Tagat, 2024). To evaluate these findings in the context of my study, Table 3.4.4 estimates equation (3.21) separatedly for male and female labor allocation.

Results show a strikingly gendered response of labor utilization to rainfall shocks: households hire in and hire out only male workers, with no changes on the use of female labor. The decrease in labor exchange in more remote areas that I found in Table 3.4.1 is also mostly driven by a reduction in the utilization of male exchange workers, although

Table 3.4.4: Labor demand by the household-farm - Pos. and Neg. Rainfall shock (by gender)

	Number of person-days (Log.)							
	Men				Women			
	(1) Total Labor	(2) Household L.	(3) Hired L.	(4) Exchange L.	(5) Total Labor	(6) Household L.	(7) Hired L.	(8) Exchange L.
Pos. Rainfall	0.05*	0.05	0.02	-0.02	-0.02	-0.02	-0.01	0.00
	(0.03)	(0.03)	(0.02)	(0.02)	(0.04)	(0.04)	(0.01)	(0.01)
Pos. Rainfall × Remoteness index	0.02	0.02	0.01	-0.01	0.02	0.01	0.01	-0.00
	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.01)	(0.01)
Neg. Rainfall	-0.07	-0.12**	0.12***	-0.02	0.00	-0.02	0.01	0.02
	(0.05)	(0.05)	(0.03)	(0.03)	(0.06)	(0.07)	(0.02)	(0.02)
Neg. Rainfall × Remoteness index	0.01	0.07	0.01	-0.06*	-0.02	-0.01	-0.01	-0.03*
	(0.04)	(0.05)	(0.03)	(0.03)	(0.06)	(0.06)	(0.02)	(0.02)
Observations	60186	60186	60012	60011	60186	60186	60012	60011
Mean of Dep. Variable	3.03	2.75	.671	.388	2.22	2.1	.241	.146
Adjusted R2	.468	.47	.385	.433	.397	.403	.24	.213
F-stat	22	27.7	6.93	5.58	9.6	10.7	4.33	4.89
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Legendre Pol.	Deg. 1	Deg. 1	Deg. 1	Deg. 1	Deg. 1	Deg. 1	Deg. 1	Deg. 1
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
β Pos. + γ Pos. × Remot. (p-value)	.033	.044	.291	.169	.953	.864	.692	.883
β Neg. + γ Neg. × Remot. (p-value)	.38	.522	.009	.054	.824	.666	.848	.572

Observations are at the household-wave-season level. Method of estimation: OLS regression with high-dimensional fixed effects. Robust standard errors clustered at the Cell level (0.1° Latitude x 0.1° Longitude) are reported in parenthesis. Controls (coefficients not shown): Log. of household size, Log. of cultivated area (ha), Percentage of land under agriculture within approx 1 km buffer, Average total rainfall in wettest quarter (mm) within 12 months, Agro-Ecological Zone, and Season (non-harvesting or harvesting). Fixed Effects: household, year, and country-by-year. Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

there is a reduction as well in female labor workers, half of their male counterparts. These results reflect stylized facts about gendered on-farm and off-farm labor allocation in Africa (Palacios-Lopez et al., 2017; van den Broeck and Kilic, 2019).[30] It is not surprising to find that person-days adjustments involve only male workforce: households use less male own-labor for on-farm activities after experiencing negative rainfall deviations, probably sending male members to work in the off-farm economy. In the case of SSA, it is known that across time and countries (and even within countries), men participate to a significantly greater extent in wage work and self-employment off-farm compared to women (van den Broeck and Kilic, 2019).

The analysis by gender also provides evidence that, despite the general results in Table 3.4.1 that showed that farmers only react to negative deviations, positive rainfall deviations can have an effect on the demand of certain types of labor for farming activities. In particular, columns 1 and 2 of Table 3.4.4 (and Figure 3.E.7 in the Appendix) show that the use of male family labor in the household's plots increases with positive rainfall deviations (and this drives the increase in total labor), but only for households in more remote locations. For households living a one standard deviation above the average remoteness, a one standard deviation increase in rainfall with respect to its historical mean makes households allocate 1.13 more person-days of male family labor to their own plots.

[30] Palacios-Lopez et al. (2017) established the share of female household members that participate in crop production in various SSA countries at 40%, with low female participation in countries like Ethiopia (29%) and Niger (24%).

3.4.3 Robustness checks

I run a battery of robustness tests to validate the results found in the previous sections. Results in the Appendix section 3.F show that the empirical findings are robust to (1) other measures of the outcome variable and different estimation methods, such as the Inverse hyperbolic sine transformation and non-linear Poisson pseudo-likelihood regression (Appendix section 3.F.1); (2) controlling for more flexible spatial and spatiotemporal trends using Legendre polynomials of second, third, and fourth degree (Appendix 3.F.2); (3) wild cluster bootstrap inference (Cameron et al., 2008; MacKinnon et al., 2023) (Appendix 3.F.3); (4) more conservative clustering of the standard errors at the municipality, district, and state levels (Appendix 3.F.4); (5) a placebo test that regress the outcomes on the rainfall shock in year $t+1$ (Appendix 3.F.5); (6) random permutations of the remoteness index and the rainfall deviations (Appendix 3.F.6); and (7) multiple hypothesis testing using stepdown adjusted p-values (Romano and Wolf, 2005a,b) (Appendix 3.F.7).

I also run a regression using a different definition of the rainfall shock, as presented in Jayachandran (2006) and Kaur (2019). The estimates in Appendix 3.F.8 present similar magnitude and direction as in my main estimation, although the coefficient of household and exchange labor fail to be statistically significant at the 10% level. Nevertheless, this way of measuring the shock as an indicator variable does not allow to exploit the full distribution of the rainfall deviation, and therefore I prefer the specification that uses the z-score.

3.5 Limitations of the study and future research

The models developed in Section 3.2, although basic in some aspects, provide important insights into the importance of accounting for labor exchange in the production functions of rural households and the input utilization decisions of farmers. They also highlight the interplay between remoteness and rainfall deviations, factors that can significantly affect agricultural yields and household profits. The empirical analysis presented in Section 3.4 validates some of the models' predictions, but also reveal interesting results that underscore the limitations of this chapter and suggest avenues for future research. Below, I outline some of these elements and provide a brief discussion of each.

No effect of positive rainfall deviations

The models in Section 3.2 are constructed to reflect "symmetric" effects of rainfall deviations on labor inputs utilization, meaning that such deviations should influence labor allocation equally but in opposite directions. However, the empirical results suggest asymmetrical effects: negative rainfall significantly alters how farmers allocate labor, while positive rainfall deviations appear to have no effect on the utilization of any type of labor at the farm level.

A natural extension to this study consists in adjusting the model to allow for asymmetric effects of negative and positive rainfall deviations. Such an adjustment would align theoretical predictions more closely with empirical findings, improving the model's explanatory power. More importantly, the asymmetric result raises the question of why farmers across the four Sub-Saharan African countries in the study do not adjust their labor utilization in response to increased rainfall. Below, I outline two hypotheses that could potentially explain this outcome and provide avenues for future research.

First, farmers may exhibit reference-dependent preferences (Kőszegi and Rabin, 2006) and income-targeting behavior. Increased rainfall likely leads to higher yields but also necessitates additional labor. If farmers are income-targeters, they might not increase labor inputs because the excess rainfall already ensures a harvest sufficient to meet a predetermined income (or consumption) level, leaving households with more time for other activities.

Reference-dependent preferences and income targeting have received significant attention in behavioral economics, challenging the assumption that individuals always exhibit standard neoclassical preferences. Instead, decisions are often influenced by reference points and varying levels of risk aversion.[31] A classical example in that field shows that taxi drivers in New York City tend to stop working when they reach a certain level of daily income (Camerer et al., 1997; Farber, 2008). By comparison, there is little research on whether farmers in rural areas of developing countries have implicit income or effort targets that could explain why they do not provide more work on-farm in the presence of positive productivity shocks, such as more rainfall.[32]

In the Sub-Saharan African context, Dupas et al. (2020) investigate the labor supply decisions of Kenyan bicycle taxi drivers. The authors document that labor supply is strongly correlated with cash needs, with drivers frequently quitting after earning enough to meet their stated needs. Their findings suggest that Kenyan bike drivers exhibit reference-dependent preferences around daily earned income targets, which reduce perceived effort costs until the target is reached.

Similar to the Kenyan bicycle taxi drivers who target daily earned income, farmers in the countries of my study might also exhibit implicit income targets. If a positive rainfall shock is expected to increase farm income (e.g., through higher crop yields),

[31] For an overview of reference-dependent behavior and other aspects of behavioral economics in development, see Kremer et al. (2019).

[32] In the context of agricultural labor, Richards (2020) examines how farm workers' labor supply in the US responds to wage changes and finds that under certain situations, after adjusting for income and hour targets, labor-supply curves of piece-rate workers can be backward bending, consistent with income-targeting behavior.

farmers may perceive that they can meet their income targets without increasing labor effort. Also, if farmers already perceive their labor effort as sufficient to meet their production goals, additional effort may be seen as unnecessary or too costly. Therefore, reference-dependent preferences and income-targeting could be a possible explanation of why farmers are not providing nor demanding more labor on-farm when they face positive rainfall deviations.

A second, distinct hypothesis, could be that households face liquidity and credit constraints, limiting their ability to exploit positive productivity shocks like increased rainfall. In the presence of such market imperfections, farmers may wish to increase on-farm labor but are unable to hire extra workers or invest in technologies to capitalize on excess rainfall, ultimately leading to no increases in on-farm labor utilization.

The models in Section 3.2 could be extended to incorporate credit constraints and the empirical analysis complemented to test this mechanism. For example, Ali et al. (2014) show that credit market imperfections hinder households' ability to maximize input use in Rwandan farming activities, estimating that alleviating these constraints could increase crop yields by at least 17%. In Zambia, Fink et al. (2020) find that improving farmers' liquidity with subsidized credit during the lean season leads to more use of on-farm labor inputs and increased farm productivity. The authors calculate that households use more than half of the credit to reallocate family labor to on-farm tasks and hire-in more external workers.

These examples in similar contexts to the ones faced by farmers in Ethiopia, Malawi, Niger, and Nigeria could suggest that liquidity constraints and credit restrictions are one potential reason of why farmers are not able to increase labor utilization in the presence of positive shocks, such as high rainfall.

Importantly, the policy implications of these two hypotheses differ significantly. Therefore, understanding which mechanism—or potentially another—is at play is critical. This largely justifies the need to further investigate why farmers do not allocate more labor when experiencing positive precipitation shocks.

Increase in the use of Hired Labor

The empirical results in Section 3.4 indicate that farmers in the countries included in this study increase their demand for hired labor (H) and use more paid workers for farming activities when they face contemporaneous negative rainfall deviations. Although it is not possible to analytically determine the effect of rainfall on hired labor from the extended model presented in Section 3.2.2, the observed increase in H is unexpected and counterintuitive within the framework of standard economic analysis. One would generally expect that negative rainfall deviations reduce the use of hired labor, as the marginal product of labor decreases.

The heterogeneity analysis in Section 3.4.2.1 reveals that the increase in hired labor following negative rainfall is driven primarily by large landowners located near population centers and markets. This finding suggests that the result, while unexpected, may not be entirely implausible as large landowners are usually net buyers of labor. One potential explanation for this behavior could be as follows.

Negative rainfall leads households in non-remote locations to allocate less family labor to on-farm activities—as predicted by the model and supported by the empirical analysis—and instead engage in off-farm activities to cope with the shock. This shift creates a larger pool of available workers seeking employment, from which large landowners may hire. If this is the case, and a significant number of workers are seeking jobs, then wages would be expected to decrease as labor supply increases, allowing large landowners to hire in more workers for a lower price.

However, Table 3.4.2 showed that negative rainfall deviations have no effect on wages paid to hire workers, undermining the idea that landowners are hiring more workers because wages are lower. Interestingly, Table 3.4.2 also shows that wages tend to increase in more remote locations under positive rainfall deviations. This pattern of results is consistent with downward nominal rigidities, as in Kaur (2019). In the context of rural villages in India, S. Kaur finds that "nominal wages rise in response to positive shocks, but are no lower during negative shocks on average" (p. 3587) and attributes this downward rigidity to social norms within communities, where cutting wages during periods of poor rainfall is viewed as unfair.

Why, then, are large landowners hiring more workers—and paying the same wage—when they face negative rainfall deviations? Understanding why farmers in Ethiopia, Malawi, Niger, and Nigeria exhibit this behavior during periods of low rainfall remains a puzzling question for further research.

Off-Farm Labor Opportunities (N_o)

The theoretical models in Section 3.2 consider off-farm labor (N_o) as the residual variable in the maximization problem. However, some of the arguments about how remoteness affects labor utilization—and particularly why family labor (F) decreases with negative rainfall—rest on the intrinsic assumption that off-farm employment opportunities are available to households, and that these opportunities enable them to cope with negative shocks. For example, Ito and Kurosaki (2009) show that, in the context of India, households increase the share of off-farm labor supply when weather risk increases, with nonagricultural paid work increasing by as much as 46 pp.

Extensive literature has demonstrated that rural households often use off-farm employment to cope with idiosyncratic or covariate shocks, such as low rainfall and droughts (Kochar, 1999; Rose, 2001; Jayachandran, 2006; Ito and Kurosaki, 2009; Mathenge and Tschirley, 2015; Gao and Mills, 2018; Call et al., 2019). It is therefore reasonable to assume that this mechanism also applies to the context of this study. Nevertheless, a natural extension for future research would be to derive specific predictions regarding the effect of rainfall deviations on N_o and empirically estimate whether—and to what extent—households in Ethiopia, Malawi, Niger, and Nigeria (and possibly other countries) substitute on-farm family labor with off-farm employment. The household module of the LSMS-ISA surveys include questions about time use and labor supply of household members in both agricultural and non-agricultural activities, allowing for the empirical estimation on off-farm labor.[33]

3.6 Conclusion

This chapter contributes to the literature on agricultural labor allocation by explicitly incorporating labor exchange into the analysis of farmers' responses to precipitation deviations in Sub-Saharan Africa (SSA). Models of agrarian households pay little to no attention to labor exchange as an input in the labor allocation decisions of farmers, neglecting the interplay between market and non-market labor institutions, and the analysis of why households in the developing world still rely on this non-market institution to access (free) labor. I show that labor exchange is widely used across farmers in different Sub-Saharan countries —with as many as 88% of rural households in Ethiopia engaging in labor-sharing— and that remoteness is a relevant factor to consider when analyzing how farmers allocate labor inputs in the presence of rainfall deviations.

The results show that farmers in remote areas rely less on labor exchange during episodes of negative rainfall, while those near population centers and markets reduce on-farm family labor in response to such shocks, potentially reallocating time to off-farm activities. Interestingly, I find a significant increase in the use of hired workers during adverse rainfall conditions.

The gendered nature of the adjustments and the lack of significant responses in labor allocation to positive rainfall deviations underscore the need to further investigate the gendered aspects of labor allocation, as well as the asymmetry in responses to posi-

[33] Nevertheless, it is important to consider the timing and the periods covered by the household and the agriculture modules. Whereas the household module asks detailed questions regarding labor activities in the past 7 days, the agriculture module covers the totality of the pre-harvesting and harvesting season. Moreover, the household questionnaire is collected during the first or second visit (within the same wave), but the agriculture module is collected twice. These factors must be considered when trying to compare "labor demand" at the farm level (agriculture module) with "labor supply" (household module).

tive and negative rainfall deviations. This will deepen our understanding of farm labor dynamics in SSA —including the use of labor exchange as part of the production decisions of african farmers. This is particularly important given that climate anomalies are becoming more frequent and are expected to disproportionately affect SSA countries, where most of the world's poor will be living in the years to come.

Appendix

Chapter 3 Appendix

3.A Definition of main variables

Household Labor (N_f) Number of person-days of family members that worked on the household's farm for agricultural activities during the season such as land preparation, planting, weeding, fertilizing, and harvesting. Person-days correspond to the aggregate number of days that all household members worked on farming.

Hired Labor (N_h) Number of person-days of external men and women (individuals who do not belong to the household) who were hired for a wage to work on the household's plots in any farming activities during the agricultural season.

Exchange Labor (N_e) Number of person-days of men and women from other households who work on the household's plots, free of charge, as exchange laborers or to assist for nothing in return.

Total Labor Total number of person-days of family members, external workers, and exchange laborers who were used on the household's plot on farming activities during the agricultural season. $TotalLabor = N_f + N_h + N_e$

Negative Rainfall Shock Standardized deviation (z-score) of rainfall during the main rainy season in year t with respect to the long-term precipitation mean of the main rainy season months. The variable only takes on negative values. That is, if rainfall in year t is below the long-term mean I assign this value to the variable. If rainfall during the rainy season is above the average, the variable takes zero for that year.

Remoteness Index Index that measures the remoteness of a household's farm location as a function of its distance (in km.) to (i) the nearest major road, (ii) the nearest major agricultural market, and (iii) the nearest population center of more than 20,000 pop. The index is constructed with the first component of a PCA linear dimensionality reduction, where a higher value indicates more remoteness or isolation. The index is standardized to have mean zero and standard deviation of one.

Household size Number of family members within the household. The variable is log transformed (Log of hosuehold size).

Cultivated area (ha) Number of hectares of land that the household cultivates during the agricultural season. Whenever available, I use the GPS-based measure of each field and then aggregate the area of all cultivated fields. If the GPS measure is not available for a field, I use the farmer's self-report measure. Total area is expressed in ha, and then I log-transformed the variable.

% of land under agriculture Percentage of land under agriculture near the household's farm within (approx.) 1km buffer. Data comes from the UCLouvain and the European Space Agency GlobCover Portal and it is measured at a resolution of 0.002778° (approximately 300 m).

Total rainfall in wettest quarter Precipitation of wettest quarter (mm) during the calendar year.

Agro-Ecological Zone Agro-ecological zones with similar characteristics related to land suitability and potential production. The zoning is based on IPFRI standardized elevation and climatology conditions. Eight zones are defined across the countries: Tropic-warm/arid/ semiarid/ subhumid/ humid, and Tropic-cool/arid/ semiarid/ subhumid/ humid

Season Refers to whether the agricultural activities took place either during pre-harvest (activities such as land preparation, planting, ridging, weeding and fertilizing) or harvest.

3.B Descriptive statistics

Distribution of households by country and wave

Table 3.B.1: Number of Household-observations by Country and Wave

	Wave				
Country	**1**	**2**	**3**	**4**	**Total**
Ethiopia	2,809	3,058	3,027	–	8,894
Malawi	1,208	1,495	1,785	1,726	6,214
Niger	1,692	1,692	–	–	3,384
Nigeria	2,884	2,889	2,845	–	8,618
Total	8,593	9,134	7,657	1,726	27,110

Note: Dashes (–) indicate that data for the corresponding wave is not available for that country.

Probability of using each type of labor

Table 3.B.2: Probability of using each type of labor

	Ethiopia	Malawi	Niger	Nigeria	Total
Household Labor	1.00	1.00	1.00	1.00	1.00
	(0.04)	(0.00)	(0.00)	(0.00)	(0.02)
Hired Labor	0.50	0.58	0.52	0.88	0.64
	(0.50)	(0.49)	(0.50)	(0.33)	(0.48)
Exchange Labor	0.88	0.56	0.33	0.31	0.55
	(0.33)	(0.50)	(0.47)	(0.46)	(0.50)
Observations	3076	1890	1692	2973	9631

For each type of labor, the first row shows the mean and the second row (in parenthesis) the standard deviation.

Average number of person-days in the farm

Table 3.B.3: Number of person-days by type of labor

	Ethiopia	Malawi	Niger	Nigeria	Total
Household Labor	88.29	36.40	69.00	119.60	84.38
	(66.68)	(24.18)	(53.91)	(98.71)	(77.03)
Hired Labor	5.25	2.14	3.23	12.10	6.40
	(11.44)	(3.55)	(6.04)	(12.81)	(10.82)
Exchange Labor	8.89	0.59	1.14	0.24	3.23
	(10.45)	(0.92)	(2.41)	(0.45)	(7.16)
All Labor	102.44	39.12	73.37	131.94	94.01
	(72.23)	(24.60)	(54.95)	(101.16)	(81.28)
Observations	3076	1890	1692	2973	9631

For each type of labor, the first row shows the mean and the second row (in parenthesis) the standard deviation.

Control variables

Table 3.B.4: Descriptive statistics

	Ethiopia	Malawi	Niger	Nigeria	Total
Household size	5.62	4.97	7.40	7.02	6.24
	(2.22)	(1.93)	(3.66)	(3.26)	(2.97)
Cultivated area (ha)	1.09	0.84	7.96	0.95	2.20
	(3.25)	(5.40)	(20.35)	(1.23)	(9.45)
Distance to road (km)	15.46	8.62	12.14	10.14	11.89
	(17.34)	(9.38)	(15.26)	(9.07)	(13.66)
Distance to Pop. Center (km)	36.88	28.01	66.35	26.08	36.98
	(28.06)	(15.22)	(47.75)	(16.70)	(31.42)
Distance to Market (km)	67.27	20.83	61.70	70.84	58.28
	(49.31)	(12.24)	(41.54)	(39.05)	(43.95)
Observations	3076	1890	1692	2973	9631

For each variable, the first row shows the mean and the second row (in parenthesis) the standard deviation.

Family and Hired Labor, and Remoteness

Figure 3.B.1: Probability of using Family Labor and remoteness

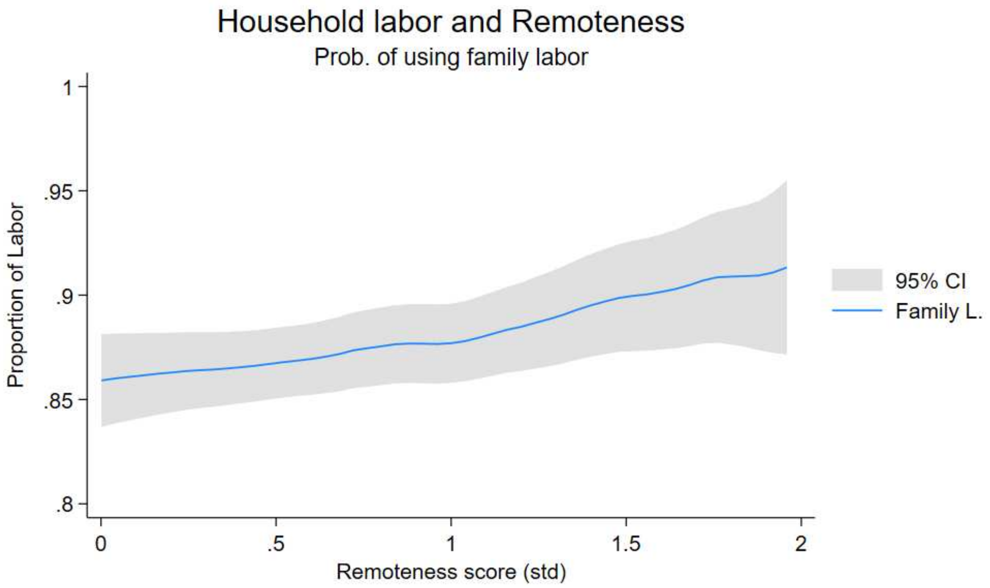
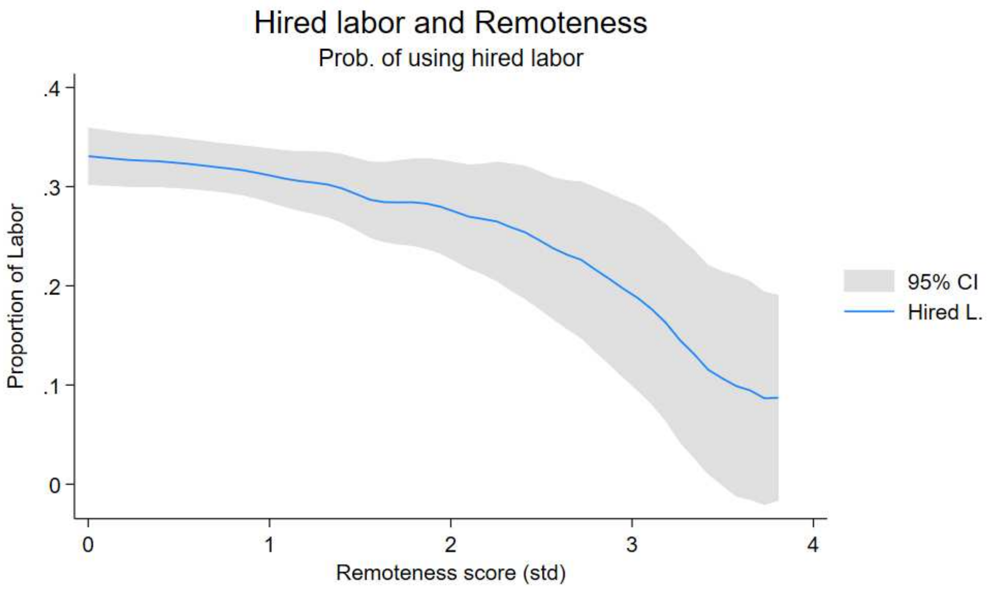


Figure 3.B.2: Probability of using Hired Labor and remoteness



3.C Details of the First Order Conditions for the Model

3.C.1 Model with two labor inputs: F and E

Utility maximization problem

We aim to maximize the utility function that depends on consumption (C) and lesiure (R): $U(C,R)$. Consumption C is given by

$$\theta G(F,E) + w_o N_o$$

and the time constraint is

$$T = R + F + (1+c_e)E + (1+c_o)N_o$$

Integrating the consumption equation and the time constraint into the utility function we obtain:

$$\max_{F,E,R} U(C,R) = U\left(\theta G(F,E) + w_o \frac{T - R - F - (1+c_e)E}{1+c_o}, R\right)$$

FOCs

$$\frac{\partial U}{\partial F} : \theta G_F - \frac{w_o}{1+c_o} = 0$$

$$\frac{\partial U}{\partial E} : \theta G_E - \frac{w_o}{1+c_o} \cdot (1+c_e) = 0$$

$$\frac{\partial U}{\partial R} : U_C\left(-\frac{w_o}{1+c_o}\right) + U_R = 0$$

Total differential of each FOC

In order to conduct a comparative static analysis and determine the effect of rainfall deviations on the utilization of family and exchange labor, I take the total differential of the FOCs and obtain the following:

$$d\left(\frac{\partial U}{\partial F}\right) : G_F d\theta + \theta G_{FF} dF + \theta G_{FE} dE - \frac{1}{1+c_o} dw_o = 0$$

$$d\left(\frac{\partial U}{\partial E}\right): G_E d\theta + \theta G_{EF} dF + \theta G_{EE} dE - \frac{1+c_e}{1+c_o} dw_o = 0$$

$$d\left(\frac{\partial U}{\partial R}\right): U_{CC}\left(-\frac{w_o}{1+c_o}\right)\frac{dw_o}{1+c_o} + U_{CR}\left(-\frac{w_o}{1+c_o}\right) dR + U_{RC}\left(-\frac{w_o}{1+c_o}\right)\frac{dw_o}{1+c_o} + U_{RR} dR = 0$$

This system of equations can be written in matrix form as:

$$\begin{pmatrix} \theta G_{FF} & \theta G_{FE} & 0 \\ \theta G_{EF} & \theta G_{EE} & 0 \\ 0 & 0 & J \end{pmatrix} \begin{pmatrix} dF^* \\ dE^* \\ dR^* \end{pmatrix} = \begin{pmatrix} -G_F d\theta + \frac{1}{1+c_o} dw_o \\ -G_E d\theta + \frac{1+c_e}{1+c_o} dw_o \\ K \end{pmatrix}$$

where $J = U_{CC}\left(\frac{w_o}{1+c_o}\right)^2 - 2\left(\frac{w_o}{1+c_o}\right) U_{CR} + U_{RR}$

and $K = \left[G\left(\frac{w_o}{1+c_o}\right) U_{CC} - U_{RR}\right] d\theta + \left[U_C + \left(\left(\frac{w_o}{1+c_o}\right) U_{CC} - U_{RR}\right)(T - R^* - F^* - (1+c_e)E^*)\right] dw_o$.

For the system to have an interior equilibrium, the Hessian matrix of second order conditions must be negative definite. That is:

$$|D_1| = \theta G_{FF} < 0 \text{ ; } |D_2| = \theta^2 \left(G_{FF} G_{EE} - G_{FE} G_{EF}\right) > 0 \text{ ; and } |D_3| = |D_2| J < 0$$

Effect of rainfall deviation

The effects of a rainfall deviations (θ) on family labor (F) and exchange labor (E) are given by solving $\frac{\partial i}{\partial \theta}, i \in \{F, E\}$ from the system of equations above.

The system $AX = B$ can be solved for X using the formula $X = A^{-1}B$, where A^{-1} is the inverse of A. We can find A^{-1} (assuming it exists) using the adjugate and determinant method:

$$X = \frac{\text{adj}(A)}{\det(A)} \cdot B$$

Family Labor F

$$\frac{\partial F}{\partial \theta} = \frac{\theta}{|D_2|} \cdot \left[G_{EE}\left(-G_F + \frac{1}{1+c_o}\frac{\partial w_o}{\partial \theta}\right) - G_{FE}\left(-G_E + \frac{1}{1+c_o}\frac{\partial w_o}{\partial \theta}\right)\right]$$

Replacing by the FOCs for F ($G_F = \frac{1}{\theta}\frac{w_o}{1+c_o}$) and E ($G_E = \frac{1}{\theta}\frac{w_o}{1+c_o}$)

$$\frac{\partial F}{\partial \theta} = \frac{\theta}{|D_2|} \cdot \left[G_{EE} \left(-\frac{1}{\theta} \frac{w_o}{1+c_o} + \frac{1}{1+c_o} \frac{\partial w_o}{\partial \theta} \right) - G_{FE} \left(-\frac{1}{\theta} \frac{w_o}{1+c_o} + \frac{1}{1+c_o} \frac{\partial w_o}{\partial \theta} \right) \right]$$

$$\frac{\partial F}{\partial \theta} = \frac{\theta}{|D_2|} \cdot \left[G_{EE} \left(\frac{1}{1+c_o} \left(-\frac{w_o}{\theta} + \frac{\partial w_o}{\partial \theta} \right) \right) - G_{FE} \left(\frac{1}{1+c_o} \left(-\frac{w_o}{\theta} + \frac{\partial w_o}{\partial \theta} \right) \right) \right]$$

$$\frac{\partial F}{\partial \theta} = \frac{\theta}{|D_2|} \cdot \left[\frac{1}{1+c_o} \left(G_{EE} \left(-\frac{w_o}{\theta} (1 - \epsilon_{w_o}) \right) - G_{FE} \left(-\frac{w_o}{\theta} (1 - \epsilon_{w_o}) \right) \right) \right]$$

where ϵ_{w_o} corresponds to the elasticity of the off-farm wage w_o with respect to the rainfall deviation.[34] It is possible to simplify the expression to:

$$\frac{\partial F}{\partial \theta} = \frac{1}{|D_2|} \cdot \gamma \left(G_{EE} - G_{FE} \right); \gamma = \frac{(-w_o)(1 - \epsilon_{w_o})}{1+c_o}$$

where $|D_2| = \theta^2 \left(G_{FF} G_{EE} - G_{FE} G_{EF} \right)$

Exchange Labor E

Solving the equation for $\frac{\partial E}{\partial \theta}$ we obtain:

$$\frac{\partial E}{\partial \theta} = \frac{\theta}{|D_2|} \cdot \left[G_{FF} \left(-G_E + \frac{1+c_e}{1+c_o} \frac{\partial w_o}{\partial \theta} \right) - G_{EF} \left(-G_F + \frac{1}{1+c_o} \frac{\partial w_o}{\partial \theta} \right) \right]$$

Again, replacing by the FOCs F and E and repeating the steps as in the case of family labor, we can express the effect of the rainfall deviation on the use of labor exchange as:

$$\frac{\partial E}{\partial \theta} = \frac{1}{|D_2|} \cdot \gamma \left[(1+c_e) G_{FF} - G_{EF} \right]$$

[34] $\epsilon_{w_o} = \frac{\partial w_o}{\partial \theta} / \frac{w_o}{\theta} \equiv \frac{\partial w_o}{w_o} / \frac{\partial \theta}{\theta}$

3.C.2 Model with three labor inputs: F, H and E

With three types of labor, the household seeks to solve the following maximization problem:

$$\max_{F,H,E,R} U(C,R) = U\left(\theta G(F,H,E) - w_h H + w_o \frac{T - R - F - (1+c_e)E - c_h H}{1+c_o}, R\right)$$

First Order Conditions (FOCs)

$$\frac{\partial U}{\partial F} : \theta G_F - \frac{w_o}{1+c_o} = 0$$

$$\frac{\partial U}{\partial H} : \theta G_H - w_h - \frac{w_o c_h}{1+c_o} = 0$$

$$\frac{\partial U}{\partial E} : \theta G_E - \frac{w_o}{1+c_o} \cdot (1+c_e) = 0$$

$$\frac{\partial U}{\partial R} : U_C \left(-\frac{w_o}{1+c_o}\right) + U_R = 0$$

Total differential of each FOC

$$d\left(\frac{\partial U}{\partial F}\right) : G_F d\theta + \theta G_{FF} dF + \theta G_{FH} dH + \theta G_{FE} dE - \frac{1}{1+c_o} dw_o = 0$$

$$d\left(\frac{\partial U}{\partial H}\right) : G_H d\theta + \theta G_{HF} dF + \theta G_{HH} dH + \theta G_{HE} dE - dw_h - \frac{c_h}{1+c_o} dw_o = 0$$

$$d\left(\frac{\partial U}{\partial E}\right) : G_E d\theta + \theta G_{EF} dF + \theta G_{EH} dH + \theta G_{EE} dE - \frac{1+c_e}{1+c_o} dw_o = 0$$

$$d\left(\frac{\partial U}{\partial R}\right) : U_{CC}\left(-\frac{w_o}{1+c_o}\right)\frac{dw_o}{1+c_o} + U_{CR}\left(-\frac{w_o}{1+c_o}\right) dR + U_{RC}\left(-\frac{w_o}{1+c_o}\right)\frac{dw_o}{1+c_o} + U_{RR} dR = 0$$

which expressed in matrix form gives:

$$\begin{pmatrix} \theta G_{FF} & \theta G_{FH} & \theta G_{FE} & 0 \\ \theta G_{HF} & \theta G_{HH} & \theta G_{HE} & 0 \\ \theta G_{EF} & \theta G_{EH} & \theta G_{EE} & 0 \\ 0 & 0 & 0 & J \end{pmatrix} \begin{pmatrix} dF^* \\ dH^* \\ dE^* \\ dR^* \end{pmatrix} = \begin{pmatrix} -G_F d\theta + \frac{1}{1+c_o} dw_o \\ -G_H d\theta + dw_h + \frac{c_h}{1+c_o} dw_o \\ -G_E d\theta + \frac{1+c_e}{1+c_o} dw_o \\ \tilde{K} \end{pmatrix}$$

$$\begin{aligned} \tilde{K} = & \left[G \left(\frac{w_o}{1+c_o} \right) U_{CC} - U_{RR} \right] d\theta - \left[\left(\frac{w_o}{1+c_o} \right) U_{CC} - U_{RR} \right] H^* dw_h \\ & + \left[U_C + \left(\left(\frac{w_o}{1+c_o} \right) U_{CC} - U_{RR} \right) (T - R^* - F^* - (1+c_e)E^* - c_h H^*) \right] dw_o. \end{aligned}$$

Effect of rainfall deviation

The effects of a rainfall deviations (θ) on family labor (F), hired labor (H), and exchange labor (E) are given by solving $\frac{\partial i}{\partial \theta}, i \in \{F, H, E\}$ from the system of equations above.

Family Labor F

$$\frac{\partial F}{\partial \theta} = \frac{\theta^2}{|D_3|} \cdot \Gamma_F$$

where $|D_3|$ is the determinant of the Hessian matrix $M_{3\times 3}$ of second order derivatives of the production function $\theta G(F, H, E)$. The matrix $M_{3\times 3}$ is:

$$M = \begin{pmatrix} \theta G_{FF} & \theta G_{FH} & \theta G_{FE} \\ \theta G_{HF} & \theta G_{HH} & \theta G_{HE} \\ \theta G_{EF} & \theta G_{EH} & \theta G_{EE} \end{pmatrix}$$

$$|D_3| = \theta^3 \left[G_{FF}(G_{HH}G_{EE} - G_{HE}G_{EH}) - G_{FH}(G_{HF}G_{EE} - G_{HE}G_{EF}) + G_{FE}(G_{HF}G_{EH} - G_{HH}G_{EF}) \right]$$

and

$$\begin{aligned} \Gamma_F = & \left(G_{HH}G_{EE} - G_{HE}G_{EH} \right) \left(-G_F + \frac{1}{1+c_o} \cdot \frac{\partial w_o}{\partial \theta} \right) + \\ & \left(G_{HF}G_{EE} - G_{HE}G_{EF} \right) \left(G_H - \frac{\partial w_h}{\partial \theta} - \frac{c_h}{1+c_o} \cdot \frac{\partial w_o}{\partial \theta} \right) + \\ & \left(G_{HF}G_{EH} - G_{HH}G_{EF} \right) \left(-G_E + \frac{1+c_e}{1+c_o} \cdot \frac{\partial w_o}{\partial \theta} \right) \end{aligned}$$

Γ_F can be further simplified by replacing the FOCs (G_F, G_H, G_E):

$$\Gamma_F = \left(G_{HH}G_{EE} - G_{HE}G_{EH}\right)\left(-\frac{w_o}{1+c_o}\cdot\frac{1}{\theta} + \frac{1}{1+c_o}\cdot\frac{\partial w_o}{\partial\theta}\right) +$$
$$\left(G_{HF}G_{EE} - G_{HE}G_{EF}\right)\left(\frac{w_h}{\theta} + \frac{1}{\theta}\cdot\frac{w_o c_h}{1+c_o} - \frac{\partial w_h}{\partial\theta} - \frac{c_h}{1+c_o}\cdot\frac{\partial w_o}{\partial\theta}\right) +$$
$$\left(G_{HF}G_{EH} - G_{HH}G_{EF}\right)\left(-\frac{w_o(1+c_e)}{1+c_o}\cdot\frac{1}{\theta} + \frac{1+c_e}{1+c_o}\cdot\frac{\partial w_o}{\partial\theta}\right)$$

Re-arranging and simplifying common terms:

$$\Gamma_F = \left(G_{HH}G_{EE} - G_{HE}G_{EH}\right)\left(\frac{1}{1+c_o}\left(-\frac{w_o}{\theta} + \frac{\partial w_o}{\partial\theta}\right)\right) +$$
$$\left(G_{HF}G_{EE} - G_{HE}G_{EF}\right)\left(\frac{w_h}{\theta} - \frac{\partial w_h}{\partial\theta} + \frac{c_h}{1+c_o}\left(\frac{w_o}{\theta} - \frac{\partial w_o}{\partial\theta}\right)\right) +$$
$$\left(G_{HF}G_{EH} - G_{HH}G_{EF}\right)\left(\frac{1+c_e}{1+c_o}\left(-\frac{w_o}{\theta} + \frac{\partial w_o}{\partial\theta}\right)\right)$$

$$\Gamma_F = \left(G_{HH}G_{EE} - G_{HE}G_{EH}\right)\left(\frac{1}{1+c_o}\left(-\frac{w_o}{\theta}\left(1-\epsilon_{w_o}\right)\right)\right) +$$
$$\left(G_{HF}G_{EE} - G_{HE}G_{EF}\right)\left(\frac{w_h}{\theta}\left(1-\epsilon_{w_h}\right) + \frac{c_h}{1+c_o}\left(\frac{w_o}{\theta}\left(1-\epsilon_{w_o}\right)\right)\right) +$$
$$\left(G_{HF}G_{EH} - G_{HH}G_{EF}\right)\left(\left(\frac{1+c_e}{1+c_o}\left(-\frac{w_o}{\theta}\left(1-\epsilon_{w_o}\right)\right)\right)\right)$$

where $\epsilon_{w_o} = \frac{\partial w_o}{\partial\theta}/\frac{w_o}{\theta} \equiv \frac{\partial w_o}{w_o}/\frac{\partial\theta}{\theta}$ and $\epsilon_{w_h} = \frac{\partial w_h}{\partial\theta}/\frac{w_h}{\theta} \equiv \frac{\partial w_h}{w_h}/\frac{\partial\theta}{\theta}$

$$\Gamma_F = \frac{1}{\theta}\cdot\frac{1}{1+c_o}\Big[\left(G_{HH}G_{EE} - G_{HE}G_{EH}\right)\left(-w_o(1-\epsilon_{w_o})\right) +$$
$$\left(G_{HF}G_{EE} - G_{HE}G_{EF}\right)\left((1+c_o)w_h(1-\epsilon_{w_h}) + c_h\left(w_o(1-\epsilon_{w_o})\right)\right) +$$
$$\left(G_{HF}G_{EH} - G_{HH}G_{EF}\right)\left(-(1+c_e)w_o(1-\epsilon_{w_o})\right)\Big]$$

$$\Gamma_F = \frac{1}{\theta}\cdot\frac{1}{1+c_o}\Bigg[\gamma_o\Big[\left(G_{HH}G_{EE} - G_{HE}G_{EH}\right) + (1+c_e)\left(G_{HF}G_{EH} - G_{HH}G_{EF}\right) - c_h\left(G_{HF}G_{EE} - G_{HE}G_{EF}\right)\Big]$$
$$+ \left[(1+c_o)\gamma_h\left(G_{HF}G_{EE} - G_{HE}G_{EF}\right)\right]\Bigg]$$

where $\gamma_o = (-w_o(1-\epsilon_{w_o}))$ and $\gamma_h = (w_h(1-\epsilon_{w_h}))$.

This gives us:

$$\frac{\partial F}{\partial\theta} = \frac{\theta}{|D_3|}\cdot\frac{1}{1+c_o}\Bigg[\gamma_o\left[\left(G_{HH}G_{EE} - G_{HE}G_{EH}\right) + (1+c_e)\left(G_{HF}G_{EH} - G_{HH}G_{EF}\right) - c_h\left(G_{HF}G_{EE} - G_{HE}G_{EF}\right)\right]$$
$$+ \left[(1+c_o)\gamma_h\left(G_{HF}G_{EE} - G_{HE}G_{EF}\right)\right]\Bigg]$$

Hired Labor H

$$\frac{\partial H}{\partial \theta} = \frac{\theta^2}{|D_3|} \cdot \Gamma_H$$

where

$$\Gamma_H = \big(G_{FH}G_{EE} - G_{FE}G_{EH}\big)\left(G_F - \frac{1}{1+c_o} \cdot \frac{\partial w_o}{\partial \theta}\right) + \big(G_{FF}G_{EE} - G_{FE}G_{EF}\big)\left(-G_H + \frac{\partial w_h}{\partial \theta} + \frac{c_h}{1+c_o} \cdot \frac{\partial w_o}{\partial \theta}\right) + \big(G_{FF}G_{EH} - G_{FH}G_{EF}\big)\left(G_E - \frac{1+c_e}{1+c_o} \cdot \frac{\partial w_o}{\partial \theta}\right)$$

Γ_H can be further simplified by replacing the FOCs (G_F, G_H, G_E):

$$\begin{aligned}\Gamma_H = {} & \big(G_{FH}G_{EE} - G_{FE}G_{EH}\big)\left(\frac{w_o}{1+c_o} \cdot \frac{1}{\theta} - \frac{1}{1+c_o} \cdot \frac{\partial w_o}{\partial \theta}\right) + \\ & \big(G_{FF}G_{EE} - G_{FE}G_{EF}\big)\left(-\frac{w_h}{\theta} - \frac{1}{\theta} \cdot \frac{w_o c_h}{1+c_o} + \frac{\partial w_h}{\partial \theta} + \frac{c_h}{1+c_o} \cdot \frac{\partial w_o}{\partial \theta}\right) + \\ & \big(G_{FF}G_{EH} - G_{FH}G_{EF}\big)\left(\frac{w_o(1+c_e)}{1+c_o} \cdot \frac{1}{\theta} - \frac{1+c_e}{1+c_o} \cdot \frac{\partial w_o}{\partial \theta}\right)\end{aligned}$$

Re-arranging and simplifying common terms as in the case of Γ_F, Γ_H can be further simplified to:

$$\begin{aligned}\Gamma_H = {} & \big(G_{FH}G_{EE} - G_{FE}G_{EH}\big)\left(\frac{1}{1+c_o}\left(\frac{w_o}{\theta}\left(1 - \epsilon_{w_o}\right)\right)\right) + \\ & \big(G_{FF}G_{EE} - G_{FE}G_{EF}\big)\left(-\frac{w_h}{\theta}\left(1 - \epsilon_{w_h}\right) - \frac{c_h}{1+c_o}\left(\frac{w_o}{\theta}\left(1 - \epsilon_{w_o}\right)\right)\right) + \\ & \big(G_{FF}G_{EH} - G_{FH}G_{EF}\big)\left(\left(\frac{1+c_e}{1+c_o}\left(\frac{w_o}{\theta}\left(1 - \epsilon_{w_o}\right)\right)\right)\right)\end{aligned}$$

$$\begin{aligned}\Gamma_H = {} & \frac{1}{\theta} \cdot \frac{1}{1+c_o}\big(G_{FH}G_{EE} - G_{FE}G_{EH}\big)\left(w_o(1 - \epsilon_{w_o})\right) + \\ & \big(G_{FF}G_{EE} - G_{FE}G_{EF}\big)\left(-(1+c_o)w_h(1 - \epsilon_{w_h}) - c_h\left(w_o(1 - \epsilon_{w_o})\right)\right) + \\ & \big(G_{FF}G_{EH} - G_{FH}G_{EF}\big)\left((1+c_e)w_o(1 - \epsilon_{w_o})\right)\end{aligned}$$

This gives us:

$$\frac{\partial H}{\partial \theta} = \frac{\theta^2}{|D_3|} \cdot \Gamma_H$$

$$\frac{\partial H}{\partial \theta} = \frac{\theta}{|D_3|} \cdot \frac{1}{1+c_o} \Bigg[\gamma_o \left[(G_{FH}G_{EE} - G_{FE}G_{EH}) + (1+c_e)\left(G_{FF}G_{EH} - G_{FH}G_{EF}\right) - c_h \left(G_{FF}G_{EE} - G_{FE}G_{EF}\right) \right] \\ - \left[(1+c_o)\gamma_h \left(G_{FF}G_{EE} - G_{FE}G_{EF}\right) \right] \Bigg]$$

where $\gamma_o = (w_o(1-\epsilon_{w_o}))$ and $\gamma_h = (w_h(1-\epsilon_{w_h}))$.
and $\epsilon_{w_o} = \frac{\partial w_o}{\partial \theta} / \frac{w_o}{\theta} \equiv \frac{\partial w_o}{w_o} / \frac{\partial \theta}{\theta}$; $\epsilon_{w_h} = \frac{\partial w_h}{\partial \theta} / \frac{w_h}{\theta} \equiv \frac{\partial w_h}{w_h} / \frac{\partial \theta}{\theta}$

Exchange Labor E

$$\frac{\partial E}{\partial \theta} = \frac{\theta^2}{|D_3|} \cdot \Gamma_E$$

where

$$\Gamma_E = \big(G_{FH}G_{HE} - G_{FE}G_{HH}\big) \left(-G_F + \frac{1}{1+c_o} \cdot \frac{\partial w_o}{\partial \theta} \right) + \big(G_{FF}G_{HE} - G_{FE}G_{HF}\big) \left(G_H - \frac{\partial w_h}{\partial \theta} - \frac{c_h}{1+c_o} \cdot \frac{\partial w_o}{\partial \theta} \right) \\ + \big(G_{FF}G_{HH} - G_{FH}G_{HF}\big) \left(-G_E + \frac{1+c_e}{1+c_o} \cdot \frac{\partial w_o}{\partial \theta} \right)$$

Following a similar approach as in the cases of $\frac{\partial F}{\partial \theta}$ and $\frac{\partial H}{\partial \theta}$ -replacing by the FOCs and simplifying common terms- the expression for Γ_E can be expressed as:

$$\begin{aligned} \Gamma_E = {} & \left(G_{FH}G_{HE} - G_{FE}G_{HH}\right) \left(\frac{1}{1+c_o} \left(-\frac{w_o}{\theta} + \frac{\partial w_o}{\partial \theta} \right) \right) + \\ & \left(G_{FF}G_{HE} - G_{FE}G_{HF}\right) \left(\frac{w_h}{\theta} - \frac{\partial w_h}{\partial \theta} + \frac{c_h}{1+c_o} \left(\frac{w_o}{\theta} - \frac{\partial w_o}{\partial \theta} \right) \right) + \\ & \left(G_{FF}G_{HH} - G_{FH}G_{HF}\right) \left(\frac{1+c_e}{1+c_o} \left(-\frac{w_o}{\theta} + \frac{\partial w_o}{\partial \theta} \right) \right) \end{aligned}$$

$$\begin{aligned} \Gamma_E = \frac{1}{\theta} \cdot \frac{1}{1+c_o} \big[& \left(G_{FH}G_{HE} - G_{FE}G_{HH}\right) \left(-w_o(1-\epsilon_{w_o})\right) + \\ & \left(G_{FF}G_{HE} - G_{FE}G_{HF}\right) \left((1+c_o)w_h(1-\epsilon_{w_h}) + c_h \left(w_o(1-\epsilon_{w_o})\right)\right) + \\ & \left(G_{FF}G_{HH} - G_{FH}G_{HF}\right) \left((1+c_e) - w_o(1-\epsilon_{w_o})\right) \big] \end{aligned}$$

where $\epsilon_{w_o} = \frac{\partial w_o}{\partial \theta} / \frac{w_o}{\theta} \equiv \frac{\partial w_o}{w_o} / \frac{\partial \theta}{\theta}$ and $\epsilon_{w_h} = \frac{\partial w_h}{\partial \theta} / \frac{w_h}{\theta} \equiv \frac{\partial w_h}{w_h} / \frac{\partial \theta}{\theta}$

Therefore,

$$\frac{\partial E}{\partial \theta} = \frac{\theta^2}{|D_3|} \cdot \Gamma_E$$

$$\frac{\partial E}{\partial \theta} = \frac{\theta}{|D_3|} \cdot \frac{1}{1+c_o} \Bigg[\gamma_o \left[(G_{FH}G_{HE} - G_{FE}G_{HH}) + (1+c_e)\left(G_{FF}G_{HH} - G_{FH}G_{HF}\right) - c_h \left(G_{FF}G_{HE} - G_{FE}G_{HF}\right) \right] + \left[(1+c_o)\gamma_h \left(G_{FF}G_{HE} - G_{FE}G_{HF}\right) \right] \Bigg]$$

with $\gamma_o = (-w_o(1-\epsilon_{w_o}))$ and $\gamma_h = (w_h(1-\epsilon_{w_h}))$.

3.C.3 More details: solving the system step by step

The system $AX = B$ can be solved for X using the formula $X = A^{-1}B$, where $X = (dF, dH, dE, dR)^\top$ and A^{-1} is the inverse of A. We can find A^{-1} (assuming it exists) using the adjugate and determinant method:

$$X = \frac{\text{adj}(A)}{\det(A)} \cdot B$$

The matrix A is a 4×4 block matrix with a 3×3 upper left block and a single element J in the lower right corner. Given the structure, we can separate A into two blocks and then use the block matrix inversion method, assuming $J \neq 0$ and the 3×3 submatrix M is invertible.

Since A has a block structure, we can partition it as:

$$A = \begin{pmatrix} M & 0 \\ 0 & J \end{pmatrix}$$

where:

$$M = \begin{pmatrix} \theta G_{FF} & \theta G_{FH} & \theta G_{FE} \\ \theta G_{HF} & \theta G_{HH} & \theta G_{HE} \\ \theta G_{EF} & \theta G_{EH} & \theta G_{EE} \end{pmatrix}$$

The inverse of A, A^{-1}, is then given by:

$$A^{-1} = \begin{pmatrix} M^{-1} & 0 \\ 0 & \frac{1}{J} \end{pmatrix}$$

where M^{-1} is the inverse of the 3×3 matrix M. We find M^{-1} using the adjugate and determinant method if M is invertible. Let's denote the components of M^{-1} as:

$$M^{-1} = \frac{1}{\det(M)} \text{adj}(M)$$

where $\text{adj}(M)$ is the adjugate of M. Computing the adjugate and determinant explicitly will yield the elements necessary to solve for each element in $X = (dF, dH, dE, dR)^\top$.

The determinant of the 3×3 matrix M is:

$$\det(M) = \theta^3 \left(G_{FF}(G_{HH}G_{EE} - G_{HE}G_{EH}) - G_{FH}(G_{HF}G_{EE} - G_{HE}G_{EF}) + G_{FE}(G_{HF}G_{EH} - G_{HH}G_{EF}) \right)$$

The adjugate adj(M) is the transpose of the cofactor matrix of M. Each entry C_{ij} in the cofactor matrix of M is given by:

$$C_{ij} = (-1)^{i+j} \det(M_{ij})$$

where M_{ij} is the 2×2 minor obtained by deleting the i-th row and j-th column of M. We can construct the adjugate adj(M) as:

$$\text{adj}(M) = \begin{pmatrix} C_{11} & -C_{12} & C_{13} \\ -C_{21} & C_{22} & -C_{23} \\ C_{31} & -C_{32} & C_{33} \end{pmatrix}$$

Let's show for the cofactors in the first row:

1. **Cofactor C_{11}:

$$\det \begin{pmatrix} \theta G_{HH} & \theta G_{HE} \\ \theta G_{EH} & \theta G_{EE} \end{pmatrix} = \theta^2 (G_{HH} G_{EE} - G_{HE} G_{EH})$$

2. **Cofactor C_{12}:

$$\det \begin{pmatrix} \theta G_{HF} & \theta G_{HE} \\ \theta G_{EF} & \theta G_{EE} \end{pmatrix} = \theta^2 (G_{HF} G_{EE} - G_{HE} G_{EF})$$

3. **Cofactor C_{13}:

$$\det \begin{pmatrix} \theta G_{HF} & \theta G_{HH} \\ \theta G_{EF} & \theta G_{EH} \end{pmatrix} = \theta^2 (G_{HF} G_{EH} - G_{HH} G_{EF})$$

Example: Calculate dF Using $X = A^{-1}B$

Now that we have M^{-1}, we calculate dF as the first row of M^{-1} multiplied by B. This gives:

$$dF = \frac{1}{\det(M)} \left(C_{11}(B_1) - C_{12}(B_2) + C_{13}(B_3) \right)$$

Therefore, the final expression for $\frac{\partial F}{\partial \theta}$ is:

$$\frac{\partial F}{\partial \theta} = \frac{1}{\theta} \cdot \frac{(G_{HH} G_{EE} - G_{HE} G_{EH})(-G_F) + (G_{HF} G_{EE} - G_{HE} G_{EF}) G_H + (G_{HF} G_{EH} - G_{HH} G_{EF})(-G_E)}{G_{FF}(G_{HH} G_{EE} - G_{HE} G_{EH}) - G_{FH}(G_{HF} G_{EE} - G_{HE} G_{EF}) + G_{FE}(G_{HF} G_{EH} - G_{HH} G_{EF})}$$

The same procedure applies for $\frac{\partial H}{\partial \theta}$ and $\frac{\partial E}{\partial \theta}$, using the corresponding cofactors.

3.D Probability of using each type of labor (LPM)

Table 3.D.1: Labor demand by the household-farm - Pos. and Neg. Rainfall shock

	Probability of using each type of labor			
	Total Labor	Household Labor	Hired Labor	Exchange Labor
	(1)	(2)	(3)	(4)
	est1	est2	est3	est4
Pos. Rainfall	-0.00	-0.00	0.00	-0.00
	(0.00)	(0.01)	(0.01)	(0.01)
Pos. Rainfall × Remoteness index	-0.00	0.00	0.01	-0.01
	(0.00)	(0.00)	(0.01)	(0.01)
Neg. Rainfall	0.01	-0.00	0.05***	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Neg. Rainfall × Remoteness index	-0.01***	-0.00	-0.00	-0.03**
	(0.00)	(0.01)	(0.01)	(0.01)
Observations	60186	60186	60186	60186
Mean of Dep. Variable	.931	.913	.287	.211
Adjusted R2	.314	.3	.346	.332
F-stat	8.19	8.53	7.92	4.98
Controls	Yes	Yes	Yes	Yes
Legendre Pol.	Deg. 1	Deg. 1	Deg. 1	Deg. 1
Fixed Effects	Yes	Yes	Yes	Yes
β Pos. + γ Pos. × Remot. (p-value)	.564	.969	.266	.372
β Neg. + γ Neg. × Remot. (p-value)	.366	.401	.003	.339

Observations are at the household-wave-season level. Method of estimation: OLS regression with high-dimensional fixed effects. Robust standard errors clustered at the Cell level (0.1° Latitude x 0.1° Longitude) are reported in parenthesis. Controls (coefficients not shown): Log. of household size, Log. of cultivated area (ha), Percentage of land under agriculture within approx 1 km buffer, Average total rainfall in wettest quarter (mm) within 12 months, Agro-Ecological Zone, and Season (non-harvesting or harvesting). Fixed Effects: household, year, and country-by-year. Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

3.E Average Marginal Effects (AME) of rainfall deviations and remoteness

3.E.1 AME: Main results - Log of. number of Person-days

Figure 3.E.1: AME of Neg. Rainfall (95% CIs) on the (Log of) person-days of Family Labor, by levels of remoteness

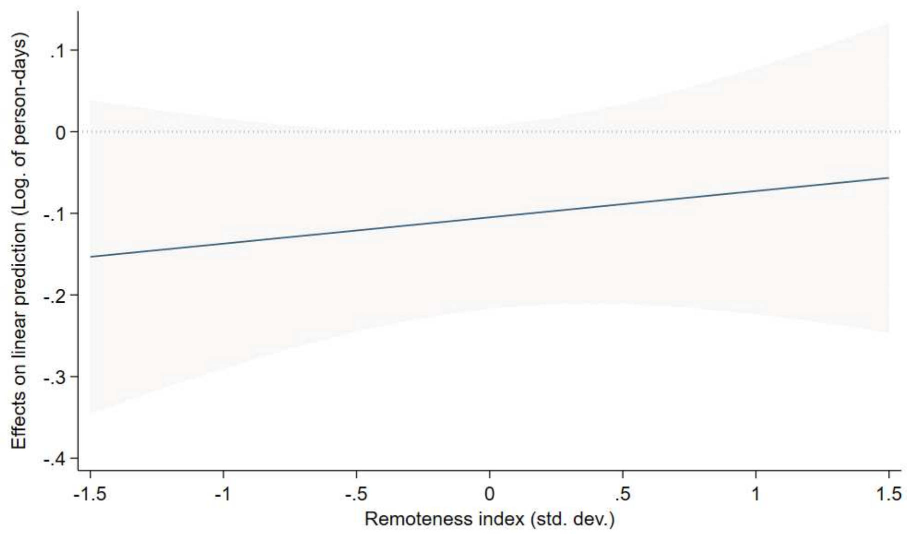


Figure 3.E.2: AME of Neg. Rainfall (95% CIs) on the (Log of) person-days of Hired Labor, by levels of remoteness

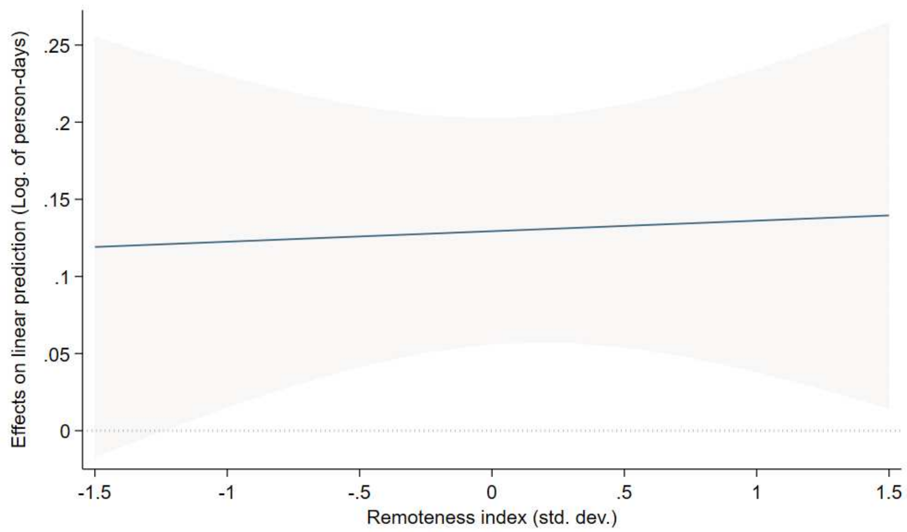
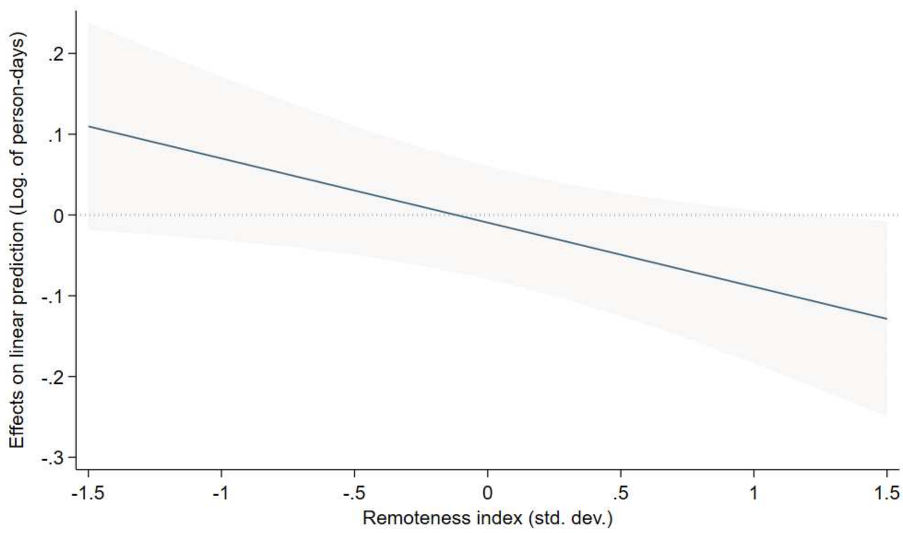


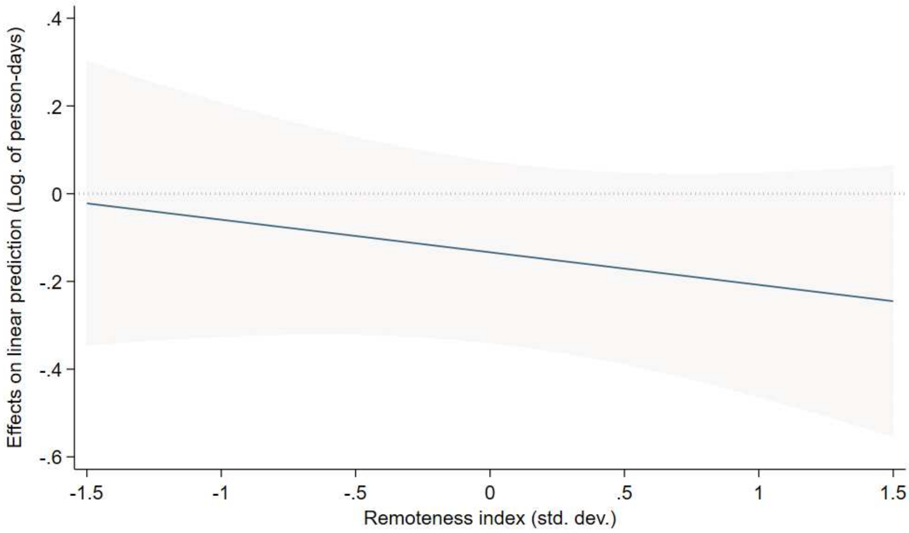
Figure 3.E.3: AME of Neg. Rainfall (95% CIs) on the (Log of) person-days of Exchange Labor, by levels of remoteness



3.E.2 AME of rainfall deviations - Land size

Figure 3.E.4: AME of Neg. Rainfall (95% CIs) on the (Log of) person-days of Family Labor, by levels of remoteness and cultivated land size.

(a) Small cultivators (below p50 land size)



(b) Large cultivators (above p50 land size)

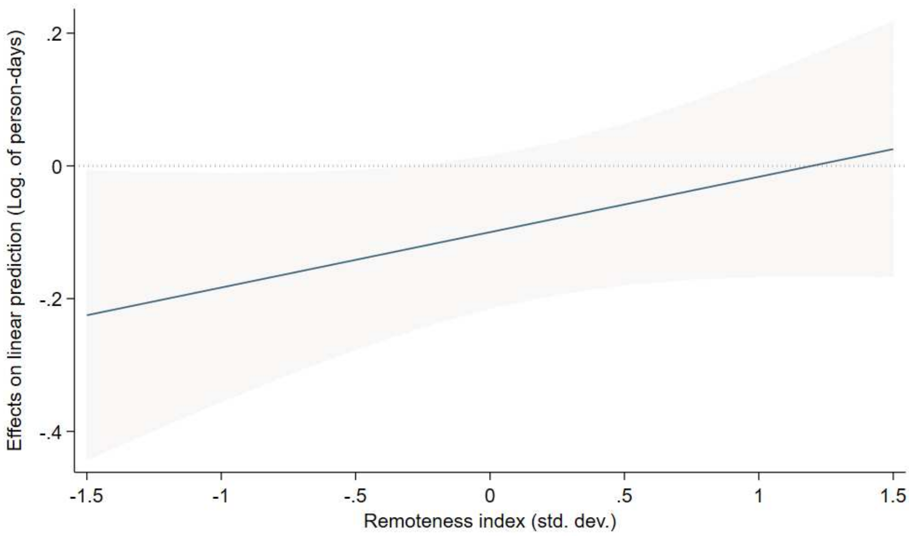
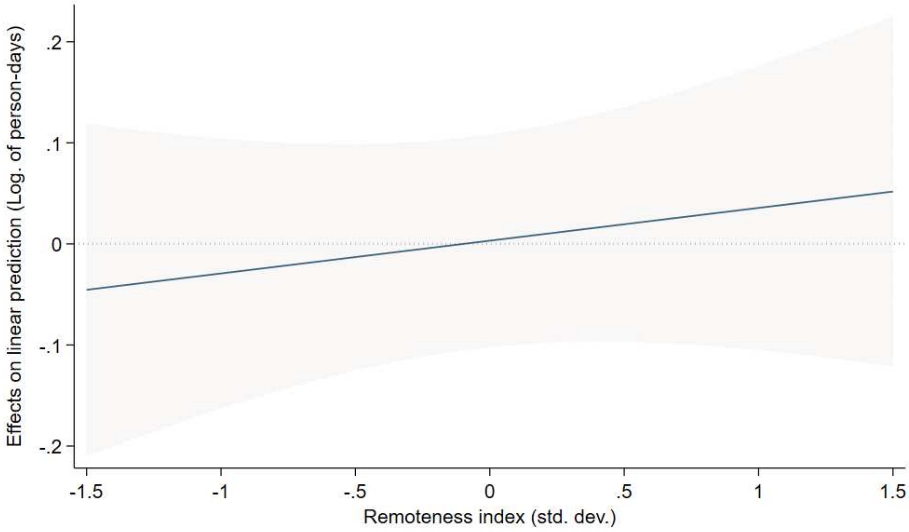


Figure 3.E.5: AME of Neg. Rainfall (95% CIs) on the (Log of) person-days of Hired Labor, by levels of remoteness and cultivated land size.

(a) Small cultivators (below p50 land size)



(b) Large cultivators (above p50 land size)

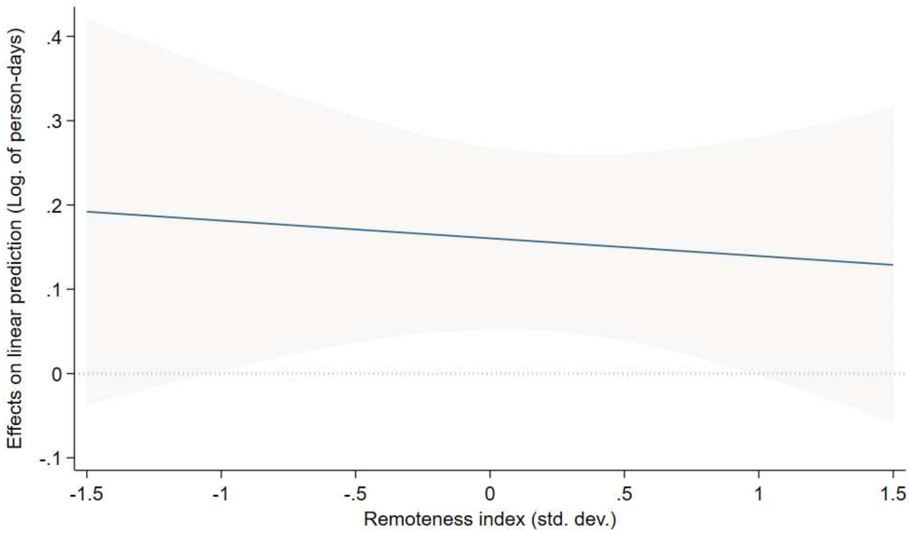
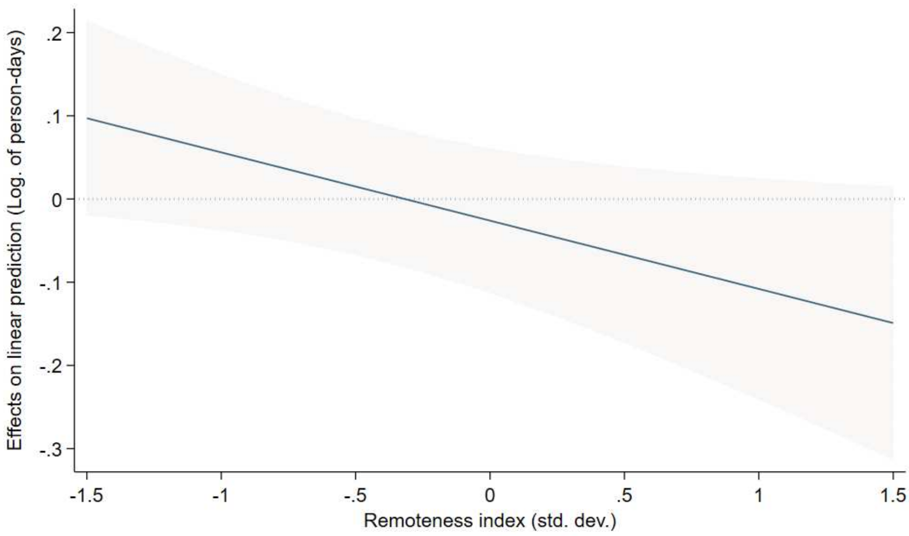
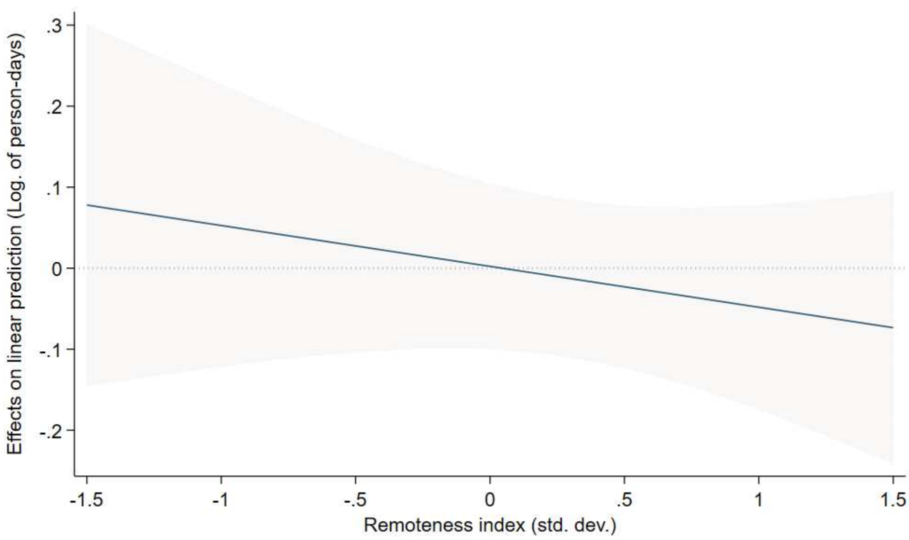


Figure 3.E.6: AME of Neg. Rainfall (95% CIs) on the (Log of) person-days of Exchange Labor, by levels of remoteness and cultivated land size.

(a) Small cultivators (below p50 land size)



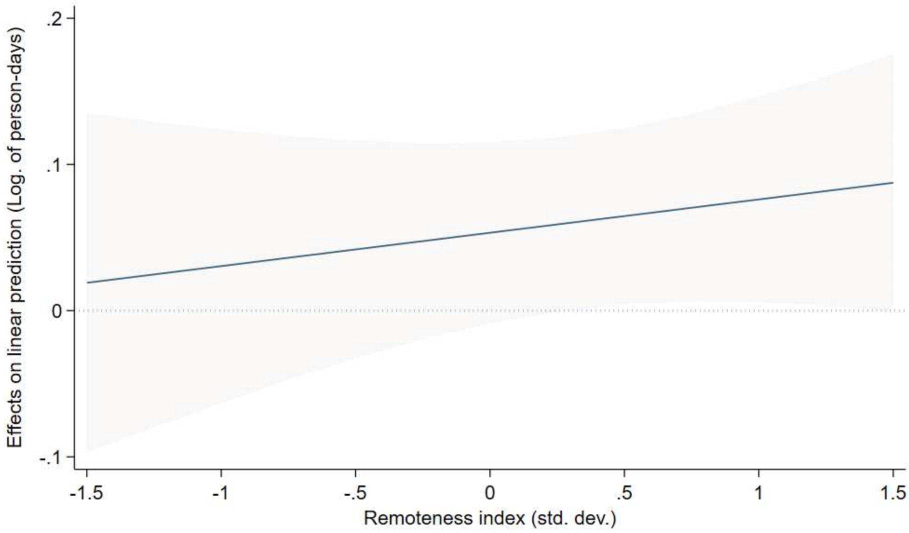
(b) Large cultivators (above p50 land size)



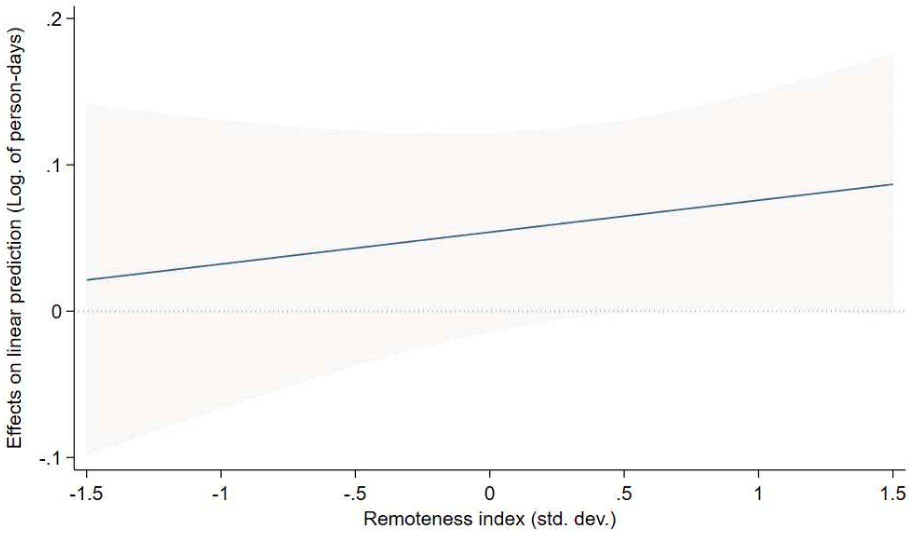
3.E.3 AME of rainfall deviations - Male labor

Figure 3.E.7: AME of Pos. Rainfall (95% CIs) on the (Log of) male person-days of Total and Family Labor, by levels of remoteness.

(a) Total male labor demand



(b) Male family labor utilization



3.F Robustness checks

3.F.1 Other measures of the outcome

Intensive margin (Pseudo-Poisson)

Table 3.F.1: Labor demand by the household-farm - Pos. and Neg. Rainfall shock (Pseudo-Poisson estimation)

	Number of person-days			
	Total Labor	Household Labor	Hired Labor	Exchange Labor
	(1)	(2)	(3)	(4)
Pos. Rainfall	0.01	0.01	0.05	-0.10
	(0.03)	(0.03)	(0.05)	(0.06)
Pos. Rainfall × Remoteness index	0.01	0.01	-0.04	-0.07
	(0.03)	(0.03)	(0.05)	(0.06)
Neg. Rainfall	-0.05	-0.07	0.16***	-0.10
	(0.04)	(0.05)	(0.06)	(0.12)
Neg. Rainfall × Remoteness index	0.02	0.04	-0.07	-0.21**
	(0.04)	(0.04)	(0.06)	(0.09)
Observations	60186	60165	39067	33399
Mean of Dep. Variable	93.2	83.8	9.95	5.33
Pseudo R2	.521	.513	.456	.506
Wald-chi2	120	118	78.8	84
Controls	Yes	Yes	Yes	Yes
Legendre Pol.	Deg. 1	Deg. 1	Deg. 1	Deg. 1
Fixed Effects	Yes	Yes	Yes	Yes
β Pos. + γ Pos. × Remot. (p-value)	.643	.582	.811	.064
β Neg. + γ Neg. × Remot. (p-value)	.56	.56	.202	.015

Observations are at the household-wave-season level. Method of estimation: Poisson pseudo-likelihood regression with high-dimensional fixed effects. Robust standard errors clustered at the Cell level (0.1° Latitude x 0.1° Longitude) are reported in parenthesis. Controls (coefficients not shown): Log. of household size, Log. of cultivated area (ha), Percentage of land under agriculture within approx 1 km buffer, Average total rainfall in wettest quarter (mm) within 12 months, Agro-Ecological Zone, and Season (non-harvesting or harvesting). Fixed Effects: household, year, and country-by-year. Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

Intensive margin (OLS)

Table 3.F.2: Labor demand by the household-farm - Pos. and Neg. Rainfall shock (OLS estimation)

	Number of person-days			
	Total Labor	Household Labor	Hired Labor	Exchange Labor
	(1)	(2)	(3)	(4)
Pos. Rainfall	4.38	4.54	0.25	-0.41
	(3.19)	(3.10)	(0.34)	(0.26)
Pos. Rainfall × Remoteness index	-1.01	-0.76	-0.19	-0.06
	(2.42)	(2.29)	(0.34)	(0.17)
Neg. Rainfall	-11.65**	-12.37**	1.23**	-0.52
	(5.70)	(5.56)	(0.51)	(0.45)
Neg. Rainfall × Remoteness index	2.28	2.98	0.12	-0.81**
	(5.11)	(4.86)	(0.59)	(0.39)
Observations	60186	60186	60186	60186
Mean of Dep. Variable	93.2	83.8	6.46	2.96
Adjusted R2	.334	.316	.333	.348
F-stat	8.81	8.43	4.93	4.58
Controls	Yes	Yes	Yes	Yes
Legendre Pol.	Deg. 1	Deg. 1	Deg. 1	Deg. 1
Fixed Effects	Yes	Yes	Yes	Yes
β Pos. + γ Pos. × Remot. (p-value)	.328	.248	.903	.094
β Neg. + γ Neg. × Remot. (p-value)	.217	.196	.074	.018

Observations are at the household-wave-season level. Method of estimation: OLS regression with high-dimensional fixed effects. Robust standard errors clustered at the Cell level (0.1° Latitude x 0.1° Longitude) are reported in parenthesis. Controls (coefficients not shown): Log. of household size, Log. of cultivated area (ha), Percentage of land under agriculture within approx 1 km buffer, Average total rainfall in wettest quarter (mm) within 12 months, Agro-Ecological Zone, and Season (non-harvesting or harvesting). Fixed Effects: household, year, and country-by-year. Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

Intensive margin (asinh transformation)

Table 3.F.3: Labor demand by the household-farm - Pos. and Neg. Rainfall shock (asinh estimation)

	No. of person-days (Inverse Hyperb. Sine Transf.)			
	Total Labor	Household Labor	Hired Labor	Exchange Labor
	(1)	(2)	(3)	(4)
	est1	est2	est3	est4
Pos. Rainfall	0.04	0.04	0.02	-0.02
	(0.03)	(0.04)	(0.03)	(0.03)
Pos. Rainfall × Remoteness index	0.02	0.02	0.02	-0.02
	(0.03)	(0.03)	(0.03)	(0.02)
Neg. Rainfall	-0.05	-0.11*	0.16***	-0.01
	(0.05)	(0.06)	(0.04)	(0.04)
Neg. Rainfall × Remoteness index	-0.03	0.03	0.01	-0.10**
	(0.05)	(0.06)	(0.04)	(0.04)
Observations	60186	60186	60186	60186
Mean of Dep. Variable	4.27	4.06	.93	.571
Adjusted R2	.362	.352	.392	.415
F-stat	21.1	23.6	7.98	6.58
Controls	Yes	Yes	Yes	Yes
Legendre Pol.	Deg. 1	Deg. 1	Deg. 1	Deg. 1
Fixed Effects	Yes	Yes	Yes	Yes
β Pos. + γ Pos. × Remot. (p-value)	.14	.118	.293	.254
β Neg. + γ Neg. × Remot. (p-value)	.235	.345	.006	.076

Observations are at the household-wave-season level. Method of estimation: OLS regression with high-dimensional fixed effects. Robust standard errors clustered at the Cell level (0.1° Latitude x 0.1° Longitude) are reported in parenthesis. Controls (coefficients not shown): Log. of household size, Log. of cultivated area (ha), Percentage of land under agriculture within approx 1 km buffer, Average total rainfall in wettest quarter (mm) within 12 months, Agro-Ecological Zone, and Season (non-harvesting or harvesting). Fixed Effects: household, year, and country-by-year. Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

3.F.2 Legendre Polynomials of higher degree

Degree 2

Table 3.F.4: Labor demand by the household-farm - Pos. and Neg. Rainfall shock (Legendre Pol. Degree 2)

	Number of person-days (Log.)			
	Total Labor	Household Labor	Hired Labor	Exchange Labor
	(1)	(2)	(3)	(4)
Pos. Rainfall	0.03	0.03	0.02	-0.01
	(0.03)	(0.04)	(0.02)	(0.03)
Pos. Rainfall × Remoteness index	0.02	0.02	0.01	-0.02
	(0.03)	(0.03)	(0.02)	(0.02)
Neg. Rainfall	-0.07	-0.11*	0.10***	-0.01
	(0.05)	(0.06)	(0.04)	(0.04)
Neg. Rainfall × Remoteness index	-0.03	0.02	0.01	-0.08**
	(0.05)	(0.05)	(0.04)	(0.04)
Observations	60186	60186	60186	60186
Mean of Dep. Variable	3.66	3.47	.764	.461
Adjusted R2	.372	.36	.394	.419
F-stat	19.3	22	6.88	4.88
Controls	Yes	Yes	Yes	Yes
Legendre Pol.	Deg. 2	Deg. 2	Deg. 2	Deg. 2
Fixed Effects	Yes	Yes	Yes	Yes
β Pos. + γ Pos. × Remot. (p-value)	.166	.145	.279	.253
β Neg. + γ Neg. × Remot. (p-value)	.146	.251	.031	.071

Observations are at the household-wave-season level. Method of estimation: OLS regression with high-dimensional fixed effects. Robust standard errors clustered at the Cell level (0.1° Latitude x 0.1° Longitude) are reported in parenthesis. Controls (coefficients not shown): Log. of household size, Log. of cultivated area (ha), Percentage of land under agriculture within approx 1 km buffer, Average total rainfall in wettest quarter (mm) within 12 months, Agro-Ecological Zone, and Season (non-harvesting or harvesting). Fixed Effects: household, year, and country-by-year. Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

Degree 3

Table 3.F.5: Labor demand by the household-farm - Pos. and Neg. Rainfall shock (Legendre Pol. Degree 3)

	Number of person-days (Log.)			
	Total Labor	Household Labor	Hired Labor	Exchange Labor
	(1)	(2)	(3)	(4)
Pos. Rainfall	0.03	0.03	0.03	-0.02
	(0.03)	(0.04)	(0.02)	(0.03)
Pos. Rainfall × Remoteness index	0.02	0.02	0.01	-0.02
	(0.03)	(0.03)	(0.02)	(0.02)
Neg. Rainfall	-0.06	-0.10*	0.10***	-0.01
	(0.05)	(0.06)	(0.04)	(0.04)
Neg. Rainfall × Remoteness index	-0.03	0.03	0.00	-0.08**
	(0.05)	(0.05)	(0.04)	(0.03)
Observations	60186	60186	60186	60186
Mean of Dep. Variable	3.66	3.47	.764	.461
Adjusted R2	.372	.36	.394	.419
F-stat	14.3	18.4	6.7	3.73
Controls	Yes	Yes	Yes	Yes
Legendre Pol.	Deg. 3	Deg. 3	Deg. 3	Deg. 3
Fixed Effects	Yes	Yes	Yes	Yes
β Pos. + γ Pos. × Remot. (p-value)	.16	.148	.233	.256
β Neg. + γ Neg. × Remot. (p-value)	.195	.343	.043	.069

Observations are at the household-wave-season level. Method of estimation: OLS regression with high-dimensional fixed effects. Robust standard errors clustered at the Cell level (0.1° Latitude x 0.1° Longitude) are reported in parenthesis. Controls (coefficients not shown): Log. of household size, Log. of cultivated area (ha), Percentage of land under agriculture within approx 1 km buffer, Average total rainfall in wettest quarter (mm) within 12 months, Agro-Ecological Zone, and Season (non-harvesting or harvesting). Fixed Effects: household, year, and country-by-year. Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

Degree 4

Table 3.F.6: Labor demand by the household-farm - Pos. and Neg. Rainfall shock (Legendre Pol. Degree 4)

	Number of person-days (Log.)			
	Total Labor	Household Labor	Hired Labor	Exchange Labor
	(1)	(2)	(3)	(4)
Pos. Rainfall	0.03	0.03	0.03	-0.01
	(0.03)	(0.04)	(0.02)	(0.03)
Pos. Rainfall × Remoteness index	0.02	0.02	0.01	-0.02
	(0.03)	(0.03)	(0.02)	(0.02)
Neg. Rainfall	-0.05	-0.09	0.08**	0.01
	(0.06)	(0.06)	(0.04)	(0.04)
Neg. Rainfall × Remoteness index	-0.02	0.03	0.01	-0.08**
	(0.05)	(0.05)	(0.04)	(0.03)
Observations	60186	60186	60186	60186
Mean of Dep. Variable	3.66	3.47	.764	.461
Adjusted R2	.372	.36	.394	.419
F-stat	12.2	13.6	7.03	3.1
Controls	Yes	Yes	Yes	Yes
Legendre Pol.	Deg. 4	Deg. 4	Deg. 4	Deg. 4
Fixed Effects	Yes	Yes	Yes	Yes
β Pos. + γ Pos. × Remot. (p-value)	.142	.154	.182	.378
β Neg. + γ Neg. × Remot. (p-value)	.285	.443	.088	.134

Observations are at the household-wave-season level. Method of estimation: OLS regression with high-dimensional fixed effects. Robust standard errors clustered at the Cell level (0.1° Latitude x 0.1° Longitude) are reported in parenthesis. Controls (coefficients not shown): Log. of household size, Log. of cultivated area (ha), Percentage of land under agriculture within approx 1 km buffer, Average total rainfall in wettest quarter (mm) within 12 months, Agro-Ecological Zone, and Season (non-harvesting or harvesting). Fixed Effects: household, year, and country-by-year. Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

3.F.3 Wild cluster bootstrap

Table 3.F.7: Labor demand by the household-farm - Wild bootstrap inference

	Coef	t-stat	Bootstr. p-value	[95% conf.	interval]
Total Labor					
Shock Pos	0.04	1.11	0.246	-0.020	0.094
Shock Pos x Remoteness	0.01	0.60	0.530	-0.032	0.057
Shock Neg	-0.06	-1.16	0.254	-0.152	0.038
Shock Neg x Remoteness	-0.02	-0.51	0.572	-0.111	0.062
Test Lincom Pos $\beta + \gamma$	0.05	1.52	0.112	-0.009	0.108
Test Lincom Neg $\beta + \gamma$	-0.08	-1.22	0.230	-0.205	0.046
Household Labor					
Shock Pos	0.04	1.05	0.252	-0.025	0.105
Shock Pos x Remoteness	0.02	0.77	0.406	-0.027	0.065
Shock Neg	-0.11	-1.85	0.062	-0.208	0.007
Shock Neg x Remoteness	0.03	0.56	0.602	-0.065	0.124
Test Lincom Pos $\beta + \gamma$	0.06	1.60	0.082	-0.008	0.120
Test Lincom Neg $\beta + \gamma$	-0.08	-0.98	0.320	-0.209	0.073
Hired Labor					
Shock Pos	0.02	0.65	0.468	-0.029	0.060
Shock Pos x Remoteness	0.01	0.61	0.548	-0.033	0.057
Shock Neg	0.13	3.46	0.000	0.063	0.194
Shock Neg x Remoteness	0.01	0.16	0.840	-0.061	0.076
Test Lincom Pos $\beta + \gamma$	0.03	0.97	0.274	-0.026	0.085
Test Lincom Neg $\beta + \gamma$	0.13	2.70	0.008	0.052	0.223
Exch. Labor					
Shock Pos	-0.02	-0.64	0.520	-0.058	0.029
Shock Pos x Remoteness	-0.02	-0.99	0.302	-0.049	0.015
Shock Neg	-0.01	-0.25	0.764	-0.069	0.053
Shock Neg x Remoteness	-0.08	-2.24	0.028	-0.145	-0.007
β Pos. + γ Pos. $\times$ Remot. (p-value)	-0.03	-1.15	0.224	-0.085	0.021
β Neg. + γ Neg. $\times$ Remot. (p-value)	-0.09	-1.82	0.068	-0.169	0.009

The table reports the wild bootstrap estimation using 1,000 repetitions for a regression where the dependent variable is the Log. of the number of person-days and the estimation method is OLS regression with high-dimensional fixed effects. The estimation follows the same dependent and indepedent variables as in the main estimation.

3.F.4 Cluster at other levels

Clustering at the municipality level

Table 3.F.8: Labor demand by the household-farm - Pos. and Neg. Rainfall shock (Clustered std. err. at the municipality level)

	Number of person-days (Log.)			
	Total Labor	Household Labor	Hired Labor	Exchange Labor
	(1)	(2)	(3)	(4)
Pos. Rainfall	0.03	0.04	0.02	-0.02
	(0.03)	(0.04)	(0.02)	(0.03)
Pos. Rainfall × Remoteness index	0.01	0.02	0.02	-0.02
	(0.02)	(0.03)	(0.02)	(0.02)
Neg. Rainfall	-0.06	-0.10*	0.13***	-0.01
	(0.05)	(0.06)	(0.04)	(0.04)
Neg. Rainfall × Remoteness index	-0.02	0.03	0.01	-0.08**
	(0.05)	(0.05)	(0.04)	(0.04)
Observations	60186	60186	60186	60186
Mean of Dep. Variable	3.66	3.47	.764	.461
Adjusted R2	.371	.359	.393	.419
F-stat	17.1	19.9	7.62	6.4
Controls	Yes	Yes	Yes	Yes
Legendre Pol.	Deg. 1	Deg. 1	Deg. 1	Deg. 1
Fixed Effects	Yes	Yes	Yes	Yes
β Pos. + γ Pos. × Remot. (p-value)	.141	.125	.315	.245
β Neg. + γ Neg. × Remot. (p-value)	.238	.347	.009	.071

Observations are at the household-wave-season level. Method of estimation: OLS regression with high-dimensional fixed effects. Robust standard errors clustered at the Municipality level are reported in parenthesis. Controls (coefficients not shown): Log. of household size, Log. of cultivated area (ha), Percentage of land under agriculture within approx 1 km buffer, Average total rainfall in wettest quarter (mm) within 12 months, Agro-Ecological Zone, and Season (non-harvesting or harvesting). Fixed Effects: household, year, and country-by-year. Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

Clustering at the district level

Table 3.F.9: Labor demand by the household-farm - Pos. and Neg. Rainfall shock (Clustered std. err. at the district level)

	Number of person-days (Log.)			
	Total Labor	Household Labor	Hired Labor	Exchange Labor
	(1)	(2)	(3)	(4)
Pos. Rainfall	0.03	0.04	0.02	-0.02
	(0.03)	(0.04)	(0.02)	(0.03)
Pos. Rainfall × Remoteness index	0.01	0.02	0.02	-0.02
	(0.03)	(0.03)	(0.02)	(0.02)
Neg. Rainfall	-0.06	-0.10*	0.13***	-0.01
	(0.06)	(0.06)	(0.04)	(0.04)
Neg. Rainfall × Remoteness index	-0.02	0.03	0.01	-0.08**
	(0.05)	(0.06)	(0.04)	(0.04)
Observations	60186	60186	60186	60186
Mean of Dep. Variable	3.66	3.47	.764	.461
Adjusted R2	.371	.359	.393	.419
F-stat	16.5	19.1	7.66	6.23
Controls	Yes	Yes	Yes	Yes
Legendre Pol.	Deg. 1	Deg. 1	Deg. 1	Deg. 1
Fixed Effects	Yes	Yes	Yes	Yes
β Pos. + γ Pos. × Remot. (p-value)	.173	.148	.312	.268
β Neg. + γ Neg. × Remot. (p-value)	.304	.405	.009	.092

Observations are at the household-wave-season level. Method of estimation: OLS regression with high-dimensional fixed effects. Robust standard errors clustered at the District level are reported in parenthesis. Controls (coefficients not shown): Log. of household size, Log. of cultivated area (ha), Percentage of land under agriculture within approx 1 km buffer, Average total rainfall in wettest quarter (mm) within 12 months, Agro-Ecological Zone, and Season (non-harvesting or harvesting). Fixed Effects: household, year, and country-by-year. Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

Clustering at the state level

Table 3.F.10: Labor demand by the household-farm - Pos. and Neg. Rainfall shock (Clustered std. err. at the state level)

	Number of person-days (Log.)			
	Total Labor	Household Labor	Hired Labor	Exchange Labor
	(1)	(2)	(3)	(4)
Pos. Rainfall	0.03	0.04	0.02	-0.02
	(0.05)	(0.06)	(0.03)	(0.03)
Pos. Rainfall × Remoteness index	0.01	0.02	0.02	-0.02
	(0.03)	(0.04)	(0.03)	(0.02)
Neg. Rainfall	-0.06	-0.10	0.13***	-0.01
	(0.07)	(0.09)	(0.05)	(0.04)
Neg. Rainfall × Remoteness index	-0.02	0.03	0.01	-0.08*
	(0.06)	(0.07)	(0.05)	(0.04)
Observations	60186	60186	60186	60186
Mean of Dep. Variable	3.66	3.47	.764	.461
Adjusted R2	.371	.359	.393	.419
F-stat	9.25	12.1	5.15	4.41
Controls	Yes	Yes	Yes	Yes
Legendre Pol.	Deg. 1	Deg. 1	Deg. 1	Deg. 1
Fixed Effects	Yes	Yes	Yes	Yes
β Pos. + γ Pos. × Remot. (p-value)	.256	.267	.393	.21
β Neg. + γ Neg. × Remot. (p-value)	.365	.498	.044	.111

Observations are at the household-wave-season level. Method of estimation: OLS regression with high-dimensional fixed effects. Robust standard errors clustered at the State level are reported in parenthesis. Controls (coefficients not shown): Log. of household size, Log. of cultivated area (ha), Percentage of land under agriculture within approx 1 km buffer, Average total rainfall in wettest quarter (mm) within 12 months, Agro-Ecological Zone, and Season (non-harvesting or harvesting). Fixed Effects: household, year, and country-by-year. Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

3.F.5 Future Shocks

Below I show the results of estimating a placebo test of the effect of rainfall deviations in future years on labor utilization in year t. I first estimate using rainfall deviations in the agricultural season $t+1$ in Table 3.F.11. Since the longitudinal LSMS-ISA surveys used in this study were conducted on a yearly or biyear basis, and one extreme case could be that rainfall deviations affect labor utilization over different years, in Table 3.F.12, I present the results of using rainfall deviations three years later to ensure there is no overlap between rainfall data from future years and survey data collection periods.

Table 3.F.11: Labor demand by the household-farm - Pos. and Neg. Rainfall shock (in t+1)

	Number of person-days (Log.)			
	Total Labor	Household Labor	Hired Labor	Exchange Labor
	(1)	(2)	(3)	(4)
Pos. Rainfall (t+1)	-0.04	-0.04	-0.02	0.02
	(0.03)	(0.03)	(0.02)	(0.02)
Pos. Rainfall (t+1) × Remoteness index	0.02	0.00	0.04**	0.03
	(0.02)	(0.02)	(0.02)	(0.02)
Neg. Rainfall (t+1)	0.01	0.06	0.02	-0.03
	(0.06)	(0.07)	(0.04)	(0.03)
Neg. Rainfall (t+1) × Remoteness index	-0.02	-0.06	0.04	0.03
	(0.04)	(0.05)	(0.03)	(0.02)
Observations	60186	60186	60186	60186
Mean of Dep. Variable	3.66	3.47	.764	.461
Adjusted R2	.371	.359	.392	.418
F-stat	21.9	24.3	7.25	6.4
Controls	Yes	Yes	Yes	Yes
Legendre Pol.	Deg. 1	Deg. 1	Deg. 1	Deg. 1
Fixed Effects	Yes	Yes	Yes	Yes
β Pos. + γ Pos. × Remot. (p-value)	.589	.341	.419	.121
β Neg. + γ Neg. × Remot. (p-value)	.908	.969	.229	.897

Observations are at the household-wave-season level. Method of estimation: OLS regression with high-dimensional fixed effects. Robust standard errors clustered at the Cell level (0.1° Latitude x 0.1° Longitude) are reported in parenthesis. Controls (coefficients not shown): Log. of household size, Log. of cultivated area (ha), Percentage of land under agriculture within approx 1 km buffer, Average total rainfall in wettest quarter (mm) within 12 months, Agro-Ecological Zone, and Season (non-harvesting or harvesting). Fixed Effects: household, year, and country-by-year. Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

Table 3.F.12: Labor demand by the household-farm - Pos. and Neg. Rainfall shock (in t+3)

	Number of person-days (Log.)			
	Total Labor	Household Labor	Hired Labor	Exchange Labor
	(1)	(2)	(3)	(4)
Pos. Rainfall (t+3)	-0.03	-0.03	0.00	0.02
	(0.03)	(0.04)	(0.02)	(0.02)
Pos. Rainfall (t+3) × Remoteness index	-0.04	-0.02	-0.01	-0.01
	(0.02)	(0.02)	(0.02)	(0.02)
Neg. Rainfall (t+3)	-0.03	-0.02	-0.01	-0.03
	(0.05)	(0.05)	(0.03)	(0.03)
Neg. Rainfall (t+3) × Remoteness index	-0.06	-0.07*	0.02	-0.01
	(0.04)	(0.04)	(0.04)	(0.02)
Observations	60189	60189	60189	60189
Mean of Dep. Variable	3.66	3.47	.764	.461
Adjusted R2	.371	.359	.392	.418
F-stat	20.3	21.9	6.71	6.26
Controls	Yes	Yes	Yes	Yes
Legendre Pol.	Deg. 1	Deg. 1	Deg. 1	Deg. 1
Fixed Effects	Yes	Yes	Yes	Yes
β Pos. + γ Pos. × Remot. (p-value)	.081	.19	.707	.821
β Neg. + γ Neg. × Remot. (p-value)	.121	.15	.806	.387

Observations are at the household-wave-season level. Method of estimation: OLS regression with high-dimensional fixed effects. Robust standard errors clustered at the Cell level (0.1° Latitude x 0.1° Longitude) are reported in parenthesis. Controls (coefficients not shown): Log. of household size, Log. of cultivated area (ha), Percentage of land under agriculture within approx 1 km buffer, Average total rainfall in wettest quarter (mm) within 12 months, Agro-Ecological Zone, and Season (non-harvesting or harvesting). Fixed Effects: household, year, and country-by-year. Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

3.F.6 Permutation test

Permutation of the Remoteness Index

Table 3.F.13: Permutation test of the Remoteness index

	Probability of using each type of labor			
	Total Labor	Household Labor	Hired Labor	Exchange Labor
	(1)	(2)	(3)	(4)
Pos. Rainfall	-0.00	-0.00	0.00	-0.00
	(0.73)	(0.81)	(0.97)	(0.94)
Pos. Rainfall × Remoteness index	0.00	0.00	0.01	-0.01
	(0.94)	(0.46)	(0.19)	(0.21)
	[0.90]	[0.24]	[0.02]	[0.03]
Neg. Rainfall	0.01	-0.00	0.05	0.01
	(0.20)	(0.69)	(0.00)	(0.40)
Neg. Rainfall × Remoteness index	-0.01	-0.00	-0.00	-0.03
	(0.01)	(0.51)	(0.96)	(0.03)
	[0.00]	[0.25]	[0.94]	[0.00]
N	60186	60186	60186	60186

The table reports a permutation test of the Remoteness Index with 1,000 random permutations. The estimation follows the same dependent and indepedent variables as in the main estimation: the dependent variable is the probability of using each type of labor and the estimation method is OLS regression with high-dimensional fixed effects.

Table 3.F.14: Permutation test of the Remoteness index

	No. of person-days (Log.)			
	Total Labor	Household Labor	Hired Labor	Exchange Labor
	(1)	(2)	(3)	(4)
Pos. Rainfall	0.04	0.04	0.02	-0.02
	(0.27)	(0.29)	(0.52)	(0.52)
Pos. Rainfall × Remoteness index	0.01	0.02	0.01	-0.02
	(0.55)	(0.44)	(0.54)	(0.32)
	[0.26]	[0.19]	[0.23]	[0.05]
Neg. Rainfall	-0.06	-0.11	0.13	-0.01
	(0.25)	(0.06)	(0.00)	(0.80)
Neg. Rainfall × Remoteness index	-0.02	0.03	0.01	-0.08
	(0.61)	(0.57)	(0.87)	(0.03)
	[0.21]	[0.17]	[0.76]	[0.00]
N	60186	60186	60186	60186

The table reports a permutation test of the Remoteness Index with 1,000 random permutations. The estimation follows the same dependent and indepedent variables as in the main estimation: the dependent variable is the Log. of the number of person-days and the estimation method is OLS regression with high-dimensional fixed effects.

Permutation of the (Negative) Rainfall Shock

Table 3.F.15: Permutation test of the Neg. Rainfall deviation (Prob.)

	Probability of using each type of labor			
	Total Labor	Household Labor	Hired Labor	Exchange Labor
	(1)	(2)	(3)	(4)
Pos. Rainfall	-0.00	-0.00	0.00	-0.00
	(0.73)	(0.81)	(0.97)	(0.94)
Pos. Rainfall × Remoteness index	0.00	0.00	0.01	-0.01
	(0.94)	(0.46)	(0.19)	(0.21)
Neg. Rainfall	0.01	-0.00	0.05	0.01
	(0.20)	(0.69)	(0.00)	(0.40)
	[0.03]	[0.38]	[0.00]	[0.00]
Neg. Rainfall × Remoteness index	-0.01	-0.00	-0.00	-0.03
	(0.01)	(0.51)	(0.96)	(0.03)
	[0.00]	[0.31]	[0.91]	[0.00]
N	60186	60186	60186	60186

The table reports a permutation test of the negative rainfall deviation with 1,000 random permutations. The estimation follows the same dependent and indepedent variables as in the main estimation: the dependent variable is the probability of using each type of labor and the estimation method is OLS regression with high-dimensional fixed effects.

Table 3.F.16: Permutation test of the Pos. Rainfall deviation (Prob.)

	Probability of using each type of labor			
	Total Labor	Household Labor	Hired Labor	Exchange Labor
	(1)	(2)	(3)	(4)
Pos. Rainfall	-0.00	-0.00	0.00	-0.00
	(0.73)	(0.81)	(0.97)	(0.94)
	[0.45]	[0.45]	[0.92]	[0.84]
Pos. Rainfall × Remoteness index	0.00	0.00	0.01	-0.01
	(0.94)	(0.46)	(0.19)	(0.21)
	[0.92]	[0.20]	[0.00]	[0.00]
Neg. Rainfall	0.01	-0.00	0.05	0.01
	(0.20)	(0.69)	(0.00)	(0.40)
Neg. Rainfall × Remoteness index	-0.01	-0.00	-0.00	-0.03
	(0.01)	(0.51)	(0.96)	(0.03)
N	60186	60186	60186	60186

The table reports a permutation test of the positive rainfall deviation with 1,000 random permutations. The estimation follows the same dependent and indepedent variables as in the main estimation: the dependent variable is the probability of using each type of labor and the estimation method is OLS regression with high-dimensional fixed effects.

Table 3.F.17: Permutation test of the Neg. Rainfall deviation

	No. of person-days (Log.)			
	Total Labor	Household Labor	Hired Labor	Exchange Labor
	(1)	(2)	(3)	(4)
Pos. Rainfall	0.04	0.04	0.02	-0.02
	(0.27)	(0.29)	(0.52)	(0.52)
Pos. Rainfall × Remoteness index	0.01	0.02	0.01	-0.02
	(0.55)	(0.44)	(0.54)	(0.32)
Neg. Rainfall	-0.06	-0.11	0.13	-0.01
	(0.25)	(0.06)	(0.00)	(0.80)
	[0.00]	[0.00]	[0.00]	[0.31]
Neg. Rainfall × Remoteness index	-0.02	0.03	0.01	-0.08
	(0.61)	(0.57)	(0.87)	(0.03)
	[0.18]	[0.10]	[0.69]	[0.00]
N	60186	60186	60186	60186

The table reports a permutation test of the negative rainfall deviation with 1,000 random permutations. The estimation follows the same dependent and indepedent variables as in the main estimation: the dependent variable is the Log. of the number of person-days and the estimation method is OLS regression with high-dimensional fixed effects.

Table 3.F.18: Permutation test of the Pos. Rainfall deviation

	No. of person-days (Log.)			
	Total Labor	Household Labor	Hired Labor	Exchange Labor
	(1)	(2)	(3)	(4)
Pos. Rainfall	0.04	0.04	0.02	-0.02
	(0.27)	(0.29)	(0.52)	(0.52)
	[0.00]	[0.00]	[0.09]	[0.02]
Pos. Rainfall × Remoteness index	0.01	0.02	0.01	-0.02
	(0.55)	(0.44)	(0.54)	(0.32)
	[0.20]	[0.09]	[0.14]	[0.02]
Neg. Rainfall	-0.06	-0.11	0.13	-0.01
	(0.25)	(0.06)	(0.00)	(0.80)
Neg. Rainfall × Remoteness index	-0.02	0.03	0.01	-0.08
	(0.61)	(0.57)	(0.87)	(0.03)
N	60186	60186	60186	60186

The table reports a permutation test of the positive rainfall deviation with 1,000 random permutations. The estimation follows the same dependent and indepedent variables as in the main estimation: the dependent variable is the Log. of the number of person-days and the estimation method is OLS regression with high-dimensional fixed effects.

3.F.7 Romano-Wolf stepdown adjusted p-values

Table 3.F.19: Multiple Hypothesis Testing (Probability of using labor)

	Model p-value	Resample p-value	Romano-Wolf p-value
Total Labor			
Shock Pos	0.733	0.624	0.978
Shock Pos x Remoteness	0.942	0.901	1.000
Shock Neg	0.200	0.063	0.180
Shock Neg x Remoteness	0.009	0.001	0.001
Household Labor			
Shock Pos	0.811	0.624	0.990
Shock Pos x Remoteness	0.463	0.161	0.754
Shock Neg	0.688	0.467	0.973
Shock Neg x Remoteness	0.508	0.277	0.831
Hired Labor			
Shock Pos	0.968	0.940	1.000
Shock Pos x Remoteness	0.189	0.008	0.158
Shock Neg	0.000	0.001	0.001
Shock Neg x Remoteness	0.964	0.933	1.000
Exch. Labor			
Shock Pos	0.944	0.893	1.000
Shock Pos x Remoteness	0.206	0.008	0.180
Shock Neg	0.395	0.068	0.620
Shock Neg x Remoteness	0.035	0.001	0.006

The table reports the Romano-Wolf step-down adjusted p-values estimation to multiple hypothesis testing with 1,000 repetitions. Col. 1 reports the original p-value, Col. 2 the standard (bootstrapped) uncorrected p-values, and Col. 3 the Romano-Wolf adjusted p-values. The estimation follows the same dependent and indepedent variables as in the main estimation: the dependent variable is the probability of using each type of labor and the estimation method is OLS regression with high-dimensional fixed effects.

Table 3.F.20: Multiple Hypothesis Testing (Number of person-days (Log.))

	Model p-value	Resample p-value	Romano-Wolf p-value
Total Labor			
Shock Pos	0.268	0.012	0.142
Shock Pos x Remoteness	0.550	0.206	0.705
Shock Neg	0.248	0.022	0.117
Shock Neg x Remoteness	0.613	0.255	0.705
Household Labor			
Shock Pos	0.293	0.018	0.185
Shock Pos x Remoteness	0.444	0.114	0.539
Shock Neg	0.064	0.001	0.001
Shock Neg x Remoteness	0.573	0.181	0.705
Hired Labor			
Shock Pos	0.517	0.187	0.705
Shock Pos x Remoteness	0.544	0.177	0.705
Shock Neg	0.001	0.001	0.001
Shock Neg x Remoteness	0.870	0.768	0.827
Exch. Labor			
Shock Pos	0.524	0.136	0.705
Shock Pos x Remoteness	0.320	0.028	0.237
Shock Neg	0.799	0.545	0.827
Shock Neg x Remoteness	0.025	0.001	0.001

The table reports the Romano-Wolf step-down adjusted p-values estimation to multiple hypothesis testing with 1,000 repetitions. Col. 1 reports the original p-value, Col. 2 the standard (bootstrapped) uncorrected p-values, and Col. 3 the Romano-Wolf adjusted p-values. The estimation follows the same dependent and indepedent variables as in the main estimation: the dependent variable is the Log. of the number of person-days employed of each type of labor and the estimation method is OLS regression with high-dimensional fixed effects.

3.F.8 Shock à la Kaur

Table 3.F.21: Labor demand by the household-farm - Pos. and Neg. Rainfall shock

	Number of person-days (Log.)			
	Total Labor	Household Labor	Hired Labor	Exchange Labor
	(1)	(2)	(3)	(4)
	est1	est2	est3	est4
Pos. Shock (p.80)=1	0.02	0.04	-0.05	-0.03
	(0.04)	(0.04)	(0.03)	(0.03)
Pos. Shock (p.80)=1 × Remoteness index	0.04	0.05	0.00	0.01
	(0.03)	(0.03)	(0.03)	(0.02)
Neg. Shock (p.20)=1	-0.04	-0.07	0.07**	0.00
	(0.05)	(0.06)	(0.03)	(0.03)
Neg. Shock (p.20)=1 × Remoteness index	-0.02	0.02	0.00	-0.04
	(0.05)	(0.05)	(0.03)	(0.03)
Observations	60186	60186	60186	60186
Mean of Dep. Variable	3.66	3.47	.764	.461
Adjusted R2	.371	.359	.392	.418
F-stat	21.2	23.9	7.51	6.56
Controls	Yes	Yes	Yes	Yes
Legendre Pol.	Deg. 1	Deg. 1	Deg. 1	Deg. 1
Fixed Effects	Yes	Yes	Yes	Yes
β Pos. + γ Pos. × Remot. (p-value)	.142	.042	.191	.591
β Neg. + γ Neg. × Remot. (p-value)	.323	.515	.099	.311

Observations are at the household-wave-season level. Method of estimation: OLS regression with high-dimensional fixed effects. Robust standard errors clustered at the Cell level (0.1° Latitude x 0.1° Longitude) are reported in parenthesis. Controls (coefficients not shown): Log. of household size, Log. of cultivated area (ha), Percentage of land under agriculture within approx 1 km buffer, Average total rainfall in wettest quarter (mm) within 12 months, Agro-Ecological Zone, and Season (non-harvesting or harvesting). Fixed Effects: household, year, and country-by-year. Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

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