College of ACES

Department of Agricultural & Consumer Economics
326 Mumford Hall, 1301 W. Gregory Dr | Urbana, IL 61801
217-333-1810

September 15, 2026

Dear Professors Breza, Chandrasekhar, and Viviano:

I am a Ph.D. candidate in Agricultural and Consumer Economics at the University of Illinois Urbana-Champaign, expecting to complete my degree in May 2027. I am an environmental and development economist studying how climate and environmental risks shape household decisions, adaptation, and economic welfare. I am writing to apply to the NBER Workshop on Development Economics and Networks for Early-Career Researchers.

My research asks how environmental risk changes long-lived investments and other adjustment decisions, and how environmental shocks affect human capital and local economies. My job market paper, *"Replanting Under Risk: Weather Shocks and Portfolio Choice in Perennial Agriculture"*, asks how weather risk shapes agricultural adaptation when crop choices involve long-lived investments that are costly to reverse. Adapting a portfolio-choice framework from the finance literature, I study this problem among Ethiopian smallholders who allocate land between coffee and khat, two cash crops with different risk-return profiles. Coffee is more profitable but more sensitive to weather, while khat is more tolerant of heat and drought and provides more stable returns. Combining the Ethiopia LSMS-ISA household panel with detailed hourly gridded weather data, I find that coffee profits are substantially more sensitive to extreme heat than khat profits and that higher predicted profit variance for a crop predicts less land allocated to that crop, suggesting return risk as a determinant of adaptation when investments are costly to reverse.

I would welcome the opportunity to engage with researchers working on empirical networks in development economics and to receive feedback as I extend my research on climate adaptation to questions involving interactions among households and local economic linkages.

If I am shortlisted for participation, Professor Andrew B. Hultgren (ahultgr@illinois.edu) and Professor Sarah A. Janzen (sjanzen@illinois.edu) can provide letters of recommendation on my behalf.

Sincerely,

Hannah Kim

Hannah Kim
Ph.D. Candidate
Department of Agricultural and Consumer Economics
the University of Illinois Urbana-Champaign

UNIVERSITY OF ILLINOIS URBANA-CHAMPAIGN

217-200-2685 · hannah16@illinois.edu

Hannah Kim

hannah16@illinois.edu
217-200-2685
https://hannahkim-econ.github.io/

RESEARCH FIELDS

Environmental Economics, Development Economics, Agricultural Economics, Applied Microeconomics

EDUCATION

University of Illinois at Urbana-Champaign
Ph.D. in Agricultural and Consumer Economics — Expected May 2027

Cornell University
M.S. in Applied Economics and Management — Aug 2021

Ewha Womans University, South Korea
B.A. in Economics — Aug 2019
Dual Major in International Development and Cooperation Studies

REFERENCES

Sarah A. Janzen
Associate Professor
Dept. of Agricultural and Consumer Economics
University of Illinois
sjanzen@illinois.edu

Andrew B. Hultgren
Assistant Professor
Dept. of Agricultural and Consumer Economics
University of Illinois
ahultgr@illinois.edu

Hope C. Michelson
Professor
Dept. of Agricultural and Consumer Economics
University of Illinois
hopecm@illinois.edu

JOB MARKET PAPER

"Replanting Under Risk: Weather Shocks and Portfolio Choice in Perennial Agriculture"
(Solo Authored) — *Draft available upon request*

This paper studies how weather risk shapes agricultural adaptation when farmers in developing countries make long-lived investments. The analysis applies a standard portfolio-choice framework from finance to a perennial agricultural setting, linking farmers' land allocation to crop-specific expected returns and return variance. Coffee and khat are both cash crops that compete for land in Ethiopia, but differ in their sensitivity to weather and their risk-return profiles. Combining a rich, geolocated household panel with detailed hourly gridded weather data, I estimate crop-specific weather-profit relationships and use recent weather histories to construct weather-induced mean profits and profit variances. These measures are then related to the coffee share of coffee-khat land. Coffee profits are highly sensitive to extreme heat, but farmers adjust gradually within coffee land rather than an immediate exit from coffee cultivation. Higher coffee profit variance predicts a lower coffee share, while higher khat profit variance predicts a higher coffee share. Higher mean predicted khat profit also predicts a lower coffee share. The results suggest that long-run adaptation depends not only on average profitability but also on the stability of returns to long-lived agricultural investments.

WORKING PAPERS

"Global Extreme Weather and Early Childhood Undernourishment"
Hannah Kim, Andrew Hultgren, Sarah Janzen

Provides global causal evidence on how early-life weather shocks affect child growth, combining DHS anthropometric data for more than 1.2 million children across 57 low- and middle-income countries with high-resolution ERA5 weather data to reconstruct daily exposure histories from conception through the survey date. Estimates how the effects of temperature and precipitation vary across developmental stages, distinguishing prenatal exposure from shocks experienced after birth. Drought and extreme cold during gestation have persistent adverse effects on child growth, with lower height-for-age observed at ages three to five, while heavy rainfall becomes more consequential after birth.

WORKS IN PROGRESS

"Wildfire Damages in the United States"
Hannah Kim, Andrew Hultgren

Estimates the local economic impacts of wildfire exposure using U.S. county-level panel data and a population- and economic-activity-weighted measure of MODIS burned area that captures where fires occur within counties. Distributed-lag estimates show limited population responses, declines in unemployment consistent with post-fire reconstruction, and heterogeneous effects across high- and low-fire-frequency regions.

SEMINAR AND CONFERENCE PRESENTATIONS

Paper: *Replanting Under Risk: Weather Shocks and Portfolio Choice in Perennial Agriculture*

· AAEA Annual Meeting 2026

Paper: *Global Extreme Weather and Early Childhood Undernourishment*

· Midwest International Economic Development Conference (MWIEDC) 2026

· AERE Annual Summer Meeting 2025

· AAEA–WAEA Joint Annual Meeting 2025

· KDIS–World Bank DIME Development Impact Conference 2024

FELLOWSHIPS AND AWARDS

ACE Travel Grant 2024–2026
AAEA–WAEA Section Sponsored Travel Grant 2025
Jonathan Baldwin Turner Fellowship 2021–2023
3rd Place, Food Law and Policy Paper Competition, National Food Safety Information Service 2020
Euncheon Scholarship, Euncheon Scholarship Foundation, Korea 2020
Appenzeller Memorial Scholarship, International Foundation for Ewha Womans University, NY 2020
Creative Social Science Academy Award, Ewha Womans University 2017
Excellence Student Scholarship, DB Cultural Foundation, Korea 2017
National Full Scholarship, Korea 2014–2018

RESEARCH EXPERIENCE

Research Assistant (Prof. Andrew Hultgren) 2023 – Present
University of Illinois

· Collaborated with private sector partners on data integration and empirical analysis of wildfire damages using county-level panel data.

Research Assistant (Prof. Henning Otte Hansen) 2020
Dept. of Food and Resource Economics (IFRO), University of Copenhagen & SEGES, Denmark

· Selected as a government-sponsored research fellow (Ministry of Agriculture, Republic of Korea).

TEACHING EXPERIENCE

TA, ACE 264: Applied Statistical Methods and Data Analytics II Spring 2025, 2026
University of Illinois at Urbana-Champaign
Teaching effectiveness: 4.18/5 (Spring 2025); 4.48/5 (Spring 2026)

TA, ACE 251: The World Food Economy Fall 2022, Spring 2023
University of Illinois at Urbana-Champaign

SERVICE

Referee

· Journal: Science Advances (AAAS), Applied Economic Perspectives and Policy (AEPP)

· Conference: Midwest International Economic Development Conference

Departmental

· GSO Courses and Curricula Committee, University of Illinois 2026–2027

SKILLS

Stata, R, Python, LaTeX, High-Performance Computing (HPC)

PH.D. COURSEWORK

Fall 2021

ACE 501	Risk and Information: Theory and Applications
ACE 592	Microeconomics
ACE 592	Tutorial Economics Statistics
ECON 532	Econometric Analysis I

Spring 2022

ACE 502	Demand, Supply, Firms, and Households
ACE 503	Equilibrium and Welfare Economics
ACE 592	Tutorial Econometrics
ECON 535	Econometric Analysis II

Fall 2022

ACE 557	Food, Poverty and Development
ACE 559	Food, Trade and Development
ACE 594	International Development and Policy Workshop
ECON 551	Topics in Development Economics
ECON 590	Applied Microeconometrics I

Spring 2023

ACE 510	Advanced Natural Resource Economics
ACE 531	Impact Evaluation
ACE 561	Advanced Research and Scholarly Communication
ACE 592	Impact Evaluation
ACE 594	Seminars and Workshops

Fall 2023

ACE 516	Environmental Economics
ATMS 517	Data Science for Geosciences *(audited)*

Dissertation Research

ACE 599	Thesis Research, Summer 2022; Fall 2023–Summer 2026 *Current: Fall 2026*

Statement of Research Interests and Motivation

Hannah Kim

The economic consequences of climate and environmental risks depend on both the shocks themselves and how people respond to them. For households with limited capacity to adapt, these shocks can have lasting effects, and adaptation decisions can shape longer-run economic outcomes. I am an environmental and development economist studying climate and environmental risk, vulnerability, and adaptation. I use applied microeconomic methods and combine household and local-area data with high-resolution environmental data. My research spans low- and middle-income countries and the United States. My research seeks to identify where environmental shocks impose economic costs, how households respond to them, and how policy can reduce vulnerability and strengthen households' capacity to adapt.

The paper I would like to present at the workshop is my solo-authored job market paper, *"Replanting Under Risk: Weather Shocks and Portfolio Choice in Perennial Agriculture."* The paper asks how weather risk shapes agricultural adaptation when farmers in developing countries make long-lived investments. In perennial agriculture, crop choice is a multi-year investment that is costly to reverse. Farmers therefore care about both the expected profitability of a crop and the variability of its returns over time. I study this problem among Ethiopian smallholders who allocate land between coffee and khat, two perennial cash crops that compete for land but have different risk-return profiles. Coffee is more profitable but more sensitive to weather, while khat is more tolerant of heat and drought. In addition, Khat can be harvested repeatedly throughout the year, providing more stable returns. I apply a standard portfolio-choice framework from the finance literature to this setting, linking farmers' land allocation to crop-specific expected returns and return variance. Combining the Ethiopia LSMS-ISA household panel with detailed hourly gridded weather data, I first examine how prior weather exposure is followed by subsequent changes in perennial crop allocation. I estimate crop-specific weather-profit relationships and use households' recent weather histories to construct weather-induced mean profits and profit variances. I then examine whether these measures predict land allocation in the direction implied by the portfolio framework.

I find three main results. First, extreme heat is followed by gradual adjustment within the existing coffee stock rather than immediate exit from coffee cultivation. Second, coffee and khat respond differently to weather. Coffee profits are substantially more sensitive to extreme heat than khat profits. Third, higher coffee profit variance predicts a lower future share of land devoted to coffee, while higher khat profit variance predicts the opposite. Higher predicted khat profits also predict a lower future coffee share, while the corresponding estimate for coffee profits is positive but statistically insignificant. Together, these results suggest that adaptation in perennial agriculture depends not only on average profitability but also on the stability of returns to long-lived investments. Perennial agriculture remains understudied in climate adaptation research, even though crop choices commit land for years. By linking weather-induced return variance to land allocation, the paper brings return risk into the study of long-run agricultural investment among smallholder farmers. The Ethiopian setting also highlights a potential tension between private adaptation and broader welfare in low income setting, as khat may provide more stable returns while its expansion raises public-health and social concerns.

Because this is a solo-authored project, I would particularly value the opportunity to receive feedback from researchers with different substantive and methodological perspectives and to identify ways to further strengthen the paper. I also hope that exposure to research beyond my immediate area, particularly work connecting development economics with network-based questions and methods, will help me identify new directions for my broader research agenda. Finally, I would welcome the opportunity to build relationships with other early-career researchers whose interests complement my own, with the possibility of future collaboration. Thank you for considering my application.

Replanting Under Risk:

Weather Shocks and Portfolio Choice in Perennial Agriculture

Hannah Kim*

*Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign. Emails: hannah16@illinois.edu © 2026 by the author.

Abstract

How does weather risk shape agricultural adaptation when farmers in developing countries make long-lived investments? I apply a standard portfolio-choice framework from the finance literature to a perennial agricultural setting, linking farmers' land allocation to crop-specific expected returns and return variance. I focus on coffee and khat in Ethiopia, two long-lived cash crops that compete for land but differ in their sensitivity to weather and their risk-return profiles. Combining a rich, geolocated household panel with detailed hourly gridded weather data, I estimate crop-specific weather-profit relationships and use households' recent weather histories to construct weather-induced mean profits and profit variances. I then relate these measures to the coffee share of coffee-khat land. My estimates indicate gradual adjustment within coffee land rather than immediate exit. Coffee profit is more weather-sensitive than khat profit, especially to extreme heat. Higher coffee profit variance predicts a lower coffee share, while higher khat profit variance predicts a higher coffee share. Higher mean predicted khat profit also predicts a lower coffee share, while the corresponding coffee estimate is positive but statistically insignificant. The findings are consistent with a portfolio model of investment under risk and suggest that profit variance is an important determinant of long-run adaptation when agricultural investments are costly to reverse. More broadly, adaptation in developing-country agriculture may depend on the stability of returns to long-lived investments, not just their average profitability.

1 Introduction

How does weather risk shape agricultural adaptation in developing countries? Adaptation often involves investments whose returns depend on future weather conditions. When these investments are costly to reverse, uncertainty about future returns matters for investment decisions (Dixit and Pindyck, 1994). This problem is especially salient in perennial agriculture. Unlike annual crop farmers, perennial crop farmers cannot easily change what they cultivate from one season to the next. Crop choice is therefore a multi-year investment. Farmers care not only about the expected profitability of a crop, but also about how variable those returns are over time. When weather affects the mean and variance of returns differently across crops, it can alter their relative attractiveness. Perennial adaptation can therefore be understood as a portfolio choice among crops with different risk-return profiles, rather than solely as a response to current production losses.

I study this question among Ethiopian smallholders who cultivate coffee and khat. These two perennial crops compete for land, but differ in their production and payoff characteristics. Arabica coffee is relatively sensitive to heat and moisture stress, while khat can be harvested repeatedly throughout the year and is relatively more tolerant of heat and drought (Woldu et al., 2015; Tofu and Wolka, 2023). Coffee and khat are generally viewed as having different risk-return profiles, with coffee more profitable and khat providing more stable returns. These differences make khat a natural alternative when weather reduces coffee returns or increases their variability. I test whether weather-induced changes in expected returns and return variance affect land allocation.

To answer this question, I adapt a mean–variance portfolio framework from the finance literature to a setting in which farmers allocate land across perennial crops based on crop-specific expected profits and profit variance (Campbell and Viceira, 2002). I use this framework to guide the empirical analysis. Using four rounds of the Ethiopia LSMS-ISA household panel matched to ERA5 weather, I

first estimate whether weather exposures have impacts on perennial crop allocation. Next, I estimate how weather affects each crop's profit. I then apply these estimates to each household's recent weather history to construct weather-induced mean profit and profit variance for each crop. Finally, I examine whether these measures predict future land allocation in the direction implied by the portfolio framework.

I have three main findings. First, I find that extreme heat leads to adjustment within coffee land rather than immediate exit from coffee cultivation. It reduces the share of coffee land that is bearing and increases non-bearing coffee area, with no statistically significant effect on total coffee area or the probability of continuing to grow coffee. Temperature exposure also increases khat entry and cultivated area among households initially growing coffee but not khat. However, I find no clear evidence of direct reallocation from coffee to khat in the short run. Together, the reduced-form results are consistent with gradual renewal or replacement of coffee trees following weather-related damage or productivity losses.

Second, I find that coffee and khat respond differently to weather, which changes their relative risk-return profiles. The clearest difference appears in their response to extreme heat. Coffee profits are much more sensitive to extreme heat than khat profits. These crop-specific weather-profit relationships generate the weather-induced return distributions used to construct expected profits and profit variance for each crop.

Third, I find that land allocation is most strongly related to profit variance. Higher weather-induced coffee profit variance predicts a lower coffee share, while higher khat profit variance predicts a higher coffee share across several weather-history windows. Mean profit matters less clearly. Higher predicted khat profit shifts land away from coffee, while the coffee mean-profit coefficient is positive but statistically insignificant. Together, these results show that weather matters for perennial

adaptation and suggest that profit variance is an important determinant in land allocation decisions.

This paper makes three contributions to the literature. First, this paper contributes to the literature on weather and agricultural adaptation by focusing on perennial systems, where crop choices are long-lived and adjustment is infrequent. Much of the empirical literature measures weather and climate impacts through yields and agricultural production (Deschênes and Greenstone, 2007; Schlenker and Roberts, 2009; Hultgren et al., 2025). Recent work by Rising (2024) shows that farmers may leave less productive coffee trees unharvested, making weather-related losses appear smaller in yield measures based on harvested area. His model also includes planting decisions, but assumes that farmers replant all coffee trees killed by weather and expand coffee area in response to prices, effectively assuming a static climate. It does not model switching between crops. I push this literature forward by focusing on how weather shapes farmers' allocation of land across competing perennial crops. Using planted area and bearing status, I examine adjustment within coffee cultivation and land allocation between coffee and khat.

Second, this paper contributes to the literature on agricultural adaptation to weather and climate by bringing return variance into adaptation decisions. Much of the empirical literature focuses on how weather and climate affect mean agricultural outcomes. In perennial systems, however planting decisions are costly to reverse, thus the distribution of future returns can matter for farmers' adaptation decisions (Dixit and Pindyck, 1994; Price and Wetzstein, 1999). A large literature in development and agricultural economics shows that risk affects crop choice and agricultural investment (Rosenzweig and Binswanger, 1993; Dercon, 1996; Karlan et al., 2014; Emerick et al., 2016). More recently, Gammans et al. (2025) find that greater temperature variability is associated with lower adoption of double cropping. I extend this idea by moving from weather variability to weather-induced return variance. Using portfolio framework, I separate expected profit from

profit variance as two determinants of land allocation across these crops. I then use crop-specific weather-profit relationships and households' weather histories to construct both measures and examine whether they predict land allocation between alternative perennial crops. The clearest results are for profit variance. Higher coffee profit variance predicts a lower coffee share, while higher khat profit variance predicts a higher coffee share. These results suggest that perennial adaptation under weather risk depends not only on average returns but also on their variance.

Third, this paper contributes to the development literature on agricultural adaptation in low-income economies. Perennial crops are particularly important in these economies, accounting for a large share of agricultural export value (Monfreda et al., 2008; Rising, 2024). Recent studies and articles document substantial replacement of coffee with khat in Ethiopia (USDA Foreign Agricultural Service, 2023; Woldu et al., 2015; Abdurehim et al., 2025). Both are important perennial cash crops for smallholder farmers, but they play different economic and social roles. Coffee is a major export crop and an important source of smallholder livelihoods, but its production is increasingly exposed to climate stress (Moat et al., 2017). Khat can be harvested several times a year and grown on relatively small or fragmented plots, providing liquidity-constrained farmers with a more regular source of cash income. At the same time, khat expansion has raised broader public-health and social concerns (Al-Motarreb et al., 2002; Al-Hebshi and Skaug, 2005; Al-Mugahed, 2008; Balint et al., 2009). An attractive adaptation for individual farmers may therefore come with broader social costs. This paper provides evidence on how weather risk shapes agricultural adaptation in developing countries, where crop choices matter for both smallholder livelihoods and broader social outcomes.

The remainder of the paper proceeds as follows. Section 2 develops the portfolio-choice framework. Section 3 describes the coffee-khat setting, the LSMS-ISA panel, and the ERA5 weather data. Section 4 presents the empirical strategy. Section 5 reports the reduced-form results, the crop-specific weather-

profit estimates, and the sufficient-statistic evidence. Section 6 concludes.

2 Theoretical Framework

2.1 Planting Opportunities and Portfolio Environment

Weather shocks alter expected returns and return variance. Farmers revise land allocation when planting opportunities arise. Let L_t denote the land requiring replanting in period t. When $L_t > 0$, the farmer chooses the coffee share $\omega_t \in [0, 1]$ on the replanting area, with the remaining share $1 - \omega_t$ allocated to an outside option k. Because both crops mature over multiple years, ω_t represents a long-horizon investment decision rather than an annual production choice. The replanting stage thus determines the long-run composition of perennial crop portfolios.

Weather shocks trigger replanting needs through observed tree loss and age-related decline. Let

$$L_t = P_{t-s}\Big(d_t^w + d_t^a\Big) + E_t$$

denote the area requiring replacement at time t, where:

- L_t: land area with planting decisions in period t,
- P_{t-s}: planted coffee area s periods earlier,
- d_t^w: weather-induced die-off or damage rate $\in [0, 1]$,
- d_t^a: age-related mortality or decline in productivity $\in [0, 1]$.
- E_t: Land expansion or reallocation for other reasons

The die-off rate d_t^w captures the need for replanting due to weather-driven tree death or productivity decline that requires replacement. When $L_t > 0$, a replanting decision is triggered, linking weather shocks to land-use choices.

2.2 Portfolio Choice Under CRRA Preferences

When $L_t > 0$, the farmer reallocates land by choosing the coffee share $\omega_t \in [0, 1]$ on the replanting area. Let W denote the farmer's terminal wealth from the perennial portfolio. Preferences follow constant relative risk aversion,

$$U(W) = \frac{W^{1-\rho}}{1-\rho}, \qquad \rho > 0,\ \rho \neq 1,$$

and portfolio returns combine two risky perennial investments,

$$R_p = (1 - \omega_t)R_{k,t} + \omega_t R_{c,t}.$$

where $R_{c,t}$ and $R_{k,t}$ denote the gross returns from coffee and the outside option k, respectively.

Following Campbell (1996); Campbell and Viceira (2002), log gross returns are assumed to be jointly normally distributed,

$$r_{c,t} \sim \mathcal{N}(\mu_c, \sigma_c^2), \qquad r_{k,t} \sim \mathcal{N}(\mu_k, \sigma_k^2), \qquad \mathrm{Cov}(r_{c,t}, r_{k,t}) = \sigma_{ck}.$$

2.3 Portfolio Solution Under CRRA Preferences

Because a mixture of lognormal components is not lognormal, the CRRA objective $\mathbb{E}[R_{p,t}^{1-\rho}]$ does not admit a closed-form expression. To obtain a tractable representation, I apply a second-order Taylor expansion of portfolio log returns following Campbell and Viceira (2002). Let

$$\eta \equiv \sigma_c^2 + \sigma_k^2 - 2\sigma_{ck}$$

denote the portfolio variance penalty. A second-order expansion of $\log R_{p,t}$ yields

$$\log R_{p,t} \approx (1 - \omega_t)r_{k,t} + \omega_t r_{c,t} + \tfrac{1}{2}\omega_t(1 - \omega_t)\eta, \tag{1}$$

where $r_{c,t}$ and $r_{k,t}$ denote the log returns of coffee and the outside option.

Because $r_{c,t}$ and $r_{k,t}$ are jointly normally distributed, $\log R_{p,t}$ is also normally distributed with mean and variance given by substituting (1). Under CRRA utility, the objective becomes

$$\mathbb{E}[R_{p,t}^{1-\rho}] = \mathbb{E}\big[\exp\big((1-\rho)\log R_{p,t}\big)\big].$$

Using the moment-generating function of the normal distribution, this expectation admits the closed form

$$\log \mathbb{E}\Big[R_{p,t}^{1-\rho}\Big] = (1-\rho)\,\mathbb{E}[\log R_{p,t}] + \frac{(1-\rho)^2}{2}\,\mathrm{Var}(\log R_{p,t}),$$

so that both the return differential and second-moment penalty enter the replanting problem in closed form. Substituting (1) and

$$\mathrm{Var}(\log R_{p,t}) = (1-\omega_t)^2\sigma_k^2 + \omega_t^2\sigma_c^2 + 2\omega_t(1-\omega_t)\sigma_{ck},$$

the farmer solves

$$\max_{\omega_t \in [0,1]} \log \mathbb{E}[R_{p,t}^{1-\rho}].$$

Taking the first-order condition yields

$$\frac{d}{d\omega_t}\log \mathbb{E}[R_{p,t}^{1-\rho}] = (1-\rho)(\mu_c-\mu_k) + \tfrac{1}{2}(1-\rho)(1-2\omega_t)\eta + (1-\rho)^2\big(\omega_t\eta + (\sigma_{ck}-\sigma_k^2)\big) = 0,$$

Solving for ω_t gives

$$\omega^* = \frac{(\mu_c-\mu_k) + \frac{1}{2}\eta - (1-\rho)(\sigma_{ck}-\sigma_k^2)}{\rho\,\eta} \tag{2}$$

This closed-form solution shows that portfolio adjustment is governed by the expected return differential $(\mu_c - \mu_k)$ and the portfolio risk structure captured by the variance terms: η, σ_{ck}, σ_c^2. Adverse weather lowers μ_c or raises σ_c^2 . Under standard assumptions of risk aversion ($\rho > 1$), higher coffee-specific risk induces coffee exit at replanting stages. Risk aversion ρ amplifies this response by raising the weight on second-moment risk relative to expected returns.

3 Data

This section describes the household panel, the construction of coffee-khat land allocation and crop profit measures, and the weather variables used in the empirical analysis.

3.1 Context: Ethiopia, Coffee, and Khat

Coffee is central to Ethiopia's agricultural economy. Ethiopia is Africa's largest coffee producer and one of the world's major Arabica exporters, and coffee accounts for roughly 30–35% of total export earnings (USDA Foreign Agricultural Service, 2023). This sector supports over five million smallholder households. Global coffee production consists of two coffee varieties: Arabica and Robusta. Ethiopia's coffee production is predominantly Arabica, a variety known to be relatively more sensitive to temperature and rainfall than Robusta. Arabica coffee performs best under moderate temperatures and adequate rainfall. Sustained heat and prolonged moisture deficits can lead improper flowering, fruit development, thus yield, and quality.

Recently, there has been a decrease in coffee production and a sharp increase in coffee bean prices worldwide. It has been reported that temperature extremes and rainfall variability are critical factors associated with it. Moreover, climate projections have indicated substantial losses in the suitability of some current coffee-growing areas in the future (Davis et al., 2012; Moat et al., 2017; Sisay, 2018). Coffee is a perennial crop, and planting it entails a multi-year commitment of land. Consequently, farmers must consider the future risks of adverse weather conditions when deciding whether to plant coffee.

Catha edulis (khat) has been becoming a increasingly important perennial alternative in several coffee-growing areas of Ethiopia (Woldu et al., 2015; Tolera and Gebermedin, 2015). It is a stimulant crop containing several chemicals, such as Cathinone, a chemical structurally related to amphetamines.

Khat is consumed in the form of fresh leaves and chewed for its euphoric properties, mainly in East Africa and parts of the Middle East (Al-Motarreb et al., 2002; Al-Mugahed, 2008). Long-term khat use has been linked to several health issues, including esophagitis, gastritis, duodenal ulcers, hepatic cirrhosis, autoimmune hepatitis, migraines, cerebral hemorrhages, pulmonary edema, and heart attacks (Al-Hebshi and Skaug, 2005; Balint et al., 2009). In contrast, khat can be harvested year-round, providing immediate cash flow and rapid financial returns. This feature makes khat particularly attractive to liquidity-constrained households. Furthermore, because khat can be cultivated on marginal or fragmented plots, it has considerably lower entry barriers than coffee (Abdurehim et al., 2025). Khat is primarily grown in both highland and relatively arid regions and is often considered more resistant to drought than Arabica coffee (Feyisa and Aune, 2003; Tofu and Wolka, 2023).

Therefore, coffee and khat create a natural portfolio choice in perennial agriculture. Both crops are long-lived, compete for land, and expose households to different risk-return profiles. As heat and rainfall variability reduce the relative value of coffee, the trade-off between maintaining coffee and shifting toward khat becomes more important. Thus, the planting choices that Ethiopian farmers face become long-horizon land-allocation decisions for crops with different production and payoff characteristics. And the economic payoffs of these two crops may respond differently to weather conditions.

Lastly, this substitution has broader policy relevance. Coffee is an important source of export earnings, whereas the expansion of khat raises public health and social concerns. Therefore, private adaptation through crop switching may not align with broader social objectives. This setting was used to examine whether weather exposure shifts land allocation away from coffee and toward an alternative perennial crop.

3.2 Household Level Farming Data

Household data come from the Ethiopia Living Standards Measurement Study–Integrated Surveys on Agriculture (LSMS-ISA). The LSMS survey consists of visits to each farmer in the post-planting and post-harvest seasons. The post-planting questionnaires include GPS-based field size measurements, crop-planted area, bearing land share for perennial crops, and input use. The post-harvest survey asks about the amount of crop harvested and revenues (realized production outcomes in cash) as well as input use in the harvest season. This allows us to track the farmer's land-use decisions made before harvest, which prevents data from being confounded by short-run adaptation and selective harvesting (Rising, 2024).

In this study, four survey rounds were used: Round 2 (2013/14), Round 3 (2015/16), Round 4 (2018/19), and Round 5 (2021/22). Rounds 2 and 3 are spaced two years apart, while Rounds 4 and 5 have a three-year interval. I use the Round 2 to Round 3 and Round 4 to Round 5 transitions for within-household analysis. Rounds 3 and 4 are not used as the same household panel because the LSMS sample was reselected beginning in Round 4. This study limits its sample to households that cultivated coffee and/or khat during the initial round of each panel(rounds 2 and 4). This is because this study aims to focus on coffee-khat production, and the main allocation outcome is defined over coffee-khat perennial land.

In the data, each round includes post-planting and post-harvest agricultural questionnaires. The post-planting survey records land use, planted area, and input use early in the agricultural season, while the post-harvest survey records harvest quantities, sales, revenues, harvest-period input use, and other realized production outcomes. This structure allows me to measure crop allocation before harvest outcomes are realized and construct crop-specific revenue and cost measures within the same agricultural year.

Table 1: Sample and Crop Allocation Characteristics

	Mean	SD	N
Panel A. Sample Composition			
Number of households			2,280
Household-round observations			3,876
Coffee cultivated (%)	72.06	44.88	3,876
Khat cultivated (%)	47.86	49.96	3,876
Both coffee and khat cultivated (%)	19.92	39.94	3,876
Panel B. Land Allocation			
Total coffee-khat planted area (ha)	0.22	1.47	3,876
Coffee planted area (ha)	0.16	1.44	3,876
Khat planted area (ha)	0.06	0.31	3,876
Coffee share of coffee-khat land (%)	62.16	45.37	3,863
Bearing coffee area / planted coffee area (%)	56.04	34.64	2,763
Bearing khat area / planted khat area (%)	62.75	33.76	1,792

Notes: The unit of observation is a household-round. The sample consists of household-round observations cultivating coffee, khat, or both. Statistics are unweighted.

Panel A of Table 1 reports the sample composition. The table includes 2280 households and 3,876 household-round observations. Of the 72% of households that participate in coffee production, 48% are involved in khat farming, and nearly 20% of farmers cultivate both crops. Panel B of Table 1 summarizes the crop allocation characteristics. The average land size of the total coffee-khat planted area is 0.22 ha ($\approx$ 0.54 ac), implying sample coverage towards smallholder farmers. On average, khat planted land is smaller than coffee. This is consistent with the attractive agronomic characteristics of khat, which can be produced on a smaller land area than coffee (Abdurehim et al., 2025). The mean coffee share of coffee-khat land is 62%, while the median is 100%, and 20% of observations have a positive coffee share below 100%. This indicates that many coffee-growing households are at a corner solution, allocating all their coffee-khat land to a single crop. This distribution motivates examining both the continuous coffee share and the coffee-exit indicator. The former captures partial reallocations between coffee and khat among households that continue cultivating coffee, whereas the latter captures a complete exit from coffee cultivation.

Observing land allocation alone, however, does not reveal the economic returns associated with each crop. Therefore, I compare the commercial returns to coffee and khat and the extent to which the land dedicated to each crop is currently mature and bearing fruits.

3.3 Crop Returns on Bearing Land

Table 2 compares the returns in profit and bearing status for coffee and khat. This sample restricts the sample to farmers who produce coffee or khat for income and sell their yields in the market. This market-oriented sample is defined as households with a positive bearing area that either reported positive market sales or did not harvest because of crop damage. Observations with zero sales are excluded when the reported reason indicates non-commercial use, such as storage for later sale or household consumption, or when the reason for zero sales cannot be clearly classified.

Table 2: Profit Distributions for Coffee and Khat

	Coffee	Khat
Panel A. Profit Distribution among Market-Oriented Growers		
Mean profit (birr/ha)	169,533	147,634
Standard deviation	604,033	451,638
Difference (t-test p-value)	0.270	
10th percentile	0	2,546
Median	23,250	39,941
90th percentile	314,330	289,347
Non-positive return (%)	10.3	5.7
Observations	1,465	1,412
Panel B. Production Characteristics		
Share of Bearing area out of Planted Area	0.55	0.65
No harvest due to damage (%)	5.53	3.33

Notes: Revenue and input-cost measures are winsorized at the 99th percentile within crop-by-round cells. Profits per hectare of total land committed to the crop, including explicit zero-return observations are reported in Appendix.

Panel A reports the profit per hectare of bearing land for each crop. Coffee has a higher mean return than khat, although the difference is not statistically significant (169,533 versus 147,634 Birr/ha; p =0.27). Coffee returns are more dispersed, with a lower median, lower lower-tail, and higher upper-tail returns. These patterns suggest that coffee offers greater upside and downside risks rather than uniformly higher returns.

Panel B shows that this higher average payoff applies to smaller share of the land committed to coffee. The share of planted area that is currently bearing is lower for coffee than for khat, and complete harvest loss due to crop damage is more common in coffee observations. One possible explanation for coffee's lower bearing share is that some fields were planted recently and have not yet matured. However, recent planting does not appear to explain the full difference. Approximately half of the households reported that most coffee trees in their fields were planted before 2000. This suggests that a substantial share of land planted with coffee contains well-established trees that are old and not currently productive, although the data do not reveal why these trees are non-bearing.

Taken together, coffee offers greater potential for high returns, while khat generates returns more consistently across committed land. These differences provide the descriptive motivation for viewing coffee-khat allocation as a portfolio problem. The LSMS panel then allows me to track households over time and examine changes in perennial land allocation.

3.4 Weather Data and Exposure Measurement

Local weather exposure is constructed by spatially matching LSMS households with weather data. The weather data were obtained from the ERA5 reanalysis data (Hersbach et al., 2023) at a 0.25-degree spatial resolution. Each household location was assigned to the nearest ERA5 grid cell. The exact GPS coordinates of the households were not publicly released for confidentiality. Households are tracked across survey rounds using household identifiers, while geographic coordinates

are publicly available only at the enumeration-area (EA) level. Within EA level, GPS coordinates of households in each EA unit were randomly displaced within a limited radius, typically up to 2 km in urban areas and up to 5 km in rural areas. The GPS points were spatially constrained to fall within the consistent administrative zone to preserve the correct administrative zone of each household.

The baseline weather measures are constructed over the January–August growing window, which covers the broader period relevant for coffee development, including onset of budding and early fruit development. Following the degree-day approach of Schlenker and Roberts (2009), I characterize temperature exposure using growing degree days (GDD), which measures cumulative thermal exposure using prespecified temperature intervals. The baseline specification consists of three temperature intervals: GDD within 8–14°C and 14–21°C, and extreme degree days(EDD) above 21°C. Precipitation was included in the linear and quadratic terms.

- **Growing Degree Days (GDD):** For a temperature interval with lower threshold $\underline{T}$ and upper threshold $\overline{T}$, cumulative degree day exposure is defined as

$$\sum_h \min\{\max(T_h - \underline{T}, 0), \overline{T} - \underline{T}\}/24.$$

  Hourly temperature exposure is aggregated over the January-August window and converted to degree-days by dividing by 24. I construct two bounded GDD measures GDD$(8, 14)$ and GDD$(14, 21)$.

- **Extreme Degree Days (EDD):** EDD measures heat exposure above the upper temperature threshold. I construct extreme heat exposure above 21°C as

$$\sum_h \max\{T_h - 21, 0\}/24,$$

EDD measurement is also aggregated over the January–August window and expressed in degree-days.

- **Precipitation:** Precipitation is total rainfall over the January–August window, measured in centimeters(cm). I allow for a nonlinear relationship with agricultural outcomes by including precipitation in levels and quadratically.

Existing studies characterize coffee temperature sensitivity using different temperature measures, including annual means, daily means, and minimum temperatures, making the reported thresholds difficult to compare directly. Studies using daily minimum temperatures find adverse effects on coffee outcomes beginning around 14°C (). I therefore use 14°C to divide the non-extreme GDD range into two bins, 8–14°C and 14–21°C. Because my measure captures cumulative hourly temperature exposure, however, I do not interpret 14°C as a physiological threshold that transfers directly to my setting.

These matched weather histories are used in the empirical analysis to estimate crop-specific weather-profit relationships and to study future changes in coffee-khat land allocation.

4 Empirical Strategy

4.1 Overview: Linking Theory and Empirical Design

The descriptive statistics suggest that coffee offers greater potential for high returns but has a more dispersed return distribution than khat. The theoretical framework captures this trade-off by allowing perennial land allocation to depend on crop-specific expected returns and return variance. The model yields a closed-form expression for the optimal coffee share. Empirically, I construct these objects by using crop-specific weather-profit relationships to map each household's recent weather history into predicted mean profit and profit variance. Weather exposure can reduce the predicted

profit of coffee relative to khat. It can also increase the predicted profit variance of coffee. The empirical design thus estimates these objects from observed weather histories and examines whether they explain perennial land allocation.

The empirical strategy is implemented in three steps. First,I begin by estimating whether prior weather exposure affects coffee land changes based on a reduced-from approach. I then examine the economic channel underlying this relationship by estimating the crop-specific weather profit functions. These estimates are used to construct the predicted profit and profit variance of each crop implied by the model from households' recent weather histories. I then test whether land allocation in the following round is consistent with the model's return-risk implications.

The primary outcome that this study focuses on is the coffee share of coffee-khat land,

$$\omega_{it} = \frac{\text{CoffeeArea}_{it}}{\text{CoffeeArea}_{it} + \text{KhatArea}_{it}}$$

which measures household i's allocation between the two perennial crops in survey round t and connects directly to the portfolio share in the model. Because coffee and khat are long-lived crops that households cannot freely reoptimize crop choice each year, changes in ω_{it} represent perennial land-use adjustment rather than annual production decisions. This measure does not observe each replanting event between the survey rounds. Instead, it captures the net effects of replanting, abandonment, and switching decisions that occur between rounds. I complement the coffee-share outcome with two additional outcomes: complete exit from coffee cultivation and a decline in coffee area, capturing full withdrawal and partial contraction, respectively.

Lastly, I focus on households that cultivated coffee in the baseline round of each panel. This sample corresponds to the core question of this study: how do coffee growers adjust their perennial crop allocation in response to prior weather exposure?

4.2 Reduced-Form Effects of Lagged Weather Exposure on Perennial Crop Adjustment

I first estimate whether prior weather exposure changes perennial crop allocation. This reduced-form analysis answers whether lagged temperature and precipitation exposure is followed by an adjustment in the existing coffee stock and movement toward khat before turning to crop-specific weather-profit relationships.

$$\text{OUTCOME}_{it} = \sum_{\ell=1}^{2} f(\text{Temperature}_{i,t-\ell}) + \sum_{\ell=1}^{2} h(\text{Precipitation}_{i,t-\ell}) + \alpha_i + \lambda_{rt} + \varepsilon_{it},$$

$$\text{where} \quad \begin{cases} f(\text{Temperature}_{i,t-\ell}) = \theta_{1\ell}\text{EDD21}_{i,t-\ell} + \theta_{2\ell}\text{GDD8_14}_{i,t-\ell} + \theta_{3\ell}\text{GDD14_21}_{i,t-\ell}, \\ h(\text{Precipitation}_{i,t-\ell}) = \theta_{4\ell}\text{Prcp}_{i,t-\ell} + \theta_{5\ell}\text{Prcp}^2_{i,t-\ell}. \end{cases} \tag{3}$$

$\text{EDD21}_{i,t-\ell}$, $\text{GDD8_14}_{i,t-\ell}$, $\text{GDD14_21}_{i,t-\ell}$, and $\text{Prcp}_{i,t-\ell}$ measure local weather exposure one and two years before survey round t over the January–August window. EDD21 accumulates extreme heat exposure above 21°C, while GDD8_14 and GDD14_21 measure cumulative temperature exposure within the 8–14°C and 14–21°C ranges. Prcp is total precipitation over the same window, and the quadratic term allows the precipitation response to be nonlinear.

I estimate equation (3) for two sets of outcomes that characterize different dimensions of perennial crop adjustment. The first set describes changes in the existing coffee stock: an indicator of coffee cultivation, log coffee area, the share of planted coffee area that is bearing, and log non-bearing coffee area. Coffee cultivation and coffee area capture retention and contraction of the existing coffee stock. The bearing-share and non-bearing-area outcomes provide complementary information on changes in the productive composition, implying the possibility of replanting. I do not interpret the

non-bearing area as a direct measure of replanting because non-bearing coffee can include newly planted trees as well as older trees that are not currently productive.

The second set of outcomes captures movement toward khat and changes in the coffee-khat portfolio. I examine an indicator for khat adoption, log khat area, and the coffee share of coffee-khat land. For these outcomes, I further restrict the sample to households that cultivated coffee but not khat in the baseline round. Under this restriction, khat cultivation captures entry into khat production, and the coffee-share outcome captures movement away from an initial allocation entirely to coffee.

The specification includes weather exposure lagged by one and two years and excludes contemporaneous weather. This choice preserves the temporal order between weather exposure and the measured land-allocation outcomes. Land use is recorded in the post-planting survey, while the January–August weather window overlaps with the agricultural period in which round-t land allocation is observed. Therefore, contemporaneous weather does not cleanly precede the measured allocation. Using weather exposure from $t-1$ and $t-2$ ensures that the exposure predates the round-t land outcomes and allows for delayed adjustment in a perennial production system.

All specifications include household fixed effects, α_i, and region-by-round fixed effects, λ_{rt}. Household fixed effects absorb time-invariant differences across households, including agricultural characteristics as well as persistent land characteristics, elevation, and fixed components of market access and crop suitability. Region-by-round fixed effects absorb shocks common to households in the same region and year of the survey, such as regional price movements, policy changes, extension programs, and other regional conditions. Because the same households are observed across rounds, the remaining variation comes from idiosyncratic changes in lagged local weather exposure within households after accounting for shocks common to the region in each year. Standard errors are

clustered at the household level.

4.3 Step 1: Crop-Specific Weather-Profit Functions

I next examine whether the weather exposure underlying the reduced-form results changes the economic returns to coffee and khat in ways that can shape the portfolio choice. I do this in two steps. First, I estimate crop-specific weather-profit functions, allowing coffee and khat to respond differently to the same weather exposure. I then use these relationships to construct weather-induced measures of return and risk and examine whether they predict future land allocation.

For each crop $j \in \{c, k\}$, I estimate

$$\pi_{jit} = f_j(\text{Temperature}_{it}) + h_j(\text{Precipitation}_{it}) + \alpha_i + \lambda_{rt} + u_{jit}, \tag{4}$$

where $f(\cdot)$ and $h(\cdot)$ use the same functional form as in equation (3), and $j \in \{\text{coffee}, \text{khat}\}$.

Here, outcome π_{jit} is realized profit per square meter of bearing area for crop j cultivated by household i in survey year t. Profit is defined as crop revenue net of measured input costs.[1] I use profit rather than physical yield because the portfolio choice in the model depends on the economic returns of each crop. I estimate the regressions separately by crop, allowing the same weather exposure to affect coffee and khat profitability differently. Each regression uses household-round observations in which the corresponding crop is cultivated.

The weather variables use the same January–August measures defined in the Data section: EDD21, GDD8_14, and GDD14_21 for temperature exposure, and total precipitation entered linearly and quadratically. In contrast to the reduced-form specification, I use contemporaneous weather in this step because the objective is to estimate how weather exposure during the production

[1] Measured input costs include fertilizer expenditures and crop-specific wages during the planting and harvesting seasons. Observations with zero harvest due to crop damage are assigned zero revenue, thus have non negative profits.

year is related to crop profits in that year.

The fixed-effects structure follows the reduced-form specification. The estimates use idiosyncratic changes in local weather exposure within households after absorbing shocks common in the same region and survey year. The resulting coefficients characterize variations in crop profitability due to local weather conditions. Standard errors are clustered at the household level.

4.4 Step2: Sufficient-Statistic Evidence on Portfolio Adjustment

I next construct weather-based predicted profit of each crop using the crop-specific weather-profit functions estimated in the previous subsection together with each household's recent weather history. The means and variances of each crop's predicted profit are used as empirical counterparts to the expected return and variance terms in the portfolio model. Then I test whether these measures predict the future coffee share in the direction implied by the theoretical framework.

For crop j, I define the weather component of predicted profit as

$$\widehat{\pi}^{W}_{jit} = \widehat{f}_j(\text{Temperature}_{it}) + \widehat{h}_j(\text{Precipitation}_{it}). \tag{5}$$

I exclude the household and region-by-round fixed effects so that predicted profit reflects only the estimated weather component.

For each household, I use the estimated coffee and khat weather-profit functions with that household's weather over the previous L years to generate annual predicted profits for both crops $\widehat{\pi}^{W}_{jit}$. Since the functions are estimated separately, a given weather history can imply different predicted profits for the two crops.

I summarize each crop-specific history by its mean and variance. For crop j, the mean weather-induced predicted profit over the previous L years is

$$Return^{W}_{jit,L} = \frac{1}{L}\sum_{\ell=1}^{L}\widehat{\pi}^{W}_{ji,t-\ell} \tag{6}$$

And the variance of weather-induced profit over the previous L years is

$$Variance^{W}_{jit,L} = \mathrm{Var}_{\ell=1,\ldots,L}\left(\widehat{\pi}^{W}_{ji,t-\ell}\right) \tag{7}$$

This measure captures the fluctuations in predicted profitability generated by recent weather exposure. It does not capture other sources of profit risk, such as weather-unrelated price shocks or household-specific shocks.

The baseline specifications use two, four, and five-year windows($L \in$2,4,5). These windows capture recent weather exposure over horizons relevant for perennial crop adjustment without relying on a single assumption regarding the specific length of the weather window.

Next, I examine whether weather-based returns and variance predict subsequent land allocations. Specifically, I regress the coffee share in the next survey round on the predicted mean profit and profit variance of coffee and khat following

$$\omega_{i,t+1} = \beta_1 \mathrm{Return}^{W}_{c,it,L} + \beta_2 \mathrm{Return}^{W}_{k,it,L} + \beta_3 \mathrm{Variance}^{W}_{c,it,L} + \beta_4 \mathrm{Variance}^{W}_{k,it,L} + \lambda_{rt} + \varepsilon_{it}. \tag{8}$$

where the outcome is $\omega_{i,t+1}$, the coffee share of coffee and khat land observed in the next survey round. The regressors are constructed during L-year window ending in the survey year t. This specification links prior weather-implied returns and variances to future coffee-khat allocation.

$\mathrm{Return}^{W}_{c,it,L}$ and $\mathrm{Return}^{W}_{k,it,L}$ are predicted mean profitability of coffee and khat. $\mathrm{Variance}^{W}_{c,it,L}$ and $\mathrm{Variance}^{W}_{k,it,L}$ are the corresponding predicted-profit variances. Because farmers choose between

coffee and khat, I include the predicted return and variance measures for both crops in the same regression. The portfolio logic predicts a higher coffee share when coffee's predicted retrun is higher or khat has lower predicted return, corresponding to positive β_1 and negative β_2. Likewise, lower coffee return variance and higher khat return variance should make coffee relatively more attractive, corresponding to $\beta_3 < 0$ and $\beta_4 > 0$. I interpret the khat-risk coefficient cautiously because the khat weather-profit first stage is less precisely estimated.

The second step regression includes region by round fixed effects but not household fixed effects and therefore relies mainly on cross-sectional differences in weather-implied return and risk. Therefore, I use these estimates to test whether portfolio allocation in the next round follows the risk-return patterns predicted by the model.

5 Results

5.1 Reduced-Form Evidence on Perennial Crop Adjustment

Table 3 reports effects of prior temperature exposure on adjustment in perennial crop allocation. Panel A examines changes in the existing coffee stock, including coffee cultivation, total coffee area, and the composition of bearing and non-bearing coffee. Panel B shows impacts on khat adoption and coffee land share, among baseline coffee farmers who did not initially grow khat. The clearest effects appear in the existing coffee bearing area, with additional evidence of khat adoption.

Table 3: Weather Exposure and Perennial Crop Adjustment

	Panel A: Existing coffee stock				Panel B: Khat adoption and portfolio adjustment		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Coffee cultivation	Log coffee area	Bearing share	Log non-bearing area	Khat adoption	Log khat area	Coffee share
GDD 8–14, t-1	-0.0000	-0.0006	0.0138**	-0.0042**	-0.0001	-0.0014	-0.0000
	(0.0000)	(0.0007)	(0.0060)	(0.0017)	(0.0000)	(0.0012)	(0.0000)
GDD 14–21, t-1	0.0000	0.0001	0.0035	-0.0003	0.0001***	0.0017***	-0.0000
	(0.0000)	(0.0004)	(0.0031)	(0.0008)	(0.0000)	(0.0006)	(0.0000)
EDD above 21, t-1	0.0000	0.0003	-0.0047***	0.0013***	-0.0000	-0.0003	0.0000
	(0.0000)	(0.0003)	(0.0017)	(0.0005)	(0.0000)	(0.0004)	(0.0000)
GDD 8–14, t-2	-0.0001**	-0.0014*	-0.0032	0.0023	0.0002***	0.0040***	-0.0000
	(0.0000)	(0.0008)	(0.0067)	(0.0019)	(0.0001)	(0.0015)	(0.0000)
GDD 14–21, t-2	0.0000	0.0002	0.0053*	-0.0009	-0.0000	-0.0005	0.0000
	(0.0000)	(0.0005)	(0.0028)	(0.0008)	(0.0000)	(0.0008)	(0.0000)
EDD above 21, t-2	0.0000	0.0001	-0.0043**	0.0009*	0.0000*	0.0007*	-0.0000
	(0.0000)	(0.0003)	(0.0019)	(0.0005)	(0.0000)	(0.0004)	(0.0000)
Observations	2280	2280	2154	2140	1606	1606	1606
Precipitation controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region x round FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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

The clearest pattern is for extreme heat. An additional degree day above 21∘C reduces the bearing share of coffee by about 0.47 and 0.43 percentage points at the one- and two-year lags, respectively, while increasing non-bearing coffee area by about 0.13 and 0.09 percent. In contrast, I find no significant effects on coffee cultivation or total coffee area. This pattern is consistent with heat damage reducing the productivity of existing coffee trees. Changes in bearing status may reflect not only damage in immature tree stock but also slow replacement or replanting decisions, although the data do not directly observe these transitions. Larger adjustments, such as coffee exit or area contraction, may take more than two years to emerge.

On the khat side, GDD14-21 predicts both khat adoption and a larger khat area at the one-year lag. GDD8-14 shows the same pattern at the two-year lag, while EDD21 also has weaker positive effects on khat adoption and area at that time. These results suggest that prior temperature exposure can be followed by khat entry and expansion among coffee farmers who did not grow khat in the baseline. I find no significant effect on the overall coffee share, suggesting that the short-run response is more visible in the underlying crop-specific changes. The remaining temperature coefficients are less straightforward to interpret in terms of agronomic characteristics.

Taken together, these results show that weather impacts on perennial crop adjustments in several aspects. The current reduced form results, however, do not directly show whether these responses are tied to differences in coffee and khat profitability. I next examine that link.

5.2 Step1: Weather Sensitivity of Coffee and Khat Profits

Table 4 shows the weather exposure impacts on profit(birr per m^2) of each crop. For coffee, an additional EDD above 21°C reduces profit per m^2 by 100 birr and is statistically significant at the 5 percent level. By contrast, GDD between 8 and 14°C is positively associated with coffee profit, with a coefficient of about 358, while the coefficient on GDD between 14 and 21°C is small

and imprecisely estimated. Taken together, the estimates indicate that coffee profitability responds nonlinearly across the temperature distribution, with the clearest adverse impact under extreme heat.

Precipitation has nonlinear effects on coffee profit, with a negative linear term and a positive quadratic term. The fitted precipitation relationship is U-shaped, but the turning point lies far in the upper tail of the precipitation distribution among coffee farmers. The fitted relationship is therefore downward sloping, with higher precipitation leading to lower predicted coffee profit. For khat, the linear term is negative and significant, while the squared term is statistically insignificant.

Taken together, the estimates suggest that coffee is more sensitive to weather than khat, particularly to extreme heat. The EDD coefficient is about 92 birr more negative for coffee than for khat, and the difference is statistically significant (p=0.040). This differential sensitivity means that the same weather history can generate different predicted profitability for the two crops. I next use these crop-specific weather-profit relationships to construct predicted mean profit and profit variance from each household's recent weather history.

5.3 Step2: Weather-Induced Return, Variance, and Portfolio Adjustment

This step asks whether weather-induced mean returns and variances are related to future portfolio choice in the direction predicted by the model. I construct these measures from the crop-specific weather-profit functions in Step 1 using the previous two, four, and five years of weather, and relate them to the coffee share among baseline coffee growers.

The clearest pattern is in profit variance. Across all three windows, higher coffee profit variance is associated with a lower future coffee share, while higher khat profit variance is associated with a higher coffee share. Both coefficients are statistically significant at the 1 percent level in every

Table 4: Weather Effects on Coffee and Khat Profits

	(1)	(2)
	Coffee	Khat
EDD (>21°)	-100.37**	-8.53
	(42.75)	(13.32)
GDD (8–14°)	357.71**	25.27
	(181.87)	(133.43)
GDD (14–21°)	10.03	-43.03
	(41.98)	(50.51)
Precipitation(cm)	-4476.34***	-5359.85**
	(1446.86)	(2188.13)
Precipitation^2	2.38***	5.25
	(0.87)	(9.67)
Observations	1972	1220
Household FE	Yes	Yes
Region × Round FE	Yes	Yes
R^2	0.5838	0.6034

Dependent variable is profit per square meter of bearing area.

Standard errors clustered at the household level in parentheses.

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

specification. The results are consistent with the portfolio model: households allocate less land to a crop when its weather-induced profitability is more variable relative to the alternative.

Table 5: Weather-induced risk-return profiles and next-round coffee share

	(1)	(2)	(3)
	2-year	4-year	5-year
Coffee profit variance $\hat{\sigma}^2_c$	-0.0022***	-0.0011***	-0.0014***
	(0.0005)	(0.0003)	(0.0004)
Khat profit variance $\hat{\sigma}^2_k$	0.0012***	0.0007***	0.0004***
	(0.0003)	(0.0002)	(0.0001)
Coffee mean predicted profit $\hat{\mu}_c$	0.0013	0.0008	0.0013
	(0.0014)	(0.0014)	(0.0014)
Khat mean predicted profit $\hat{\mu}_k$	-0.0082***	-0.0077***	-0.0088***
	(0.0021)	(0.0022)	(0.0023)
N	1022	1022	1022
Sample	Base coffee	Base coffee	Base coffee
Household FE	No	No	No
Region$\times FE$	Yes	Yes	Yes
R^2	0.2057	0.1915	0.1924

The mean-return estimates are less precise. Higher predicted khat profit is associated with a lower coffee share in all three windows, and the coefficients are statistically significant at the 1 percent level. Higher predicted coffee profit has the expected positive sign in each specification, but the estimates are statistically insignificant. The evidence on mean returns is therefore stronger for

khat profitability than for coffee.

Taken together, the return and variance coefficients have the signs predicted by the portfolio model across the two-, four-, and five-year windows and the results are clearest for the variance. It is consistent with households allocating land toward the crop with the more favorable weather-induced return and variance profile.

6 Conclusion

This paper studies how weather exposure shapes land allocation across long-lived crops when alternative crops differ in expected returns and return variance. In the Ethiopian coffee-khat setting, this tradeoff is particularly relevant because the two crops respond differently to weather, so the same weather history can change their relative risk-return profiles. I develop a portfolio model that links these crop-specific return distributions to perennial land allocation. I then use crop-specific weather-profit functions and households' recent weather histories to construct empirical counterparts to the model's return and variance terms and test whether subsequent land allocation moves in the direction predicted by theoretical model.

The results are consistent with the model and clearest for return variance. Coffee profitability is substantially more sensitive to extreme heat than khat profitability, so the same weather history generates different predicted return distributions across the two crops. Higher coffee profit variance is associated with a lower coffee share, while higher khat profit variance is associated with a higher coffee share. Mean predicted khat profit also enters with the expected negative sign, whereas the coffee mean-return estimate is positive but imprecise. The evidence is therefore strongest for the role of return variance in portfolio adjustment.

These risk-return responses matter differently for perennial crops than for annual production

decisions. Farmers begin from an existing stock of long-lived plants and cannot freely reoptimize crop choice each season. Consistent with this constraint, the reduced-form results show adjustment within the existing coffee stock following extreme heat even when changes in total coffee area are less pronounced. This pattern suggests that weather-induced changes in profitability can affect perennial land allocation gradually, through adjustments in the composition of existing crop portfolios.

More broadly, this study suggests that adaptation in perennial agriculture depends not only on changes in expected profitability, but also on changes in return variance. When crop choices are long-lived and costly to reverse, farmers face a portfolio problem over both the level and variability of returns. Weather can therefore shape adaptation by changing the relative risk-return profiles of competing crops, with consequences for land allocation that may persist beyond the initial production shock. In this setting, adaptation is a portfolio choice under risk, not simply a response to changes in average profitability.

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