RISK AND RAINFALL: SPECIFICATION SENSITIVITY IN ESTIMATING SMALLHOLDER RISK PREFERENCES

by

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A Dissertation Submitted to the Faculty of the

DEPARTMENT OF AGRICULTURAL AND RESOURCE ECONOMICS

In Partial Fulfillment of the Requirements

For the Degree of

MASTER OF SCIENCE

In the Graduate College

THE UNIVERSITY OF ARIZONA

2025

THE UNIVERSITY OF ARIZONA
GRADUATE COLLEGE

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ACKNOWLEDGMENTS

I would like to express my sincere gratitude to my advisors, Dr. Anna Josephson and Dr. Jeffrey Michler, whose generous guidance and support made it possible for me to pursue and complete this part of my academic journey.

I would also like to thank the faculty and staff of the Department of Agricultural and Resource Economics for their invaluable contributions to both my academic and professional development.

Finally, I am deeply grateful to my friends and family, whose continuous love and support means more than I can fit into this acknowledgment.

LAND ACKNOWLEDGMENT

We respectfully acknowledge the University of Arizona is on the land and territories of Indigenous peoples. Today, Arizona is home to 22 federally recognized tribes, with Tucson being home to the O'odham and the Yaqui. Committed to diversity and inclusion, the University strives to build sustainable relationships with sovereign Native Nations and Indigenous communities through education offerings, partnerships, and community service.

DEDICATION

To my dog Wes and my cat Tom, for keeping me company and my lap warm as I wrote this.

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ABSTRACT

Rainfall variability in Sub-Saharan Africa creates significant production risks for subsistence farmers who rely on rainfed agriculture. Weather shocks can alter farmers' risk preferences, potentially influencing their decision to adopt adaptation strategies. We employ a moments-based approach (Antle, 1983, 1987) to estimate risk aversion among smallholder farmers in Ethiopia, Malawi, and Nigeria in response to weather shocks. Using this framework, we estimate Arrow-Pratt and downside risk coefficients across more than 200 model specifications, incorporating various rainfall and rainfall shock metrics derived from six remote sensing weather products. Our findings reveal that estimates of farmers' risk preferences are highly sensitive to the choice of weather product, while risk preferences are relatively insensitive to different weather shocks. This underscores how data source and model specification choices critically shape risk preference estimates, highlighting key limitations in current empirical methods.

Chapter 1

Introduction

Subsistence farmers around the world rely on rainfed agriculture. This makes them susceptible to weather shocks and variability in weather. Changing climate conditions have amplified this variability and made rainfall patterns increasingly unpredictable. This is particularly true in Sub-Saharan Africa (SSA), where frequent dry spells and drought characterize climate change. To cope with such shocks, technology adoption and the adoption of agricultural practices are necessary to mitigate negative effects on agricultural production. As farmers navigate these challenges, their responses to weather shocks are shaped by external conditions and evolving risk preferences. Weather shocks may alter risk preferences (Page et al., 2014), which may, in turn, affect risk-related behaviors, including a farmer's decision to adopt agricultural technologies like fertilizer and improved seeds. This framework challenges traditional economic models, which assume that preferences remain stable over time (Stigler and Beckler, 1977).

This study seeks to analyze how weather shocks influence the risk preferences of smallholder farmers in Ethiopia, Malawi, and Nigeria. Given the uncertainty in the existing literature on the role adverse weather shocks play on individuals' risk preferences, this research aims to clarify this relationship by examining farmers' behavioral responses to weather variability. Specifically, we examine whether exposure to weather shocks increases risk aversion and heightens downside risk preferences. By identifying patterns in risk preferences, we contribute to a broader understanding of the factors influencing technology adoption and the use of adaptation strategies among smallholder farmers.

Across all three countries, we find that risk preferences remain stable across different shock specifications and rainfall measures but vary substantially depending on the remote sensing weather product used. Because results can shift so dramatically with changes in the weather data, it becomes difficult to discern which specification truly reflects farmers' risk preferences. This sensitivity to weather data sources raises broad concerns about the reliability of such estimates. As noted by Just and Just (2011) and Josephson et al. (2025), without additional data to support models that predict risk behavior, estimates may be shaped by researchers' specification choices rather than the underlying preferences themselves, making it difficult to draw meaningful conclusions from such models. Our results reveal more about the influence of different weather datasets than they do about the stability of risk after shock.

This variation in estimated risk preferences stems from the challenge of measuring weather itself. In much of Africa, there is a gap in ground station coverage, meaning that the weather observed by farmers is rarely recorded. Researchers rely on Earth Observation (EO) products to address this gap, which generates weather estimates using different sensors and data interpretation methods. While they aim to capture the weather from the same location and day, they often produce drastically different estimates. These discrepancies make it difficult to determine which estimate is closest to the actual weather farmers observe. As a result, a researcher's choice of remote sensing weather product can significantly influence model outcomes.

To investigate the effects of weather shock on smallholder farmers' risk preferences, we use a moments-based approach (Antle, 1983). This approach allows us to analyze risk preferences in the context of weather shocks by using statistical moments (mean, variance, and skew) to describe the distribution of agricultural outcomes. Specifically, we estimate Arrow-Pratt (AP) and Downside (DS) coefficients to measure risk aversion. In simple terms, the mean represents average crop yields, providing insight into how changes in inputs affect production; the variance reflects the level of risk associated with yields, and farmers experiencing high variance may respond differently depending on their risk preferences, risk-averse farmers may reduce input use to minimize potential losses, while not risk averse farmers may increase input use despite uncertainty in an attempt to maximize yields; finally, skewness captures the likelihood of poor outcomes or low yields, further informing risk behavior. Consider, if a farmer increases input use when the yield distribution suggests a higher probability of low yields, it could indicate a less risk-averse response to uncertainty. By examining these statistical moments, we can better understand how farmers' risk preferences evolve in response to weather shocks and how these preferences shape their adaptation strategies.

Standard economic models have no clear consensus on the stability of risk preferences. Stigler and Beckler (1977) argue that preferences remain stable over time and that changes in external factors or new information better explain unexpected behaviors. In the context of weather shocks and farmers' risk preferences, this perspective suggests that shifts in risk-taking behavior are responses to new information or external conditions rather than changes in true risk attitudes.

However, whether individuals become more or less risk averse is likely due to many factors. An individual's access to resources such as weather information, agricultural-related assets, or their participation in social institutions. Sagemüller and Mußhoff (2020) find that wealth, such as livestock ownership, decreases the effects of loss aversion. This supports the notion that limited access to resources may result in increased risk aversion. Conversely, Andrade and Iyler (2009) show that individuals' risk aversion decreases after experiencing loss. Individuals in this study started with more conservative bets, and after losing their first gamble, bet significantly more than their first round. These contrasting findings underscore the complexity of how shocks shape risk preferences.

To better understand the relationship between risk preferences and weather shocks, examining how farmers adjust their use of agricultural inputs in response to adverse weather shocks is essential. Brüssow et al. (2019) find that many smallholders in Tanzania either do not adopt adaptation measures or rely primarily on short-term strategies in response to perceived weather variability. Farmers' perceptions of weather-related risk are often informed by past shock experiences and their adaptive capacity, significantly shaping their decisions on whether and how they adjust their adoption of agricultural inputs (Brüssow et al., 2019). The findings suggest that adaptive capacity, a farmer's ability to respond to climate change impacts, plays a critical role in shaping adaptation decisions, often outweighing intrinsic risk preferences. This aligns with the arguments presented in Stigler and Beckler (1977), suggesting that responses to climatic shocks are shaped by external factors rather than fundamental changes in risk preferences.

However, Brüssow et al. (2019) also find that past experiences of loss due to weather shocks influence decision-making, which could indicate that risk preferences evolve over time. Similarly, Mulungu et al. (2024) suggest that repeated exposure to climatic shocks makes farmers more risk-averse than those experiencing isolated events. These varying findings highlight the ongoing debate over whether risk preferences remain stable or change in response to external shocks.

While most risk studies focus on a single country, we provide evidence from three Sub-Saharan African countries: Ethiopia, Malawi, and Nigeria. Each country has unique climate characteristics, enabling us to evaluate heterogeneous farmer responses to weather shocks. Ethiopia is experiencing a long-term decline in rainfall marked by strong year-to-year variability, increasingly unpredictable rains, and more frequent droughts, particularly in central and northern regions (World Bank Group, 2021a). Malawi's climate is vulnerable to extreme weather events, including droughts, dry spells, and floods, which have become more frequent and intense over the past two decades (World Bank Group and Global Facility for Disaster Reduction and Recovery (GFDRR), 2011). Nigeria's climate varies from humid in the south to semi-arid in the north, with a decreasing rainfall gradient from south to north and distinct rainy and dry seasons; the north experiences high rainfall variability, making it prone to both floods and drought (World Bank Group, 2021b). Differences in climate expose farmers to different types of weather-related risks, shaping their risk preferences and influencing their adoption of agricultural inputs. By capturing this variation, our study provides a broader understanding of how risk preferences drive responses to weather shocks in SSA.

We contribute to the literature in several key ways. First, we provide comparative evidence on how weather shocks affect farmer risk preferences and input decisions across multiple countries and contributes to the growing climate risk literature by applying Antle's moments-based approach in new geographic contexts. Second, we explore multiple measures of rainfall shocks and evaluate the impacts of different remote sensing weather products on our estimates of risk preferences. Rather than reinforcing the robustness of results, our findings suggest that the selection of weather data can substantially influence estimated risk preferences, more so than the inclusion of shock variables. Lastly, we clarify the mixed evidence in the literature on whether weather-related shocks shift risk preferences. This contributes to a clearer understanding of how weather shocks influence technology adoption among smallholder farmers. Our contribution does not offer evidence on the stability of risk preferences but instead demonstrates that risk preference estimates using this approach are primarily driven by weather data choices.

Chapter 2

Data

We use the Living Standards Measurements Study–Integrated Surveys on Agriculture (LSMS-ISA) to examine risk preferences among smallholder farmers in Ethiopia, Malawi, and Nigeria. To capture the weather variability and shocks, we use remotely sensed rainfall and weather shock measures from six weather datasets (ARC2, CHIRPS, CPC, ERA5, MERRA-2, and TAMSAT), which allow us to observe how differences in rainfall measurement affect our estimates.

2.1 Household Survey Data

The LSMS-ISA consists of a series of longitudinal surveys collected and designed by the World Bank in collaboration with national statistics offices (World Bank Group, 2025). The surveys are designed to capture and improve the understanding of household and individual welfare, livelihoods, and smallholder agriculture in SSA. We focus on Ethiopia, Malawi, and Nigeria. Data in this region were previously characterized by a lack of high-quality data (Bentze and Wollburg, 2024). And so the World Bank launched these surveys, in collaboration with national statistical offices, to address persistent data gaps, particularly in the agricultural sector, enabling nationally and sub-nationally representative samples of agricultural production.

We use the Harmonized Panel dataset compiled by Bentze and Wollburg (2024). This dataset brings together longitudinal, multi-topic household and agricultural survey data from seven countries: Ethiopia, Malawi, Mali, Niger, Nigeria, Tanzania, and Uganda (Bentze and Wollburg, 2024). The nationally representative panel tracks households, farms, and individuals over time. The HP was created by constructing and harmonizing approximately

150 agricultural, household, and individual indicators across household, individual, and plot levels to provide a ready-to-use dataset for cross-country and multi-level analysis.

We use five rounds of the Ethiopia Socioeconomic Survey (ESS), designed and implemented with the support of the LSMS-ISA program. The ESS was implemented every two years (Central Statistical Agency of Ethiopia and The World Bank, 2012, 2015, 2016, 2019, 2021). Respondents were visited in 2011, 2013, and 2015. In 2018, a new panel was launched to serve as the baseline for subsequent rounds, including ESS 2021. We use 10,393 household observations.

We use 8,351 household observations drawn from four rounds of surveys from the Malawi Integrated Household Survey (IHS) program. The IHS launched the Third Integrated Household Survey (IHS3) in 2010, which was followed by the Integrated Household Panel Survey (IHPS) in 2013, re-interviewing the same respondents from the 2010 survey (National Statistical Office (Malawi) and The World Bank, 2012, 2014, 2017, 2020). The Fourth and Fifth Integrated Household Survey (IHS4 and IHSP5) were implemented in 2016 and 2019, respectively.

In Nigeria, data were collected from the General Household Survey (GHS) across four waves: 2010/2011, 2012/2013, 2015/2016, and 2018/2019. A partial panel refresh was conducted in round four, but split-off households were not tracked (National Bureau of Statistics (Nigeria) and The World Bank, 2012, 2013, 2016, 2019). While the survey remains representative at the regional and urban/rural levels, some areas were inaccessible in 2018/2019 due to security concerns. As a result, round four is only representative of the regions that could be surveyed (National Bureau of Statistics, 2021a). From this dataset, we use 8,809 household observations.

Each country in our study included a household, agriculture, and community survey (Bentze and Wollburg, 2024). The household survey contains information about the household as well as information at the individual level, including demographics such as education of household heads and household members five years and older, health, financial inclusion, and labor. The survey inquired about food and non-food expenditures, consumption, and income, among others. From the agriculture survey, we took information such as agricultural input use, harvest, access to extension, and plot area. We also incorporated data from the community survey, particularly for our instrumental variables, such as distance to the market and distance to the nearest population center.

We selected Ethiopia, Malawi, and Nigeria because they represent different regions in SSA and capture a more comprehensive view of the weather and environmental conditions in SSA. Ethiopia is experiencing a long-term decline in rainfall, characterized by substantial variability, increasingly unpredictable rains, and more frequent droughts, particularly in central and northern regions (World Bank Group, 2021a). Malawi's climate is marked by exposure to extreme weather events, including droughts, dry spells, and floods, which have become more frequent and intense over the past two decades (World Bank Group and Global Facility for Disaster Reduction and Recovery (GFDRR), 2011). Nigeria has three distinct climate zones, ranging from humid in the south to semi-arid in the north. Rainfall declines along this gradient, and the northern regions experience high rainfall variability, contributing to drought and flood risk (World Bank Group, 2021b).

2.2 Descriptive Statistics

The variables in our analysis include household size, crop yield, fertilizer application rate, improved seed use, electricity access, and distance to population center, weekly market, extension services and nearest major road. Household size is measured as the total number of members in a household. Yields are measured in harvest value (USD) by plot area in hectares. Fertilizer use is measured in kilograms per hectare. Improved seed use is calculated as the proportion of improved seeds relative to traditional seeds. All distance variables are measured in kilometers. Electricity access is a binary variable, where 1 indicates access and 0 indicates no access. Extension access is binary for Ethiopia and Nigeria, indicating whether a household has access to agricultural extension services.

Table 2.1 presents summary statistics for household and agricultural variables across five survey waves in Ethiopia. Yields fluctuate considerably over time, peaking at an average of 1627 (harvest value per hectare) in Wave 3 and reaching the lowest at 570.07 in Wave 2. Fertilizer use demonstrates a clear upward trend, increasing from an average of 18 kg in Wave 1 to 32 kg in Wave 5. Similarly, the adoption of improved seed varieties also shows gradual growth, rising from 5% to 14% across the study period. Electricity access improves significantly, rising from just 8% in Wave 1 to 63% in Wave 5. Average distances to the nearest population center decrease over time from 37 km in Wave 1 to 24 km in Wave 4.

Table 2.1: Summary Statistics Across Five Survey Waves in Ethiopia

Variable	Wave 1		Wave 2		Wave 3		Wave 4		Wave 5	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Household size	5.35	2.12	5.42	2.23	5.42	2.27	4.98	2.16	5.14	2.17
Yield	654.15	4558.82	570.07	2163.80	1627.40	5058.69	693.03	2406.58	865.78	1259.66
Fertilizer use (kg)	18.60	126.91	27.01	361.89	27.00	170.87	28.07	151.65	32.66	167.89
Improved seed use	0.05	0.18	0.06	0.16	0.07	0.18	0.10	0.23	0.14	0.26
Electricity access	0.08	0.27	0.16	0.37	0.29	0.46	0.48	0.50	0.63	0.48
Dist. to pop. center (km)	37.21	26.21	36.02	26.30	35.96	26.29	24.30	16.04	27.28	19.88
Dist. to weekly market (km)	6.60	9.59	6.54	10.53	5.98	12.80	5.25	9.14	5.31	9.34
Maize price	0.25	0.06	0.25	0.06	0.25	0.06	0.31	0.13	0.36	0.13
Extension access (1 = Yes)	0.37	0.48	0.40	0.49	0.44	0.50	0.44	0.50	0.39	0.49

Table 2.2 presents descriptive statistics for key household and agricultural variables across four survey waves in Malawi. Fertilizer use gradually decreases over time, from an average of 60 kg in Wave 2 to 44 kg in Wave 4. The adoption of improved seed varieties is nonexistent in Waves 1 and 2 but rises notably to 39% in Wave 3 before decreasing slightly to 27% in Wave 4. The average distance to the nearest population center decreases notably from approximately 34 km in Waves 1 and 2 to roughly 21 km in Wave 4. In contrast, distances to the nearest weekly market vary significantly, peaking at an unusually high average of 28 km in Wave 3 where Waves 1, 2, and 4 reported distances from 5 to 7 km. Distance to extension services fluctuates notably, averaging between approximately 6 km in Wave 2 and 47 km in Wave 4, suggesting considerable variability in the proximity of households to extension agents across survey waves.

Table 2.2: Descriptive Statistics for Malawi

Variable	**Wave 1**		**Wave 2**		**Wave 3**		**Wave 4**	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Household size	5.06	2.33	5.32	2.32	5.13	2.25	5.13	2.27
Yield	231.90	368.29	289.56	794.97	191.84	330.26	134.05	553.29
Fertilizer use (kg)	56.91	71.04	60.10	241.96	46.05	110.21	44.38	120.11
Improved seed use	0.00	0.00	0.00	0.00	0.39	0.38	0.27	0.32
Electricity access	0.05	0.22	0.06	0.24	0.08	0.27	0.10	0.30
Dist. to pop. center (km)	34.29	19.68	34.24	19.64	32.48	18.55	20.95	13.24
Dist. to weekly market (km)	7.13	36.00	5.49	9.47	28.22	187.36	5.41	22.08
Maize price	0.22	0.03	0.22	0.03	0.21	0.02	0.21	0.02
Extension (dist. to office, km)	11.31	56.57	6.56	32.12	12.17	59.38	47.40	381.10

Table 2.3 presents summary statistics for key household and agricultural variables across four survey waves in Nigeria. Mean yield is highest in Wave 1 at 1915 (harvest value per hectare) and lowest in Wave 4 at 546, showing large differences between waves. Fertilizer use shows substantial variability, ranging from 45 kg in Wave 3 to 750 kg in Wave 4. Distance to road access decreases consistently from 17 km in Wave 1 to 6 km in Wave 4. Finally, household access to extension services shows considerable variation, dropping sharply from 24% in Wave 1 to just 1% in Wave 2, with minimal increases in subsequent waves.

Table 2.3: Descriptive Statistics for Nigeria

Variable	Wave 1		Wave 2		Wave 3		Wave 4	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Household size	5.19	2.80	6.37	3.22	6.51	3.27	6.52	3.53
Yield	1915.17	12126.01	795.29	1274.46	1323.04	4512.03	546.87	1010.98
Fertilizer use (kg)	244.26	6377.51	112.42	947.25	45.46	148.52	750.66	17583.84
Improved seed use	0.00	0.00	0.00	0.00	0.12	0.30	0.08	0.23
Electricity access	0.31	0.46	0.34	0.47	0.44	0.50	0.34	0.48
Dist. to pop. center (km)	25.82	21.05	22.23	15.12	29.48	19.79	23.24	17.59
Dist. to weekly market (km)	71.20	38.89	70.82	39.07	71.39	38.61	60.67	45.11
Dist. to road (km)	17.41	18.57	7.37	7.84	7.15	7.71	6.04	8.00
Maize price	0.34	0.14	0.34	0.14	0.34	0.14	0.32	0.11
Extension access (1 = Yes)	0.24	0.43	0.01	0.12	0.03	0.18	0.04	0.20

2.3 Remote Sensing Weather Data

Accurate weather measurement is crucial for understanding how smallholders respond to weather shock and how it influences their risk preferences and input decisions. However, capturing rainfall accurately remains a persistent challenge in SSA (Josephson et al., 2025). Reliable ground-based weather data is often sparse in this region, prompting researchers to rely on remotely sensed weather data to fill critical data gaps. While these sources improve coverage, they vary considerably in how they estimate rainfall. Discrepancies across weather datasets may affect the reliability and interpretation of empirical models examining the relationship between weather shocks and risk preferences.

To account for the impact of different remote sensing technologies, following Josephson et al. (2025), we include six different remote sensing weather products: Climate Hazards Group Infrared Precipitation with Stations (CHIRPS), Climate Prediction Center (CPC), European Centre for Medium-Range Weather Forecasts Reanalysis v5 (ERA5), Tropical Applications of Meteorology using SATellite data and ground-based observations (TAMSAT), African Rainfall Climatology version 2 (ARC2), and the NASA Modern-Era Retrospective analysis for Research and Applications (MERRA-2). Measurement errors that exist in each weather dataset can influence the results of models examining the relationship between weather and smallholder agricultural productivity (Josephson et al., 2025). In our analysis, we use four metrics: rainfall (measured as total, mean, and lagged rainfall) and weather shock (measured as anomalies such as deviation in rainy days, longest dry spell, and Z-score of total seasonal rainfall).

Our remote sensing weather products derive rainfall data using different methodologies, algorithms, and technologies. CHIRPS combines satellite-based Cold Cloud Duration (CCD) estimates with rain gauge data, producing preliminary and refined rainfall estimates (Funk et al., 2015). CPC generates gauge-based rainfall estimates using spatial interpolation techniques to account for elevation changes, blending data from multiple sources (Michler et al., 2021). ERA5 is a reanalysis dataset that integrates weather observations from stations, satellites, and other sources through data assimilation (Hennermann and Berrisford, 2020). ARC2 blends rain gauge data with satellite infrared data for Africa (Novella and Thiaw, 2013), while

TAMSAT uses satellite and rain gauge data (Tarnavsky et al., 2014). MERRA-2 provides rainfall and temperature estimates using satellite and weather station data (Bosilovich et al., 2016).

Rainfall distributions vary significantly across Ethiopia, Malawi, and Nigeria, as well as across the six weather data sets used in our analysis. These differences reflect underlying weather variability and methodological discrepancies in measuring and estimating rainfall. Recognizing this variation is essential for accurately identifying the relationship between rainfall and yield outcomes and interpreting risk preference estimates, which are highly sensitive to differences in rainfall estimates, distribution, and intensity.

In Ethiopia, the rainfall distributions from all six weather data sources show distinct patterns in Figure 2.1. The CPC dataset has a sharp peak at lower rainfall values with a right-skewed distribution, indicating that it records lower precipitation amounts most frequently and with less variability. CHIRPS also peaks at lower values but has a wider distribution, capturing a broader range of rainfall amounts. ARC2, MERRA-2, and TAMSAT show more variability, with more spread-out distributions. ERA5 has the most extensive distribution, frequently covering higher rainfall values and including more extreme events. This suggests that ERA5 estimates greater rainfall variability compared to CPC and CHIRPS. ERA5 produces such large outliers because it captures intense bursts of rainfall, or rain bombs, which can lead to overestimating total rainfall.

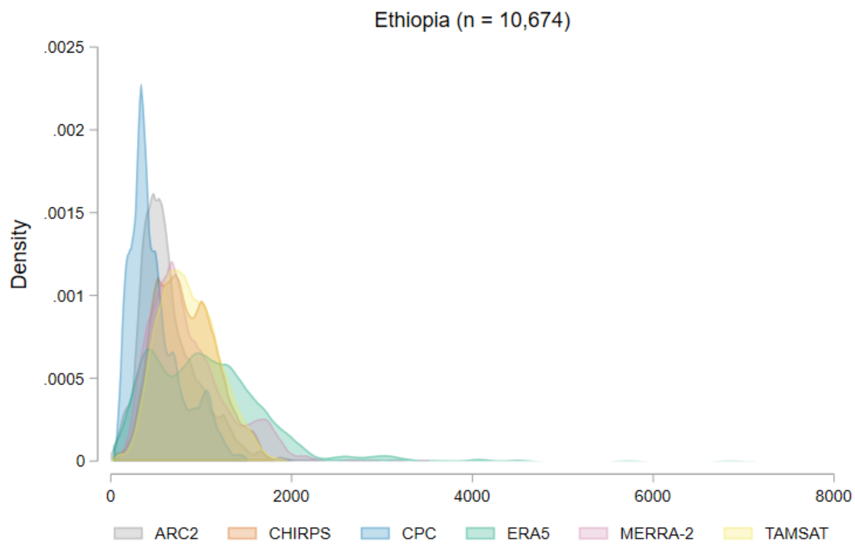


Figure 2.1: Ethiopia: Rainfall distributions from ARC2, CHIRPS, CPC, ERA5, MERRA-2, and TAMSAT.

In Malawi, Figure 2.2 shows a similar pattern. CPC produces a large proportion of lower rainfall estimates, indicating a tendency to capture smaller amounts of precipitation. CHIRPS, ARC2, and MERRA-2 have wider distributions, reflecting greater variability in recorded rainfall. ERA5 again captures higher values but with fewer extreme outliers than in Ethiopia, indicating fewer intense, localized rainfall events. But still, differences across datasets are large enough to influence our risk preference estimates. In Nigeria, Figure 2.3 shows tighter distributions than Ethiopia and Malawi. CPC still records a higher proportion of low rainfall estimates, but the overall distribution is more narrow than in Ethiopia and Malawi. ARC2, CHIRPS, MERRA-2, and TAMSAT capture greater variability across higher values. ERA5 still extends into higher rainfall values, though much less pronounced than in Ethiopia and Malawi.

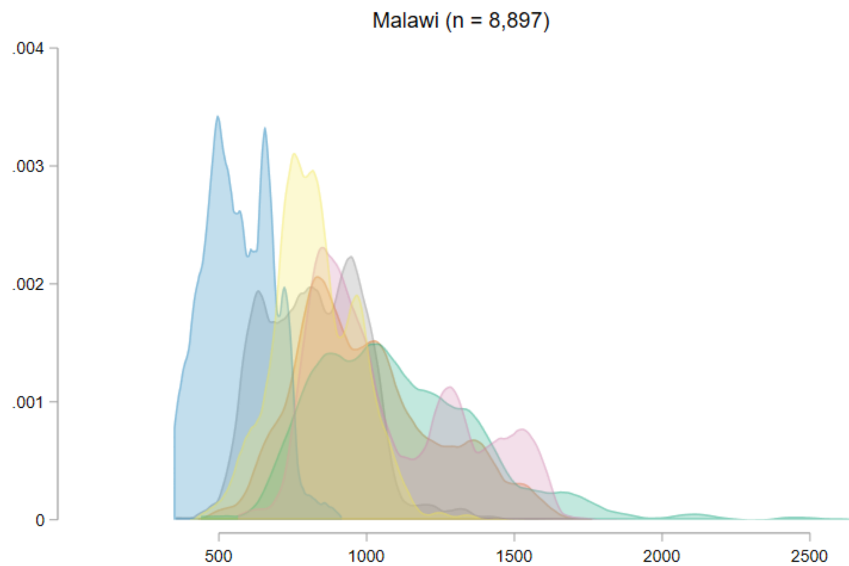


Figure 2.2: Malawi: Rainfall distributions from ARC2, CHIRPS, CPC, ERA5, MERRA-2, and TAMSAT.

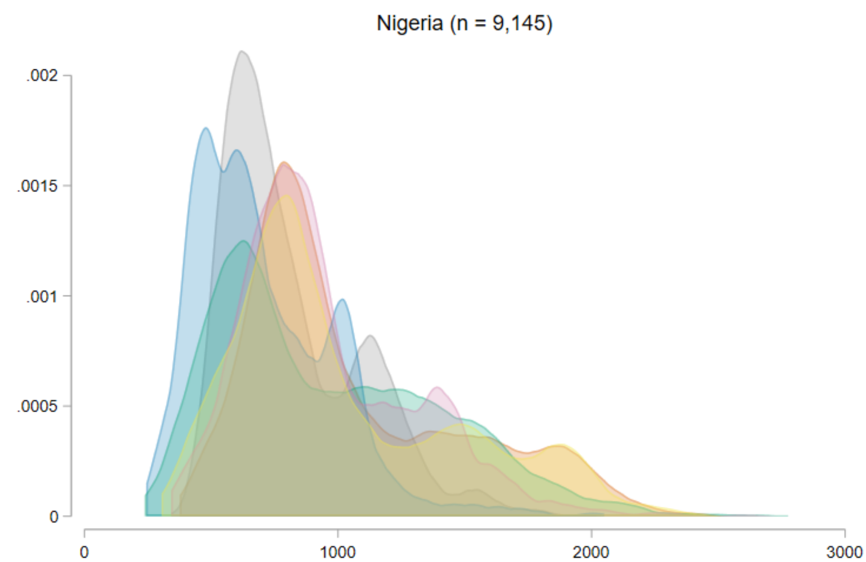


Figure 2.3: Nigeria: Rainfall distributions from ARC2, CHIRPS, CPC, ERA5, MERRA-2, and TAMSAT.

The differences in rainfall distributions across Ethiopia, Malawi, and Nigeria reflect underlying variability in weather between the countries. Ethiopia's broader distributions and outliers, especially in ERA5, indicate occurrences of localized, intense rainfall. While Malawi and Nigeria also display variation across data sources, the differences are more moderate, indicating comparatively less extreme precipitation patterns. These differences underscore the need to consider multiple weather datasets when using them in empirical models. By comparing results across different remote sensing products, we can assess the robustness of our results and better understand how variation in rainfall measurement may shape our conclusions about smallholder risk preferences after weather shock.

Chapter 3

Conceptual and Empirical Model

To assess how weather shocks influence changes in risk preference, we adopt a moments-based approach developed by Antle (1983, 1987), which has been widely used in the literature to estimate risk attitudes (Groom et al., 2008; Bozzola and Finger, 2021; Mulungu et al., 2024). This framework allows us to examine how fertilizer and improved seed influence the expected value of crop yield and its variability and downside risk. By examining the first three moments (mean, variance, and skewness), the approach allows us to assess how input choices shape risk in crop production and how weather shocks influence production decisions through their effect on farmers' risk attitudes.

The Antle (1983, 1987) framework enables us to evaluate AP and DS risk aversion by examining how input use impacts household crop yields. Using AP and DS to measure risk attitude helps us avoid input-specific risk aversion measures (Simtowe et al., 2006; Groom et al., 2008; Bozzola and Finger, 2021). The first moment, mean, represents the average crop yield, and changes in input use indicate how increased inputs influence crop production. The higher moments, variance, and skewness capture different dimensions of production risk. Variance reflects output variability and measures production risk: farmers may be less risk-averse if they increase input use despite uncertainty. Conversely, if the farmer reduces input use when output variability is high, they may be more risk-averse, as lower climate adaptation strategies are associated with greater risk aversion (Mulungu et al., 2024). Skew captures downside risk, representing the likelihood of poor outcomes such as low yields. A positively skewed yield distribution suggests a higher probability of extreme low yields, which may lead risk-averse farmers to adjust their input use to mitigate potential losses.

Through analyzing how input choices influence these statistical moments, we capture how farmers respond to risk in crop production, gaining insight into their decision-making under uncertainty.

3.1 Addressing Endogeneity

As we are interested in input use, we must address endogeneity issues from fertilizer and improved seed use that may bias our estimates. These variables are likely correlated with the error term in our model due to omitted variable bias, reverse causality, and measurement error. Without accounting for this, our estimates of risk preference and production outcomes may be inconsistent and unreliable.

Endogeneity may result from unobserved heterogeneity in farmer characteristics such as farm traits, market access, or other economic factors such as household wealth or input prices. This introduces omitted variable bias when these unobserved factors are correlated with input use and yield. For example, wealthier households may be more likely to be able to afford and apply higher amounts of fertilizer and improved seed, a factor that influences yield independently of inputs and would be unobserved in our model, resulting in omitted variable bias. If these factors are not included in the model, their influence is incorrectly attributed to the observed inputs, biasing the estimated effects.

Reverse causality poses another complication in our model. If farmers make input decisions based on expected yield, causality may run in both directions. A farmer anticipating higher yields may be more willing to invest in increased fertilizer and improved seed use to maximize their returns, whereas a farmer expecting lower yields may be more hesitant to apply more inputs to minimize potential losses. Moreover, consistent under use of fertilizer and improved seeds may contribute to sustained low yields. If this pattern is persistent over time, this could conflate the causal relationship between input use and yield outcomes.

Measurement error in self-reported survey data, particularly regarding input quantities and yields, introduces additional bias. Inaccurate farmer responses can weaken our identification of the true relationship between input use and production risk.

3.1.1 Instrumental Variables

Our key variables of interest for understanding risk preferences, fertilizer application rate and improved seed proportion, introduce endogeneity to our model, as they may be correlated with the error term. Decisions on applying these inputs are not random but are rather influenced by unobserved factors such as farm characteristics, infrastructure, market access, and economic factors (Jebesa, 2019; Taramuel-Taramuel et al., 2023). We include several instrumental variables (IVs) in our model to address this.

The five endogenous variables, fertilizer application rate, improved seed proportion, the square of fertilizer application, the square of improved seed proportion, and the interaction of fertilizer and improved seed use, are instrumented using country-specific IVs, chosen based on the country context and data availability. The full list of instruments by country is presented in Figure 3.1

Instrumental Variable	**Ethiopia**	**Malawi**	**Nigeria**
Distance to population center	✓	✓	✓
Distance to weekly market	✓	✓	✓
Distance to input supplier		✓	
Distance to major road			✓
Access to extension services	✓	✓	✓
Electricity access	✓	✓	✓
Regional maize price	✓	✓	✓
Lagged rainfall	✓	✓	✓

Figure 3.1: Instrumental Variables Used by Country

In Ethiopia, we select distance to population center, distance to nearest weekly market, access to extension services, regional maize price, and lagged rainfall, following the approach in Mulungu et al. (2024), who use similar instruments to address endogeneity. Distance to market and population center capture the transportation costs associated with acquiring inputs. Households located further from markets may face higher prices or lower availability of inputs, affecting both the level, type, and quality of input use. Access to electricity can reflect infrastructure development, influencing farmers' access to and propensity to use inputs. Access to extension services is associated with the likelihood that a farmer adopts inputs like fertilizer or improved seeds as extension officers offer information about agricultural practices and often advise farmers on the use of these inputs. Maize prices reflect market conditions that affect expectations about the potential value of output, which may affect potential investments in inputs during the cropping season. We include lagged rainfall as past weather outcomes may influence farmers' expectations about their productivity and potential conditions. If a farmer is expecting poor yields due to previous weather conditions, they may adjust their input use accordingly. The inclusion of these IVs is reasonable in capturing factors that may influence farmers' decisions to adopt fertilizer and improved seeds while not directly impacting yield outcomes.

For Malawi and Nigeria, our IVs are slightly different due to differences in the surveys and availability for each country. We consistently include distance to population center, electricity access, access to extension services, regional maize price, and lagged rainfall as instruments across all country models. However, in addition to these IVs, in Malawi, we also include distance to daily market and distance to nearest input supplier. Additionally, in Nigeria, we include distance to nearest major road. The justification for selecting these IVs remains the same: we select them to reflect access to services, markets, and infrastructure. Distance to daily markets and input suppliers in Malawi and distance to major roads in Nigeria similarly capture variation in access and transaction costs likely to affect input use.

3.2 Calculating Arrow-Pratt (AP) and Downside (DS) Risk Coefficients

Having addressed potential endogeneity in input use, we examine farmers' input decisions using a utility-maximizing framework that incorporates the moments of the yield distribution. We assume that farmers' behavior is consistent with expected utility theory (Just and Peterson, 2010), choosing inputs to maximize expected utility as a function of the distribution's moments. Farmers' input decisions can be modeled using the von Neumann-Morgenstern utility framework:

$$\max_{X} \quad \mathbb{E}[U(Y)] = F\big[\mu_1(X), \mu_2(X), \ldots, \mu_m(X)\big] \tag{3.1}$$

where $U(Y)$ represents the utility function and Y represents yield, $\mu_1, \ldots, \mu_m$ represent the statistical moments of yield distribution, and X represents the same vector of explanatory variables (household size, the fertilizer application rate, the proportion of improved seed use, the squared terms of fertilizer and improved seed use, their interaction, and rainfall) for each moment. We derive the moments using the procedure below, beginning with estimating the expected crop yield, which is the foundation for obtaining higher-order moments used in our risk analysis.

This procedure is applied to Ethiopia, Malawi, and Nigeria using household-level panel data and multiple rainfall and weather shock measures (total seasonal rainfall, mean daily rainfall, deviation in rainy days, Z-score of total seasonal rainfall, and longest dry spell) from six weather datasets. To account for differences in how these datasets capture rainfall and how they may influence our estimates, we estimate the models across over 200 specifications, varying the weather dataset and the specific rainfall or shock metric used. To address potential bias from unobserved heterogeneity and control for time-invariant household-level characteristics, we use the panel structure of our data to estimate the moment equations using two-way fixed effects with instrumental variables.

$$y_{ht} = f(X_{ht}, R_{ht}, R_{ht}^2, Z_{ht}; \boldsymbol{\vartheta}) + \alpha_h + T_t + \epsilon_{ht} \tag{3.2}$$

Table 3.1: Key Variables Included in the Yield Estimation Model

Variable	**Description**
y_{ht}	Crop yield for household h in year t
X_{ht}	Vector of inputs: fertilizer use, improved seed use, their squares, and interaction
R_{ht}	Rainfall
R_{ht}^2	Square of rainfall
Z_{ht}	Household size
α_h	Household fixed effects
T_t	Year fixed effects
ϵ_{ht}	Error term

First, crop yield is regressed on household size, rainfall, the square of rainfall, fertilizer application rate and improved seed proportion, including their squares and the interaction of these inputs. The predicted values from this equation serve as the basis for calculating higher moments of the yield distribution, specifically variance and skewness. Following (Antle, 1983) and (Groom et al., 2008), we compute these moments by squaring and cubing the predicted yield values. We do not include higher-order moments beyond skewness, as coefficients associated with these moments are not statistically significant (Antle, 1983; Groom et al., 2008). The mean of the yield distribution indicates how input use affects average crop yield. However, mean alone is not used to infer risk and does not provide information about production risk. Risk is captured in the higher moments. We use this equation to examine how fertilizer and improved seeds impact crop yield and to obtain predicted values that are then used to calculate the second and third moments of the yield distribution.

The next step is to calculate the second moment, variance, which helps us to understand production risk. To do this, we use the same set of explanatory variables included in the first moment equation. We square the residuals from the first stage yield regression to estimate the variance of yield for households. Then, we regress the squared residual term on our explanatory variables, fertilizer use, improved seed proportion, their squared terms and interaction, rainfall, household size, and fixed effects. This equation provides information about production risk and represents how input use affects the variability of yield.

$$(\hat{\epsilon}_{ht})^2 = g(x_{ht}, R_{ht}, R_{ht}^2, Z_{ht}; \boldsymbol{\rho}) + \alpha_h + T_t + \nu_{ht} \tag{3.3}$$

We then follow a similar process for estimating the skewness of yield. To estimate the third moment, we raise the residuals to the third power and regress the residual term on the explanatory variables used in the previous steps to give us the skewness of yield. By evaluating skewness and asymmetry in yield outcomes, we can examine how inputs influence downside risk.

$$(\hat{\epsilon}_{ht})^3 = h(x_{ht}, R_{ht}, R_{ht}^2, Z_{ht}; \boldsymbol{\phi}) + \alpha_h + T_t + \eta_{ht} \tag{3.4}$$

The estimated coefficients ($\boldsymbol{\vartheta}$, $\boldsymbol{\rho}$, $\boldsymbol{\phi}$) from Equation 3.2, Equation 3.3, and Equation 3.4 are then used to calculate the partial derivatives of each moment with respect to input use, fertilizer, and improved seed use. Shown by the following first-order conditions where k represents each input :

$$\frac{\partial \mu_1(x)}{\partial x_k} = \theta_{1k} + \theta_{2k}\frac{\partial \mu_2(x)}{\partial x_k} + \theta_{3k}\frac{\partial \mu_3(x)}{\partial x_k} + u_k \tag{3.5}$$

These parameters θ_{2k} and θ_{3k} can be estimated using a third-order Taylor series expansion of the utility function around the expected output, μ_1. As we can approximate the first-order conditions using a Taylor series expansion, we follow Antle (1983, 1987) and Chavas (2004) to estimate a series of derivatives for each input. These derivatives capture the sensitivity of each moment of the yield distribution to changes in input use. We calculate six expressions, one for each of the three moments (expected yield, variance, and skew) for fertilizer and improved seed use. These derivatives provide insight into how input choices influence average yield, production risk, and downside outcomes.

The most critical aspect of the model is that the estimated parameters, θ_{2k} and θ_{3k}, are interpretable as the AP and DS aversion coefficients. Specifically, θ_{2k} corresponds to the AP risk aversion coefficient, which measures the degree to which a farmer is averse to risk. In contrast, θ_{3k} captures downside risk aversion, reflecting the farmer's sensitivity to yield distributions that are skewed toward negative outcomes (Antle, 1987; Chavas, 2004; Groom et al., 2008).

A positive AP coefficient indicates that the farmer is risk averse, preferring to minimize exposure to uncertain yield outcomes. In this case, an increase in yield variance raises the cost of bearing risk, leading the farmer to adopt risk-reducing strategies. Conversely, a negative AP coefficient indicates not risk-averse behavior, where the farmer is willing to accept greater yield variability in pursuit of higher potential returns.

A positive downside risk aversion coefficient indicates that the farmer is averse to negative deviations from expected yield. In other words, the farmer is more sensitive to potential yield shortfalls than to yield gains. As a result, risk-averse farmers are more likely to adopt precautionary measures such as conservative input use to avoid loss. Such farmers are also less likely to engage in strategies that increase the probability of extreme negative outcomes, even if such strategies offer potential for high yields.

The AP absolute risk aversion coefficient can be approximated by:

$$AP = -\frac{\mathbb{E}\left(\frac{\partial^2 U}{\partial \pi^2}\right)}{\mathbb{E}\left(\frac{\partial U}{\partial \pi}\right)} \approx -\frac{\partial F(x)/\partial \mu_2(x)}{\partial F(x)/\partial \mu_1(x)} = 2\theta_2 \tag{3.6}$$

The downside risk coefficient is approximated by:

$$DS = \frac{\mathbb{E}\left(\frac{\partial^3 U}{\partial \pi^3}\right)}{\mathbb{E}\left(\frac{\partial U}{\partial \pi}\right)} \approx \frac{\partial F(x)/\partial \mu_3(x)}{\partial F(x)/\partial \mu_1(x)} = -6\theta_3 \tag{3.7}$$

We use a three-stage least square (3SLS) model to obtain the population average AP and DS risk aversion measures.To ensure consistent interpretation of risk preferences across inputs, we constrain the risk parameters by setting $\hat{\theta}_{2k} = \hat{\theta}_2$ and $\hat{\theta}_{3k} = \hat{\theta}_3$. This constraint reflects the assumption that while different inputs can affect the yield moments to varying degrees, a farmer's underlying risk preference remains constant across inputs. So, the AP and DS coefficients reflect overall attitudes towards those moments and are not input-specific.

Our model includes several instruments to address the endogeneity issue introduced by fertilizers and improved seed inputs. However, we recognize that the inclusion of IVs in risk analysis is still debated in empirical applications (Staiger and Stock, 1997; Heckman and Urzúa, 2010; Larcker and Rusticus, 2010). As previously discussed in Chapter 3, in Ethiopia, we distance to population center, distance to the nearest weekly market, access to extension services, access to electricity, regional maize price, and lagged rainfall. For Malawi and Nigeria, the set of instrumental variables differs slightly, though we still use distance to population center, electricity access, access to extension services, regional maize price, and lagged rainfall. In addition to these, in Malawi, we include distance to the nearest daily market and distance to the nearest input supplier, while in Nigeria, we include distance to the nearest major road. We assume that these exogenous variables are correlated with fertilizer and improved seed use decisions but are exogenous to risk preferences. Additionally, we obtain robust standard errors by bootstrapping and resampling over individuals to account for heteroskedasticity.

We examine differences between households that have experienced weather shocks and those that did not by interacting the weather shocks with the input variables in the second and third moment equations. This allows us to estimate whether exposure to weather shocks influences the AP and DS risk aversion in production decisions.

The model is augmented by incorporating lagged weather shock indicators, $t2$ and $t3$, which capture exposure to weather two and three years prior. Through this, we can examine whether lagged weather shocks influence risk preferences and if a series of consecutive weather shocks may compound their impact on risk preferences. We capture this by including interaction terms that reflect two and three year consecutive weather shocks with the AP and DS coefficients. Positive coefficients on these interaction terms suggest that the compounded effect of repeated weather shocks increases farmers' sensitivity to risk, potentially leading them to avoid taking risks.

Chapter 4

Results

In this section, we present the results of our empirical analysis on how inputs, fertilizer and improved seed use, influence risk preferences among smallholder farmers in Ethiopia, Malawi, and Nigeria. We estimate how input use affects the mean, variance, and skew of crop yields using the moments-based approach developed by Antle (1983). We used these estimates to calculate AP and DS coefficients. These AP and DS risk aversion coefficients are interpreted as farmers' risk preferences.

We begin by estimating the first three moments (mean, variance, and skew) of the crop yield distribution for each household. The moments are derived using household and year fixed effects for a set of regressions using household-level data from the LSMS-ISA, as well as data from six different remote sensing weather sources (CHIRPS, CPC, ERA5, TAMSAT, ARC2, and MERRA-2). From these datasets, we took two rainfall metrics (total rainfall, mean daily rainfall, and lagged rainfall) and several weather shock metrics (deviations in rainy days, deviations in percent rainy days, deviations in no rain days, longest dry spell, Z-score of total rainfall, and lagged weather shock up to three past periods). The predicted values are the foundation for calculating the AP and DS risk aversion coefficients in three-stage least square regressions to reflect risk preferences with no shock, after shock, and after consecutive shock.

We run more than 200 model specifications, varying by rainfall and shock measures across six weather datasets.

4.1 Arrow-Pratt and Downside Risk

We estimate three models to evaluate how weather shocks influence risk preferences:

- **Model 1** provides baseline estimates of AP and DS coefficients without including shock variables, capturing risk preferences in the absence of weather shock.
- **Model 2** introduces weather shocks by interacting them with the second and third moments of the production function to assess whether shocks modify risk behavior.
- **Model 3** extends this by including lagged shocks to capture the effect of repeated or consecutive weather shocks on farmers' risk preferences.

4.2 Overall Arrow-Pratt (AP) and Downside Risk (DS) Estimates by Model

4.2.1 Ethiopia

We begin with Ethiopia, where we run 54 different regressions. Table 4.1, summarizes our results, showing that the range of estimated AP and DS coefficients vary considerably across weather datasets rather than model structure. This indicates that our results are primarily driven by data choice and not by the inclusion or exclusion of weather shock. Overall, we observe substantial variation in the magnitude and sign of estimated risk preferences within models. The occurrence of both positive and negative values reflects a mix of both risk-averse and not risk-averse behavior, as positive coefficients indicate risk aversion. So, our estimates reveal conflicting insights on risk preferences.

In **Model 1**, which excludes weather shocks, the estimated AP coefficients range from -0.7027 to 0.2947, while DS coefficients ranged from -0.0044 to 0.0042. The occurrence of both positive and negative values reflects a mix of both risk-averse and not risk-averse behavior, as positive coefficients indicate risk aversion. At baseline, the direction of estimated risk preferences varies significantly, suggesting a difference in how each specification for **Model 1** captures farmers' risk aversion in the absence of weather shocks.

After introducing our shock variables in **Model 2**, we observe a pattern similar to **Model 1** where there are occurrences of both positive and negative risk aversion coefficients, indicating a mix of risk-averse and not risk averse preferences among farmers. AP coefficients ranged from -0.7099 to 0.2902 and DS coefficients ranged between -0.0043 to 0.0043. Between the

Model 1 and **Model 2** results, the similarity in the coefficient ranges demonstrates that risk preferences are relatively stable after including a single period shock.

Risk preferences appear stable after adding consecutive weather shocks in **Model 3**. Again, AP and DS coefficients indicated different risk preferences, -0.7153 to 0.3039 and -0.0045 to 0.0046, respectively. Although results appear stable across models, the variation in estimates within models underscores how specification choices drive risk preference estimates.

While the inclusion of shocks may not significantly impact risk estimates, the fact that the shocks themselves do not drive these estimates limits our ability to draw reliable conclusions about the impact of weather shocks on risk preferences. Instead, variation in estimates across weather datasets makes it clear that data choice significantly shapes estimated risk preferences.

Table 4.1: Ethiopia: AP and DS Coefficient Ranges by Model and Remote Sensing Product

Model	AP Coefficients	DS Coefficients
Overall		
Model 1	[-0.7027, 0.2947]	[-0.0044, 0.0042]
Model 2	[-0.7099, 0.2902]	[-0.0043, 0.0043]
Model 3	[-0.7153, 0.3039]	[-0.0045, 0.0046]
ARC2		
Model 1	[-0.2473, -0.2207]	[0.0048, 0.0049]
Model 2	[-0.2523, -0.2169]	[0.0048, 0.0049]
Model 3	[-0.2556, -0.2166]	[0.0048, 0.0049]
CHIRPS		
Model 1	[0.0365, 0.0365]	[0.0001, 0.0001]
Model 2	[0.0367, 0.0367]	[0.0001, 0.0001]
Model 3	[0.0376, 0.0376]	[0.0001, 0.0001]
CPC		
Model 1	[-0.2022, -0.2009]	[-0.0036, -0.0036]
Model 2	[-0.2061, -0.199]	[-0.004, -0.0034]
Model 3	[-0.1972, -0.1929]	[-0.0033, -0.0031]
MERRA-2		
Model 1	[-0.2059, -0.2059]	[-0.0014, -0.0014]
Model 2	[-0.206, -0.2057]	[-0.0014, -0.0014]
Model 3	[-0.206, -0.2058]	[-0.0014, -0.0014]
TAMSAT		
Model 1	[-0.0446, -0.0446]	[-0.0, -0.0]
Model 2	[-0.0453, -0.0453]	[-0.0, -0.0]
Model 3	[-0.0468, -0.0468]	[-0.0, -0.0]

As shown in Table 4.1, risk preferences span a wide range within models, from -0.7153 to 0.3039 for AP and -0.0045 to 0.0046 for DS. The results demonstrate how this variation emerges from changes in weather data choices and reveals inconsistencies in the sign and magnitude of estimated risk preferences across these choices. For instance, regressions using CHIRPS consistently produce positive AP and DS estimates, suggesting that farmers are risk averse. In contrast, ARC2, CPC, and MERRA-2 consistently produce negative values, suggesting that farmers are not risk-averse. Further, estimates from TAMSAT are close to zero, indicating that farmers are closer to being risk-neutral. These discrepancies highlight that conclusions about farmers' risk preferences may be driven more by differences in the data than the actual effects of weather shocks, making estimates unreliable.

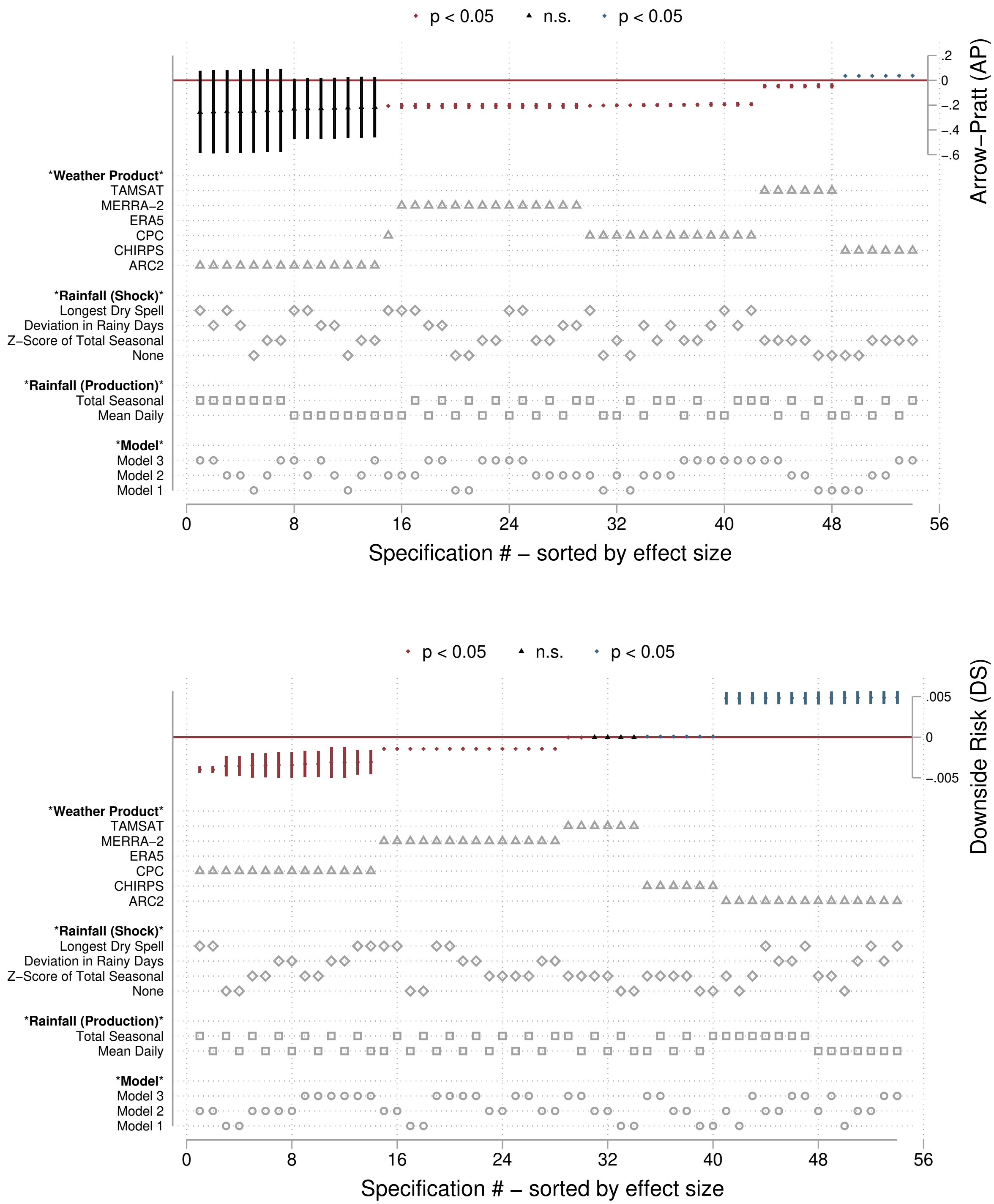


Figure 4.1: Ethiopia: Estimated AP and DS Risk Coefficients across Model Specifications

This pattern is further illustrated in the coefficient plots in Figure 4.1. Across both AP and DS estimates, the regression results tend to cluster tightly by weather dataset, with each weather dataset producing estimates with similar signs and magnitude. This clustering suggests the role that weather data choices play in our risk estimates. We do not observe this pattern across other specification choices, such as rainfall shock or model. Instead, the results appear more scattered or random within each dataset cluster, demonstrating that other specification choices are not driving estimated risk preferences.

4.2.2 Malawi

In Malawi, where we ran 84 model specifications, the conclusions are similar to Ethiopia. As with Ethiopia, the results show that estimated risk preferences appear stable across models but vary significantly across weather datasets. As shown in Table 4.2, AP coefficients range from -0.7153 to 0.3039, and DS coefficients range from -0.0045 to 0.0046.

In **Model 1**, AP coefficients range from -0.7027 to 0.2947, and DS coefficients range from -0.0044 to 0.0042. We observe both positive and negative values, which suggests a mix of risk-averse and not risk-averse behavior among farmers. This variation in estimates within models like Ethiopia points to specification sensitivity.

After incorporating shock variables in **Model 2**, the estimates remain similar with AP coefficients between -0.7099 and 0.2902 and DS from -0.0043 to 0.0043. These results continue to reflect a combination of risk-seeking and risk-averse estimates. The similarity in ranges across **Models 1** and **2** suggests that the inclusion of a single-period shock does not shift the overall pattern of risk preferences.

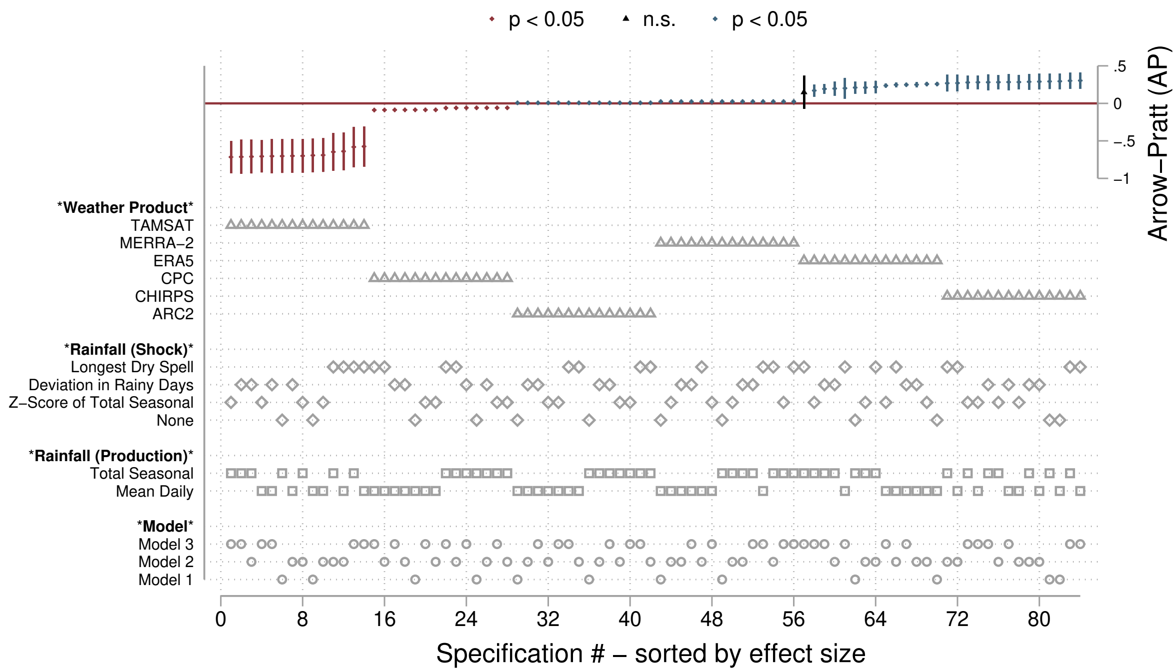
Model 3 estimates remain consistent after including consecutive shocks. AP estimates range from -0.7153 to 0.3039 and DS from -0.0045 to 0.0046, reinforcing that adding weather shocks does not drive our risk estimates.

Table 4.2: Malawi: AP and DS Coefficient Ranges by Model and Remote Sensing Product

Model	AP Coefficients	DS Coefficients
Overall		
Model 1	[-0.7027, 0.2947]	[-0.0044, 0.0042]
Model 2	[-0.7099, 0.2902]	[-0.0043, 0.0043]
Model 3	[-0.7153, 0.3039]	[-0.0045, 0.0046]
ARC2		
Model 1	[0.0075, 0.0077]	[-0.0001, -0.0001]
Model 2	[0.0076, 0.0078]	[-0.0001, -0.0001]
Model 3	[0.0076, 0.0078]	[-0.0001, -0.0001]
CHIRPS		
Model 1	[0.2926, 0.2947]	[-0.0044, -0.0044]
Model 2	[0.2689, 0.2902]	[-0.0043, -0.0039]
Model 3	[0.2793, 0.3039]	[-0.0045, -0.0042]
CPC		
Model 1	[-0.0863, -0.0591]	[0.0007, 0.0009]
Model 2	[-0.0873, -0.0588]	[0.0007, 0.0009]
Model 3	[-0.0885, -0.0589]	[0.0007, 0.001]
ERA5		
Model 1	[0.2104, 0.2577]	[0.0018, 0.0024]
Model 2	[0.1974, 0.2572]	[0.002, 0.0026]
Model 3	[0.1486, 0.2485]	[0.0017, 0.0025]
MERRA-2		
Model 1	[0.0242, 0.0244]	[-0.0017, -0.0017]
Model 2	[0.0242, 0.0245]	[-0.0017, -0.0017]
Model 3	[0.0243, 0.0248]	[-0.0017, -0.0017]
TAMSAT		
Model 1	[-0.7027, -0.6928]	[0.0042, 0.0042]
Model 2	[-0.7099, -0.6389]	[0.0035, 0.0043]
Model 3	[-0.7153, -0.574]	[0.0027, 0.0046]

Similar to Ethiopia, risk estimates in Malawi vary considerably across weather datasets, as shown in Table 4.2. Positive AP and DS estimates are consistently produced by ARC2, CHIRPS, ERA5, and MERRA-2, indicating risk aversion among farmers. In contrast, CPC and TAMSAT suggest that farmers are not risk averse by producing negative risk estimates. However, between Ethiopia and Malawi, ARC2 changes from negative to positive, demonstrating that estimated risk estimates may also be sensitive to differences in how rainfall is measured across countries. As shown in Figure 2.1 and Figure 2.2, ERA5 captures heavy, localized rainfall events, or rain bombs. Rain bombs are captured more frequently in Ethiopia, which may drive these differences in risk estimates. This adds further evidence of the sensitivity of risk preference estimates to the choice of weather data and reinforces the broader challenge of drawing reliable conclusions when shifts in estimates stem from changes in specification rather than actual changes in risk preferences.

The coefficient plot for Malawi, Figure 4.2, illustrates a pattern comparable to the one observed in Ethiopia, Figure 4.1. Regression results tend to be grouped by weather dataset, each producing relatively similar estimates. This trend supports the conclusion that variation in estimated risk preferences is driven more by weather data choices than the inclusion of shock.



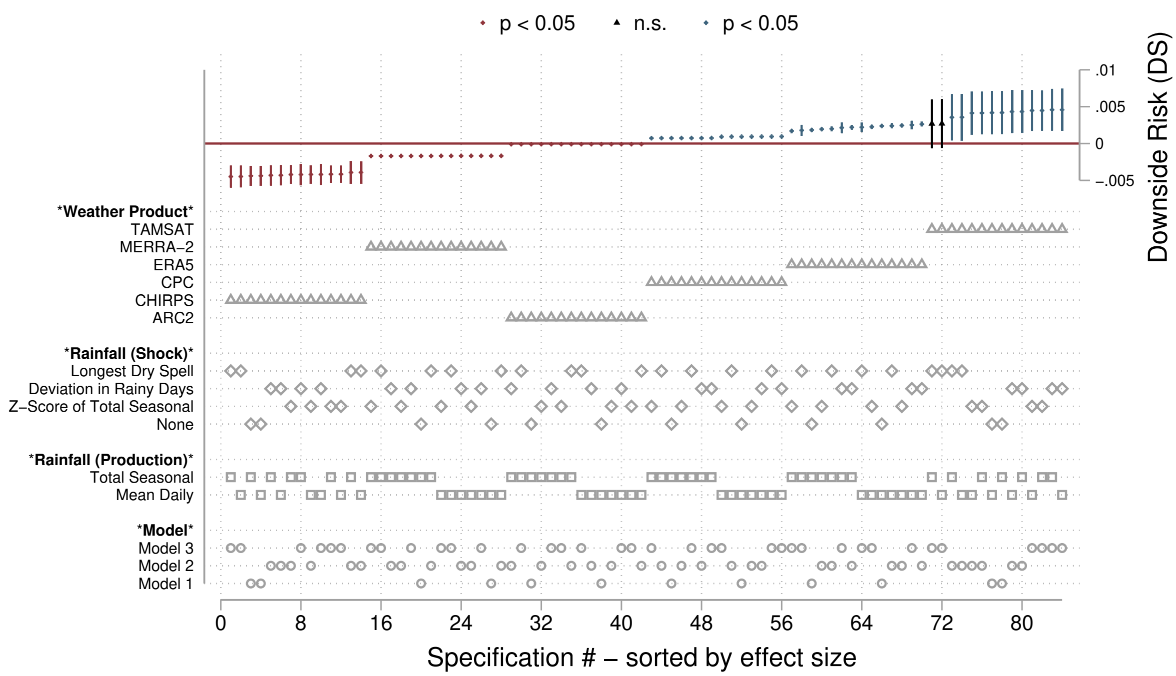


Figure 4.2: Malawi: Estimated AP and DS Risk Coefficients across Model Specifications

4.2.3 Nigeria

Finally, we turn to Nigeria, where we estimate 84 different model specifications. As shown in Table 4.3, AP coefficients range from −1.7071 to 0.5032, while DS coefficients range from −0.0161 to 0.0587 across all models. This extensive range of estimates again reflects conflicting insights on risk preferences among farmers, suggesting both risk-averse and not risk-averse attitudes. As in Ethiopia and Malawi, including shock and consecutive shock has little influence on overall risk estimates. Consistent with the findings of other countries, Nigeria's risk estimates appear to be primarily driven by the choice of weather dataset.

The distribution of AP and DS coefficients in Table 4.3 again points to the choice of weather dataset as a key driver of the results. For instance, estimates from CHIRPS and TAMSAT are consistently positive, and estimates from ARC2, CPC, ERA5, and MERRA-2 are all negative. These patterns mirror those observed in Ethiopia and Malawi, confirming that the impact of weather shocks on risk preferences among farmers is not being effectively captured in our approach, leaving the true nature of farmers' risk preferences uncertain.

Table 4.3: Nigeria: AP and DS Coefficient Ranges by Model and Remote Sensing Product

Model	AP Coefficients	DS Coefficients
Overall		
Model 1	[-1.6784, 0.5032]	[-0.0161, 0.0577]
Model 2	[-1.6975, 0.5032]	[-0.0161, 0.0584]
Model 3	[-1.7071, 0.5031]	[-0.0161, 0.0587]
ARC2		
Model 1	[-0.8554, -0.6653]	[0.0251, 0.0307]
Model 2	[-0.8534, -0.6579]	[0.0248, 0.0306]
Model 3	[-0.8541, -0.6571]	[0.0248, 0.0307]
CHIRPS		
Model 1	[0.3805, 0.5032]	[-0.0161, -0.0139]
Model 2	[0.3805, 0.5032]	[-0.0161, -0.0139]
Model 3	[0.3805, 0.5032]	[-0.0161, -0.0139]
CPC		
Model 1	[-1.6784, -1.2933]	[0.0436, 0.0577]
Model 2	[-1.6975, -1.285]	[0.0433, 0.0584]
Model 3	[-1.7071, -1.2867]	[0.0434, 0.0587]
ERA5		
Model 1	[-0.2979, -0.1416]	[0.0112, 0.0161]
Model 2	[-0.2976, -0.1417]	[0.0111, 0.0161]
Model 3	[-0.2977, -0.1419]	[0.011, 0.0161]
MERRA-2		
Model 1	[-0.8069, -0.4542]	[0.0214, 0.0303]
Model 2	[-0.8096, -0.4523]	[0.0212, 0.0304]
Model 3	[-0.8169, -0.4506]	[0.0211, 0.0308]
TAMSAT		
Model 1	[0.0338, 0.0869]	[-0.0004, 0.0022]
Model 2	[0.033, 0.0874]	[-0.0005, 0.0022]
Model 3	[0.0323, 0.0876]	[-0.0005, 0.0022]

In Nigeria, Figure 4.3 reaffirms a key finding in our study. Across all three countries, risk preference estimates are highly sensitive to specification choices, particularly the choice of weather dataset. Each dataset's results are relatively consistent in sign and magnitude across models, demonstrating that estimates do not reflect the impact of weather shock but rather just a specification change. Unlike weather data specification choices, the measure or inclusion of weather shock produces no clear or consistent pattern in the estimates, meaning that we cannot draw reliable conclusions about the effect of weather shocks on farmers' risk preferences. This persistent finding across Ethiopia, Malawi, and Nigeria underscores the critical role of data selection in empirical approaches seeking to estimate risk preferences, highlighting the evident sensitivity of results to specification choices.

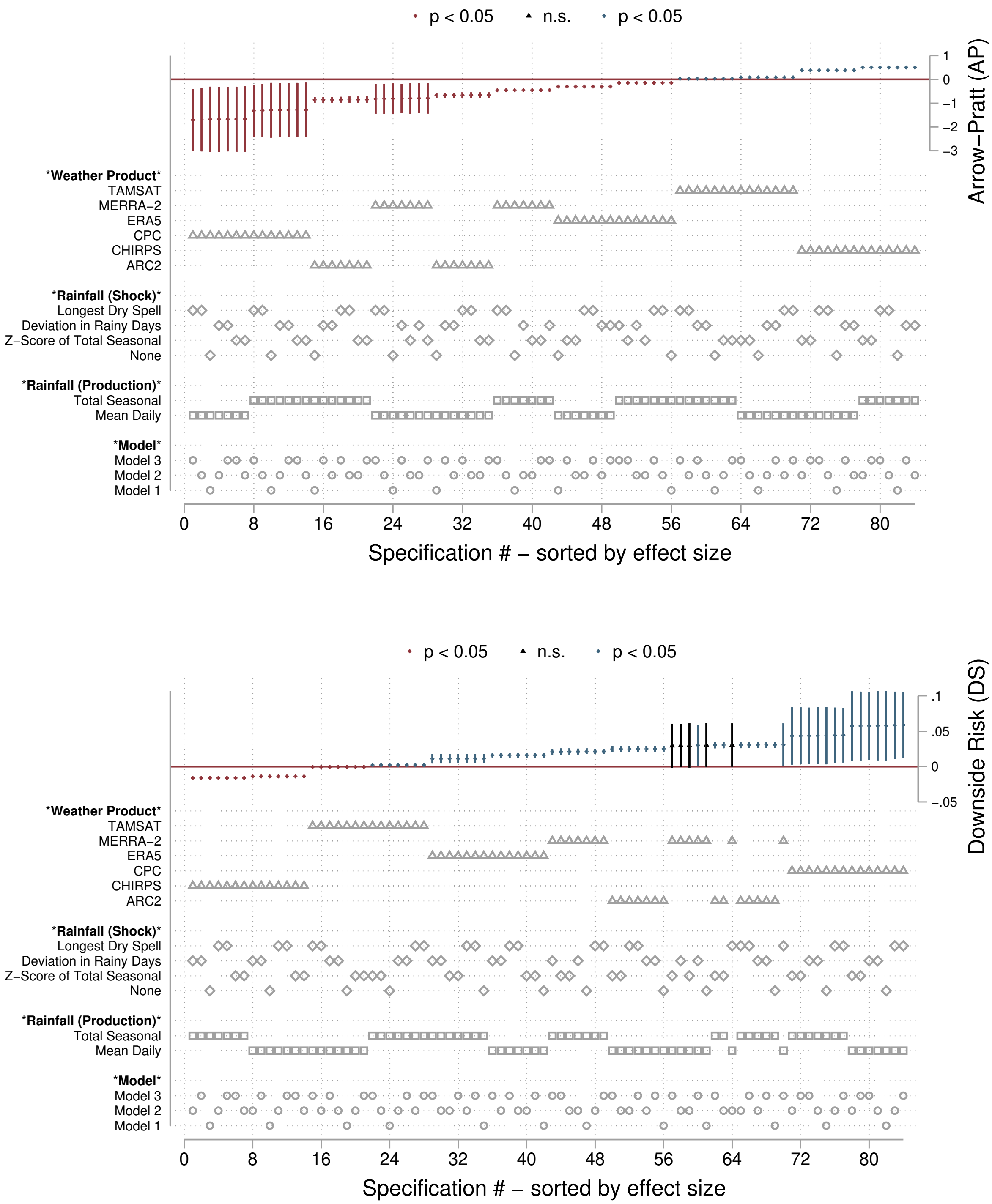


Figure 4.3: Nigeria: Estimated AP and DS Risk Coefficients across Model Specifications

4.3 Discussion

Our results from Ethiopia, Malawi, and Nigeria demonstrate more about the influence of different weather datasets than they do about the stability of risk after shock. While we observe variation in estimated risk preferences, the direction and magnitude of these estimates are heavily dependent on the specific weather dataset used. This sensitivity limits our ability to draw conclusions about the true nature of farmers' risk preferences and their relationship to weather.

But still, interpreting these coefficients, the signs of the AP and DS estimates provide insight into farmers' risk preferences. The AP coefficient reflects aversion to outcome variability, while the DS coefficient captures sensitivity to losses specifically. Positive values for either indicate risk-averse behavior, whereas negative values suggest that farmers are risk-neutral or even risk-seeking. In Ethiopia, we find that the choice of remote sensing product significantly influences the direction of these coefficients. For instance, regressions using CHIRPS and CPC consistently produce positive AP estimates, suggesting that farmers are risk averse. In contrast, specifications based on TAMSAT and ARC2 generate negative AP coefficients, implying that farmers are not risk-averse under those datasets. These conflicting findings underscore how selecting a specific remote sensing product can lead to fundamentally different conclusions about farmers' behavior, even when all other model components remain constant.

Moreover, while we expect the AP and DS coefficients to have the same sign, they often differ within weather datasets. A risk-averse farmer should be both averse to variability and downside losses; however, our results show that these risk measures do not always align. This inconsistency further highlights that the variation in estimated risk preferences is shaped more by the choice of weather data than by the presence of shock.

The coefficient ranges across countries reinforce the importance of specification choice in shaping estimated risk preferences. In all three countries, we observe both positive and negative values for AP and DS coefficients across models, regardless of whether shocks are included. This consistency suggests that model structure alone does not account for variation in results. Instead, the differences across specifications, particularly the choice of remote sensing product in our case, emerge as the primary driver of variation. These findings highlight the sensitivity of estimated risk preferences to modeling decisions, and they caution against interpreting individual coefficients without considering the underlying specification choices.

Chapter 5

Conclusion

In regions like SSA, where variability in weather is increasing, identifying how smallholder farmers respond to uncertainty is essential for shaping policies that support resilient agriculture. One approach is to examine whether and how risk preferences shift in response to weather shocks. We set out to evaluate the stability of farmers' risk preferences after weather shocks in Ethiopia, Malawi, and Nigeria by estimating AP and DS risk aversion coefficients using the moments-based approach developed by Antle (1983).

Despite a growing body of literature, the stability of risk preferences remains an open question. Our findings contribute to this ongoing discussion by highlighting a critical issue in model specification: the sensitivity of estimated risk preferences to the choice of weather dataset. Across Ethiopia, Malawi, and Nigeria, our results show that while risk aversion estimates appear to remain fairly stable, they vary significantly depending on the weather dataset used to measure rainfall and weather shocks. This variation suggests that methodological choices, particularly the choice of remote sensing weather data, can considerably influence how risk preferences are inferred from agricultural outcomes.

This raises concerns about the reliability and comparability of risk preference estimates within our models, where we set out to compare the effects of no shock, singular shock, and consecutive shock exposure, as well as the broader comparability of risk preference estimates across studies. When different studies rely on different weather datasets, this may lead to divergent conclusions about the nature and stability of smallholder risk preferences.

As Just and Just (2011) argue, relying solely on observed behavior without additional information can lead to risk preference estimates that mirror specification choices rather than true risk preferences. Similarly, Josephson et al. (2025) show that estimates of weather impacts on agricultural outcomes can vary widely depending on the Earth Observation dataset used. This supports that differences in risk preferences may stem from the data source rather than actual shifts in preferences. Our findings are consistent with the findings of Just and Peterson (2010) and Josephson et al. (2025), supporting that specification choices, particularly weather data choices, play a significant role in shaping estimated risk preferences.

Recognizing the sensitivity of risk preference estimates to weather data and model specification, our findings point to best practices that should be adopted in future research to strengthen the reliability of findings and ensure they can effectively inform policy. Researchers should test their models with multiple weather datasets and report these comparisons. As weather datasets can significantly influence results, relying on one weather dataset can result in inaccurate or misleading estimates. Comparing across datasets allows for more transparent, credible conclusions by demonstrating whether results are robust or driven by the choice of weather data.

Further, a characteristic of the weather data a researcher should consider is its spatial aggregation, as it may also influence results (Michler et al., 2021). Some datasets are more coarse in aggregation and may not measure weather as precisely as others, introducing measurement error. However, the appropriate scale and degree of aggregation required depend on the research question at hand. Due to these different scales, researchers may misestimate the true impact of weather shocks on farmers' risk preferences or input decisions. To mitigate this, researchers should aggregate their data to the same spatial scale and select datasets which are appropriate for the scale of their research question.

As our findings demonstrate and as noted by Just and Just (2011), risk preference estimates may reflect model specification choices rather than underlying preferences without supplemental data. To address this, future research would benefit from exploring alternative approaches to estimate risk preferences beyond models that rely on the assumptions of expected utility theory, including the moments-based approach developed by Antle (1983, 1987) we use in our analysis. A growing body of research suggests that cumulative prospect theory more accurately reflects risk preferences than models based on expected utility theory, including among farmers and in agricultural contexts (Bocquého et al., 2014; Bosilovich et al., 2016; Chavas et al., 2019). Studies that follow cumulative prospect theory use data from field experiments to elicit risk preferences, allowing researchers to investigate the measurement of risk exposure and its relationship to input decisions. Incorporating field experiment data through a cumulative prospect theory based model may address concerns raised by our findings that risk preference estimates reflect model specification rather than actual risk preferences.

Our results draw attention to these concerns and demonstrate how sensitive risk estimates can be to specification and data decisions. Changes in weather dataset choice can considerably influence the magnitude and sign of risk coefficients, introducing bias and making our results unreliable. This variation makes drawing consistent or meaningful conclusions from our findings difficult. More broadly, this highlights a greater challenge in estimating behavioral equations. It points to a key limitation in current empirical approaches, where results are primarily driven by specification choices rather than true behavior. This limitation has serious policy implications. As demonstrated in our results, changing the remote sensing weather product can alter the magnitude and even the sign of the estimated risk aversion coefficients, making it challenging to identify farmers' true risk preferences. If these estimates do not accurately reflect true farmer risk preferences, interventions designed to encourage agricultural input adoption may fall short or be ineffective.

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