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Farmers' Adaptation Behavior to Climate Change: The Case of Central Colombia

Dissertation submitted by

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For the degree of Doctor of Agriculture (Dr. Agr.)

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Declaration

I declare that I have completed this dissertation independently and without unauthorized outside help and only with the help that I have indicated in the dissertation. All text passages literally or analogously from published works and all information based on verbal information are labelled as such. In the research conducted by me and mentioned in the dissertation, I have complied with the principles of good scientific practice as laid down in the “Statutes of the Justus Liebig University Giessen” to ensure good scientific practice.

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Date	Alexander Cano Saldana

Acknowledgments

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Zusammenfassung

Der Klimawandel stellt die Landwirtschaft vor erhebliche Herausforderungen, insbesondere für Kleinbauern, die sich kontinuierlich an veränderte Bedingungen anpassen müssen, um die Ernährungssicherheit zu gewährleisten und die ländliche Armut zu verringern. Diese Probleme sind besonders kritisch in Zentral-Kolumbien, einer Region zwischen der Zentral- und Westkordillere der Anden, in der historische Daten eine zunehmende Häufigkeit extremer Wetterereignisse wie Erdrutsche und Dürren zeigen, die die Lebensgrundlagen der ländlichen Bevölkerung beeinträchtigen. Obwohl die Literatur zur Anpassung an den Klimawandel in den letzten Jahren zugenommen hat, gibt es unseres Wissens nach keinen integrierten Ansatz zur Untersuchung des Anpassungsverhaltens von Landwirten in Zentral-Kolumbien. Diese Dissertation schließt diese Lücke, indem sie systematisch alle Einflussfaktoren des Anpassungsverhaltens untersucht und sich auf finanzielle, erfahrungsbezogene und kognitive Faktoren konzentriert, die die Anpassungsentscheidungen der Landwirte beeinflussen. Dabei wird ein dreistufiger analytischer Ansatz verwendet.

Erstens wurde eine systematische Literaturübersicht (Systematic Literature Review, SLR) durchgeführt, um die wichtigsten Einflussfaktoren für Anpassungsentscheidungen zu identifizieren. Insgesamt wurden 179 Faktoren identifiziert und nach Typ kategorisiert, was zur Entwicklung des 3F-SEC-Rahmens (Farmer-Farm-Financial-Situational-Experiential-Cognitive) führte. Dieser Rahmen wurde im ersten Artikel dieser kumulativen Dissertation mit dem Titel *„Drivers of farmers' adaptive behavior to climate change: The 3F-SEC framework"* veröffentlicht. Das Modell diente als Grundlage für die Untersuchung des Anpassungsverhaltens von Landwirten in Zentral-Kolumbien in Bezug auf drei Hauptfaktoren: finanzielle, erfahrungsbezogene und kognitive Aspekte. Basierend darauf wurde ein Mixed-Methods-Ansatz

entwickelt, um die verschiedenen Dimensionen des Anpassungsverhaltens zu analysieren. Dies bildete die empirische Grundlage für den zweiten und dritten Artikel.

Insgesamt wurden 12 Dörfer ausgewählt, und eine Stichprobe von 360 Landwirten wurde zwischen November 2022 und März 2023 befragt. Die Forschungsstandorte wurden basierend auf ihrer Exposition gegenüber Wetterextremen ausgewählt: vier Dörfer, die Erdrutsche erlebt haben, vier mit wiederkehrenden Dürren und vier ohne gemeldete Extremereignisse als Referenzdörfer. Eine strukturierte Befragung wurde durchgeführt, ergänzt durch vertiefte Interviews mit einigen Landwirten, um ein umfassendes Verständnis der Faktoren zu gewinnen, die ihre Anpassungsentscheidungen beeinflussen.

Der zweite Artikel, mit dem Titel *„The Role of Financial Literacy in Climate Mitigation: The Case of Central Colombia“*, verwendet einen Mixed-Methods-Ansatz, der Logit-Modelle mit qualitativen Interviewdaten kombiniert. Er untersucht die finanziellen Entscheidungen der Landwirte als Reaktion auf Wetterextreme, mit besonderem Fokus auf die Rolle der finanziellen Bildung beim Kreditaufnahmeverhalten. Die Ergebnisse zeigen, dass finanziell gebildete Landwirte nach Wetterextremen eher Kredite aufnehmen. Allerdings bleibt die informelle Kreditaufnahme die dominierende Strategie, da sie einfacher zugänglich ist und es ein allgemeines Misstrauen gegenüber formellen Finanzinstitutionen gibt.

Der dritte Artikel, mit dem Titel *„Farmers' Climate Change Perceptions in Central Colombia: A Propensity Score Matching Approach Using Protection Motivation Theory and Psychological Distance“*, vergleicht Landwirte in Dörfern, die von Dürren oder Erdrutschen betroffen sind, und bewertet, wie die direkte Erfahrung solcher Ereignisse ihre Wahrnehmung des Klimawandels beeinflusst. Die Ergebnisse zeigen, dass Dürren das Bewusstsein der Landwirte für die Schwere und Verwundbarkeit durch den Klimawandel erheblich erhöhen, während Erdrutsche einen weniger starken Einfluss haben.

Zusammenfassend unterstreichen die Ergebnisse dieser Dissertation die Bedeutung eines multidimensionalen Ansatzes zur Analyse von Anpassungsentscheidungen. Aus politischer Sicht könnte ein integrierter Ansatz, der verschiedene Verhaltensfaktoren berücksichtigt, zu einem besseren Verständnis der Anpassungsfähigkeit von Landwirten an den Klimawandel beitragen. Wenn das Ziel darin besteht, den Zugang der Landwirte zu formellen Krediten zu verbessern, könnten maßgeschneiderte Finanzbildungsprogramme helfen, Kreditentscheidungen besser zu navigieren. Ebenso könnte die Integration lokaler Klimadaten in Schulungen zu nachhaltigen landwirtschaftlichen Praktiken fundiertere Entscheidungen insbesondere in dürregefährdeten Regionen unterstützen. Darüber hinaus könnten Kommunikationsstrategien, die sich auf die direkte Erfahrung der Landwirte mit extremen Wetterereignissen stützen, das Bewusstsein für Klimarisiken stärken. Letztendlich kann eine breitere Perspektive, die finanzielle, erfahrungsbezogene und kognitive Faktoren einbezieht, tiefere Einblicke in die Komplexität des Anpassungsverhaltens von Landwirten im Kontext des Klimawandels liefern.

Summary

Climate change poses significant challenges to agriculture, particularly for small-scale farmers who must continuously adapt to changing conditions to ensure food security and reduce rural poverty. These issues are especially critical in central Colombia, a region located between the Central and Western Andes Mountain ranges, where historical data indicate a rising frequency of extreme weather events, such as landslides and droughts, that affect rural livelihoods. Although the literature on adaptation to climate change has increased in recent years, to the best of our knowledge, there is not an integrated approach to studying farmers' adaptive behavior in central Colombia. This thesis bridges this gap by systematically examining all the drivers of adaptive behavior and focusing on the financial, experiential, and cognitive factors that shape farmers' adaptation decisions, using a three-step analytical approach.

First, a Systematic Literature Review (SLR) was conducted to identify the key factors of adaptation decisions. A total of 179 drivers were identified and categorized by type, leading to the development of the Farmer-Farm-Financial-Situational-Experiential-Cognitive (3F-SEC) framework, which was published in the first article of this cumulative thesis titled "Drivers of farmers' adaptive behavior to climate change: The 3F-SEC framework". This framework provided the basis for studying the adaptive behavior of farmers in central Colombia across three types of drivers: financial, experiential, and cognitive. Given this, a mixed-method approach was designed to analyze the different aspects of farmers' adaptive behavior, forming the empirical foundation for the second and third articles. A total of 12 villages were selected, with a sample of 360 farmers that were visited between November 2022 and March 2023. The research locations were selected according to their exposure to weather shocks: four villages that experienced landslides, four with recurrent droughts, and four with no reported events as reference villages. A structured

questionnaire was administered alongside in-depth interviews with some of the farmers, allowing for a comprehensive understanding of the factors shaping their adaptation decisions.

The second article, titled "The Role of Financial Literacy in Climate Mitigation: The Case of Central Colombia," employs a mixed-methods approach, combining logit models with qualitative data from interviews. It examines farmers' financial decisions in response to weather shocks, with a particular focus on the role of financial literacy in borrowing behavior. The findings reveal that financially literate farmers are more likely to seek loans following weather shocks. However, informal lending sources remained the dominant financial strategy due to easier access and distrust of formal financial institutions.

The third article, titled "Farmers' Climate Change Perceptions in Central Colombia: A Propensity Score Matching Approach Using Protection Motivation Theory and Psychological Distance," compares farmers living in droughts and landslide-prone villages, assesses how direct exposure to these events influences climate change perceptions. The findings indicate that droughts significantly increased farmers' awareness of climate change severity and vulnerability, while landslides had a more limited effect.

Taken together, the findings of this thesis highlight the relevance of considering multiple behavioral drivers when analyzing adaptation decisions. From a policy perspective, adopting an integrated approach that considers different behavioral drivers may offer a more comprehensive understanding of farmers' adaptative capacity to climate change. If the goal is to improve farmers' access to formal credit, strengthening tailored financial literacy programs may help farmers navigate borrowing decisions. Similarly, integrating localized climate data into training on sustainable agricultural practices could support more informed decision-making, particularly in drought-prone regions. Additionally, communication strategies that draw on farmers' direct experiences with extreme weather events may reinforce climate risk awareness. Ultimately, adopting a broader perspective that accounts for financial, experiential, and cognitive drivers can provide deeper insights into the complexities of farmers' adaptive behavior in the face of climate change.

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Abbreviations

3F-SEC	Farmer-Farm-Financial-Situational-Experiential-Cognitive
ATE	Average Treatment Effect
ATET	Average Treatment Effect on the Treated
ENSO	El Niño-Southern Oscillation
GDP	Gross Domestic Product
IPCC	Intergovernmental Panel on Climate Change
MPPACC	Model of Private Proactive Adaptation to Climate Change
PMT	Protection Motivation Theory
PS	Propensity Score
PSM	Propensity Score Matching
SLR	Systematic Literature Review
SPAR-4-SLR	Scientific Procedures and Rationale for Systematic Literature Reviews
UNPGRD	National Unit for Disaster Risk Management
VBN	Values-Beliefs-Norms
WoS	Web of Science

List of Publications

1. Cano, A., & Castro Campos, B. (2024). Drivers of farmers' adaptive behavior to climate change: The 3F-SEC framework. Journal of Rural Studies, 109, 103343. https://doi.org/10.1016/j.jrurstud.2024.103343

2. Cano, A., & Castro-Campos, B. (2025). The Role of Financial Literacy in Climate Mitigation: The Case of Central Colombia. Environmental Development, 54, 101164. https://doi.org/10.1016/j.envdev.2025.101164

3. Cano, A., & Castro-Campos, B. (2025). Farmers' Climate Change Perceptions in Central Colombia: A Propensity Score Matching Approach Using Protection Motivation Theory and Psychological Distance. Climate Risk Management, 49, 100720. https://doi.org/10.1016/j.crm.2025.100720

Chapter 1: Extended Summary

1.1. Introduction

Agriculture is highly dependent on climatic conditions, making farming operations vulnerable to the effects of climate change (de Sousa et al., 2018). These effects can result from changes in weather patterns, rising temperatures, water availability, and extreme weather events (Liu et al., 2022; Mulwa et al., 2016). While climate change has global repercussions, its effects are not homogeneous, and each region experiences them according to its specific context (Gupta et al., 2020). According to the Intergovernmental Panel on Climate Change (IPCC):

> Climate change refers to a change in the state of the climate that can be identified (e.g., by using statistical tests) by changes in the mean and/or the variability of its properties and that persists for an extended period, typically decades or longer. (IPCC, 2018, p. 544)

The three articles comprising this cumulative thesis focus on the central region of Colombia, which includes the departments of Caldas, Risaralda, and Quindío. The central region of Colombia is located between the Andes' west and central mountain ranges; this region has an economy that remains highly dependent on agriculture. According to the Ministerio de Comercio, Industria y Turismo (2023), farming, livestock, and fishing activities contribute to 8.90% of the regional Gross Domestic Product (GDP). Additionally, 18.6% of the GDP is derived from "commerce, hotels, and repairs", which includes agritourism, an essential economic activity in the region. Although agriculture accounts for less than 10% of the GDP directly, it has a significant indirect impact on the region's leading economic sector. Moreover, as of 2023, exports represented the second-largest share of total exports (28.2%), while agro-industrial products ranked third (8.8%) (Ministerio de Comercio, Industria y Turismo, 2023).

Climate projections indicate that temperatures in the region will rise regardless of the IPCC scenario. The national mean temperature is projected to increase by approximately 0.7°C to 1.49°C between 2020–2039 and 2040–2059, depending on the scenario (The World Bank Group, 2023b). In the three departments of the region, which are in high-altitude areas, temperatures are also projected to rise. By 2040–2059, temperatures could increase between 1.46°C and 1.71°C compared to historical values from 1995–2014 (The World Bank Group, 2023b). Additionally, precipitation patterns are expected to become more irregular, with increased rainfall in some months and decreased precipitation in others, leading to more pronounced dry and wet seasons (The World Bank Group, 2023a).

Extreme weather events pose an increasing threat and are expected to become more frequent due to climate change (IPCC, 2023). Specifically, extreme precipitation events are projected to nearly double in frequency by 2050. For example, during the period 2035–2064, the probability of 1-day precipitation events associated with historical 100-year return periods will increase by a factor of 2.19 in Caldas, 2.14 in Risaralda, and 2.07 in Quindío (The World Bank Group, 2023b, p. 31). Given that 87% of landslides in the region are caused by heavy rainfall (Aristizábal & Sánchez, 2020), this increase suggests that the risks of landslides will also rise. Meanwhile, drought conditions are expected to intensify due to shifting rainfall patterns. According to The World Bank Group (2023b), drought-related conditions in Colombia have already become 2.2 times more frequent. The frequency and intensity of droughts associated with El Niño-Southern Oscillation (ENSO) events are expected to increase, particularly in the Cauca River basin, where the region is located. During El Niño, dry seasons can become more prolonged and severe, affecting seasonal onset and leading to heightened drought and temperature extremes (The World Bank Group, 2023b).

Given the anticipated rise in temperatures and increasing frequency of extreme weather events and shocks, adaptation is essential for mitigating risks against climate variability (Ranasinghe et al., 2023), so that farmers can sustain their agricultural production and secure their livelihoods. In this context, adaptation is understood as:

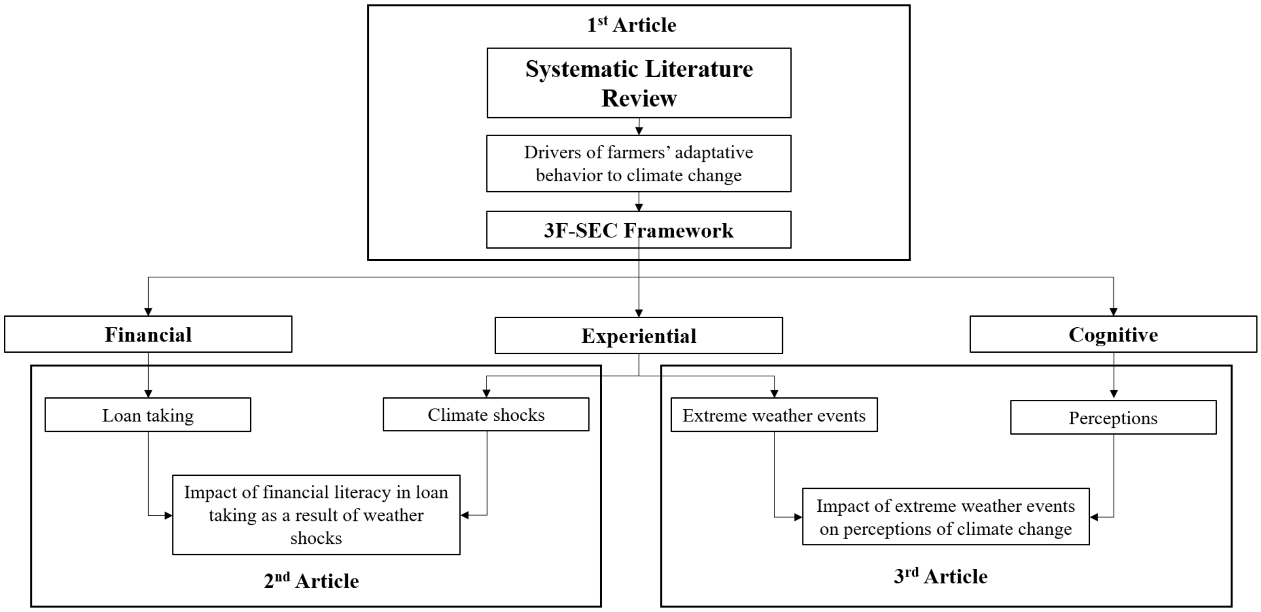
> The process of adjustment to actual or expected climate and its effects, in order to moderate harm or exploit beneficial opportunities. In natural systems, adaptation refers to the adjustment to actual climate and its effects, where human intervention may facilitate adjustment to expected climate. (IPCC, 2018, p. 542)

Accordingly, common adaptation practices include protection of water sources, agroforestry, maintaining soil cover, diversifying off-farm income, and taking loans (see Arifah et al., 2022; Azadi et al., 2019a; Guo et al., 2022; Petersen-Rockney, 2022; Tomlinson & Rhiney, 2018). In the context of central Colombia, interviews with institutional representatives indicate that these practices remain prevalent, along with the construction of retaining walls to prevent landslides. However, effective adaptation requires knowledge, resources, and decision-making capabilities to respond to climate-induced shocks (Deressa et al., 2011). To this end, it is necessary to acknowledge all the drivers that influence farmers' decision-making on adapting to climate change. While studies on this topic have increased in recent years (see Feola et al., 2015; Lyle, 2015; Soubry et al., 2020; van Valkengoed & Steg, 2019; Wiederkehr et al., 2018), gaps remain, as most research focuses on specific drivers or a single type of adaptation, lacking a comprehensive conceptual framework.

The first article of this cumulative thesis addresses this gap through a systematic literature review (SLR) conducted to identify and systematize all types of behavioral drivers. As a result, 179 drivers were identified and classified into 22 categories, which were later consolidated into six key types of drivers: socio-demographic characteristics, farm characteristics, financial resources, situational factors, experiential aspects, and cognitive factors. This led to the development of the Farmer-Farm-Financial-Situational-Experiential-Cognitive (3F-SEC) framework. These drivers are organized from the most commonly measured, such as socio-demographic characteristics, to the cognitive factors. However, this order holds no particular significance, as all drivers interact and influence farmers' decision-making. Each type consists of specific categories. For instance, cognitive factors include perceptions and beliefs, among others, while experiential drivers encompass climate change experiences, adaptation practices, and costs of adaptation (a detailed explanation of the framework is provided in Chapter 2; page 66). Although this framework provides a holistic approach to understanding farmers' adaptive behavior, it also enables the study of specific aspects individually.

Based on the 3F-SEC framework, we identified three key types of drivers to study within the context of Colombia's central region: financial, experiential, and cognitive. Figure 1 illustrates how these drivers are articulated with the other two articles in this cumulative thesis. The second article focuses on financial and experiential drivers. Specifically, within the financial type, we examine loan taking, as adaptation often requires financial resources, leading farmers to rely on credit to implement adaptive strategies (Arifah et al., 2022; Running et al., 2019). One of the main factors affecting farmers' access to credit is financial literacy. In Colombia, financial literacy levels are generally low, with studies indicating that residents have limited financial knowledge (Novoa-Hoyos et al., 2022; Ramos-Hernández et al., 2020). However, these assessments have primarily focused on urban populations. Given the disparities in educational access and financial services between urban and rural areas, the financial literacy levels among the rural population are expected to be even lower (Das & Maji, 2023).

Figure 1 Structure of the Cumulative Thesis



Source: Authors

Note: This figure illustrates the conceptual structure of the cumulative thesis, highlighting the connections between the three articles. The first article develops an SLR to identify the drivers influencing farmers' adaptive behavior to climate change, resulting in the 3F-SEC framework. This framework categorizes adaptation drivers into six types (socio-demographic characteristics, farm characteristics, financial resources, situational factors, experiential aspects, and cognitive factors). Given the context of the region, the thesis focuses on the financial, experiential, and cognitive drivers.

Within the experiential type, two distinct drivers are analyzed: general experiences with climate shocks and specific exposure to extreme weather events (e.g., landslides and droughts), which represent more defined climate shocks. These drivers provide a more tangible context for understanding climate change, as they capture different ways farmers experience climatic variability. The second article focuses on loan taking (financial) and climate shocks (experiential), analyzing how financial literacy influences borrowing decisions in response to climate shocks. The third article examines extreme weather events (experiential) and perceptions (cognitive), investigating how direct experiences with these events shape farmers' perceptions of climate change. The arrows indicate the relationships among these components, showing how the framework guides the empirical analyses.

The experiential driver of the second article focuses on weather shocks, as farmers' past exposure to these events can shape their adaptation decisions. Experiencing these shocks may alter their risk perceptions, influence their financial behavior, and affect their willingness to take on debt for mitigation or adaptation purposes. Despite the growing interest in financial literacy, most studies primarily focus on its role in business management (Idris et al., 2023). For instance, some studies have explored the relationship between financial literacy and business growth (e.g. Hossain et al., 2023; Owusu et al., 2019), its influence on firms' performance (e.g. Brownhilder Ngek, 2016; Li & Qian, 2019), and its role on financial inclusion (Mindra & Moya, 2017; Rastogi et al., 2021). However, to the best of our knowledge, no studies directly address the connection between financial literacy and access to credit as a consequence of weather shocks. This second article fills this gap by assessing this relationship while also examining how subjective factors (e.g. trust and ease of access) shape farmers' preferences for different lending sources.

The third article of this cumulative thesis explores how the behavioral drivers can interact with each other. In this case, we also focus on an experiential driver (extreme weather events) and cognitive drivers (perceptions of climate change). We have already seen how climate shocks affect financial decisions related to mitigation and adaptation. Similarly, climate experiences can also affect farmers' perception of climate change. Previous research has demonstrated that experiencing extreme weather events can shape individuals' climate perceptions (Dai et al., 2015), increasing awareness of risks and potential impacts (Borick & Rabe, 2017). Cognitive factors such as perceived severity, vulnerability, and psychological distance (spatial, temporal, social, and hypothetical) are crucial determinants of whether farmers take action in response to climate risks or not (Guo et al., 2021; Pakmehr et al., 2020; Rodríguez-Cruz & Niles, 2021). This connection between personal experience and climate perception is crucial for understanding how farmers respond to environmental challenges (Fahad et al., 2020).

The structure of this chapter is as follows: Section 1.2 presents the research questions and objectives, Section 1.3 outlines the theoretical framework, and Section 1.4 provides an overview of the research design and methods. Section 1.5 summarizes the results, Section 1.6 discusses the findings, and Section 1.7 concludes the chapter. Chapter 2 corresponds to the first article, which introduces the 3F-SEC framework. Chapter 3 presents the second article, analyzing the role of financial literacy in loan taking in central Colombia, and Chapter 4 contains the third article, which examines the effects of extreme weather events on farmers' perceptions of climate change.

1.2. Research Questions and Objectives

Table 1 presents the research questions and objectives of this thesis, outlining the main aspects explored in each article. These elements serve as the foundation for the analysis developed throughout the cumulative thesis.

Table 1 Research Questions and Objectives

Article	Research Question	Research Objective
1. Drivers of farmers' adaptive behavior to climate change: The 3F-SEC framework	What are the drivers influencing farmers' decision-making processes for climate change adaptation, and how do these drivers interact to shape adaptive behaviors?	To systematically identify the behavioral drivers that influence farmers' adaptive behaviors in response to climate change and to assess how these drivers interact to shape such behaviors.
2. The Role of Financial Literacy in Climate Mitigation: The Case of Central Colombia	How does financial literacy influence farmers' borrowing decisions in response to weather shocks, particularly in their choice between financial and non-financial lending sources in central Colombia?	To examine the impact of financial literacy on farmers' borrowing decisions in response to weather shocks, particularly their choice between financial and non-financial sources in central Colombia.
3. Farmers' Climate Change Perceptions in Central Colombia: A Propensity Score Matching Approach Using Protection Motivation Theory and Psychological Distance	How does farmers' exposure to extreme weather events (landslides and droughts) shape their perceptions of climate change in central Colombia?	To analyze how farmers' exposure to landslides and droughts influences their perceptions of climate change in central Colombia.

Source: Authors

1.3. Theoretical Framework

The three articles comprising this cumulative thesis are based on distinct theoretical frameworks that underpin the analysis of the decision-making processes explored throughout the thesis. Most of them were identified during the SLR developed in the first article (Chapter 2). The key theories include Prospect Theory by Kahneman and Tversky (1979, 2000), the Protection Motivation Theory (PMT) by Rogers (1975, 1983), and the concept of psychological distance from the Construal Level Theory by Liberman and Trope (1998, 2014). Each offers unique insights into individuals' responses to risks associated with climate change. While the following section gives a brief overview of these theories, more detailed discussions can be found in the individual articles.

1.3.1. Prospect Theory

To assess how financial literacy influences farmers' financial decisions in response to climate shocks, particularly in their selection of loans and lenders (article 2; Chapter 3), we applied Prospect Theory developed by Kahneman and Tversky (1979). Unlike Expected Utility Theory, which assumes that individuals make rational decisions aimed at maximizing expected outcomes, Prospect Theory explains that financial choices are often influenced by subjective perceptions rather than purely rational calculations (De Martino et al., 2006; Ruggeri et al., 2020), where the value function (V) is determined by:

$$V(x,p;y,q) = \pi(p)\nu(x) + \pi(q)\nu(y) \quad (1)$$

Where π and ν are two scaling factors, p and q represent probabilities, and x and y are the outcomes. The function π is associated with each probability and captures the influence of p on the overall value of the prospect. Addtionally, ν assigns a numerical value to each outcome, reflecting its subjective value. According to this, risk attitudes are established by the combined effect of π and p, and not solely by the utility function.

Understanding how these deviations from Expected Utility Theory influence financial decisions becomes evident when analyzing individuals' preferences for loan types. Individuals evaluate potential outcomes relative to specific reference points, which leads to asymmetrical perceptions of gains and losses. In the context of loan decisions, they often rely on their own experiences, or the terms offered to friends and family, shaping their preferences (Choudhury et al., 2022; Fu, 2020). This dependence on reference points highlights how financial decisions are influenced by personal history and social networks, determining how risks and benefits are assessed.

Moreover, Prospect Theory suggests that individuals tend to give greater weight to potential losses, such as high interest rates or the risk of default, as more significant than equivalent gains (Bylander, 2015). In the context of borrowing, this implies that farmers may be more risk-averse when evaluating loan options (Fong et al., 2021). As a result, they are likely to prefer stable and predictable loan terms to uncertain alternatives (Brick & Visser, 2015; Mori et al., 2009). This psychological tendency highlights that financial decisions are not solely based on objective analysis but are also driven by a preference for security and consistency in uncertain financial contexts.

1.3.2. Protection Motivation Theory (PMT)

PMT provides a framework to understand how individuals respond to a threat, in our case, extreme weather events. This framework is relevant to the third objective of this thesis, which examines how individuals perceive climate change after experiencing landslides or droughts (article 3; Chapter 4). Developed by Rogers (1975), the theory initially identified three primary components that influenced perceptions toward a fear-inducing event: (1) the severity of the threat, (2) the perceived probability of it occurring, and (3) the efficacy of protective responses. Together, these elements drove cognitive processes that encouraged individuals to take action to avoid or mitigate the threat.

Rogers (1983) revised the theory by moving away from the idea that cognitive processes are triggered by fear-inducing events to a broader range of influences, including environmental and personal information sources. Additionally, he expanded the framework by including new components. The theory identifies two main appraisal processes: threat and coping. The threat appraisal involves assessing both the severity of the threat and one's vulnerability to it, while the coping appraisal considers the effectiveness of protective actions and the individual's perceived capacity to implement them. This latter aspect, known as self-efficacy, highlights the belief in one's ability to take effective action and has become a central element in motivating protective behaviors. Together, these processes shape individuals' intentions to change their behavior in response to perceived threats.

1.3.3. Psychological Distance

For the third objective, the concept of psychological distance from the Construal Level Theory was used alongside the PMT to explore how individuals assess and respond to threats. Psychological distance refers to "the extent of divergence from direct experience of me, here and now along the dimensions of time, space, social perspective, or hypotheticality" (Liberman & Trope, 2014, p. 365). Events or threats that are perceived closer, either in time, space, or social connection, are psychologically represented with more concrete, specific, and vivid details. In contrast, events or threats that feel psychologically distant are perceived in a more abstract and general manner.

Temporal distance affects whether a threat seems immediate and pressing or distant and removed in time (Schattman et al., 2021). Spatial distance influences the sense of tangibility and physical proximity to the threat (Nie et al., 2023). Social distance relates to how similar or close one feels to the people or groups affected by the threat (Hess et al., 2018). Lastly, hypothetical distance concerns the perceived probability or likelihood of the threat actually occurring (Zobeidi et al., 2023). Together, these four dimensions of psychological distance shape how people perceive, interpret, and ultimately respond to potential threats and hazards.

1.4. Synthesis of Methods & Data

1.4.1. Research Locations

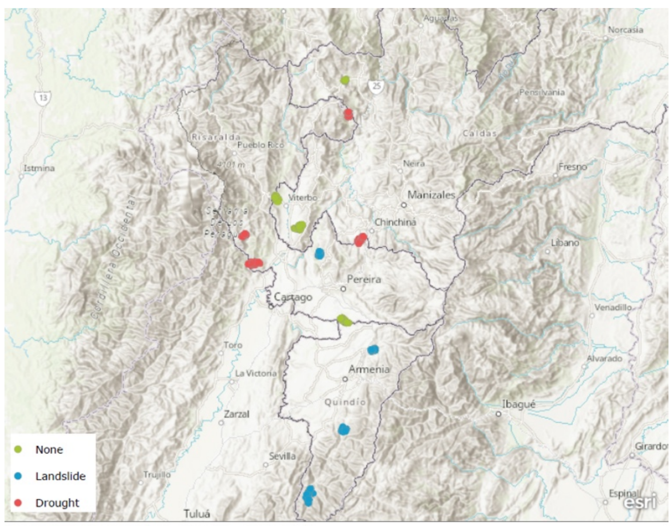
The central region of Colombia is situated between the Central and Western Andes Mountain ranges (Figure 2). Due to the region's topography, it is vulnerable to extreme weather events such as landslides and droughts. A review of reports from the National Unit for Disaster Risk Management (UNPGRD) revealed that between 2005 and 2021, the number of reported landslides increased by 42%, from 55 in 2005 to 78 in 2021. Similarly, droughts have shown considerable variation over time. In 2010, only two municipalities reported droughts, but by 2013, this number increased to 11 municipalities, and by 2016, to 25 municipalities. However, in 2020 only one single municipality reported drought conditions. These trends suggest that extreme weather events are not only a recurring issue but may also be increasing in frequency and unpredictability due to climate change.

Figure 2 Central Region of Colombia

Source: Authors

Esri, USGS | Esri, HERE, Garmin, FAO, NOAA, USGS

Figure 3 Research Locations



Esri, USGS | Esri, HERE, Garmin, FAO, NOAA, USGS

Source: Cano and Castro-Campos (2025)

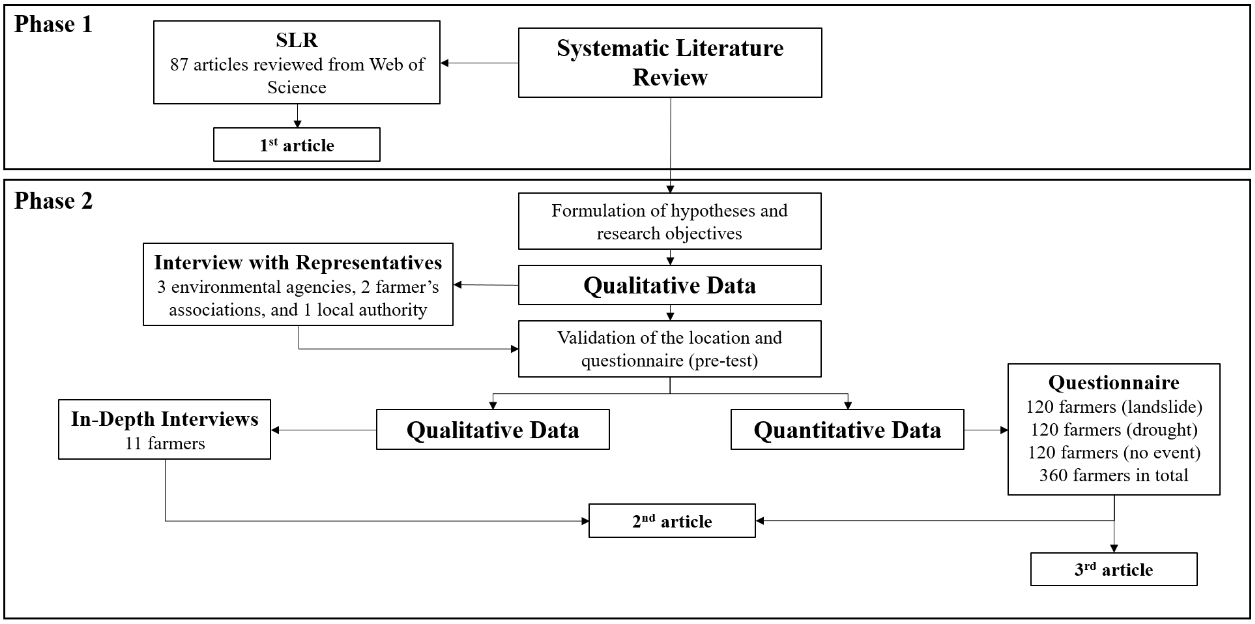
To further investigate, thresholds were set based on the observed frequency of extreme weather events. Villages that experienced three or more landslides (out of a recorded maximum of six) and those with at least two droughts (from a range of one to three) were identified for analysis. From these, four villages were randomly selected for both types of extreme weather event. Additionally, villages that had no reports of these events were also identified as reference villages, and four were randomly selected. In total, 12 villages were chosen (Figure 3), and within each village, 30 farmers were randomly selected, resulting in a total sample of 360 farmers.

Each village visit was carefully planned in advance. First, we contacted the agricultural secretariat of the municipality where the village is located to determine whether the village had experienced any extreme climate events. Through these offices, we also obtained the contact information for each village leader. We double-checked with them whether the selected village had experienced only one of the studied events or none if it was a reference village. Additionally, we coordinated with the village leaders to agree upon a visit date, and they took on the responsibility of informing the entire community about our visit.

1.4.2. Research Design & Data

The research design involved two main phases (Figure 4). In the first phase, an SLR was conducted in the Web of Science (WoS) database, focusing on the adaptive behavior of farmers facing climate change. The review followed the Scientific Procedures and Rationale for Systematic Literature Reviews (SPAR-4-SLR) protocol by Paul et al. (2021), explained in section 0 and in more detail in article 1 (Chapter 2) along with the metadata from the articles. The findings from this phase served as inputs for the first article and for formulating the research questions and objectives in Phase 2 (refer to section 1.2).

Figure 4 Research Design



Source: Authors

The second phase involved fieldwork, in which interviews were conducted with representatives from different institutions from the central region of Colombia. These took place in October 2022 and included three environmental agencies (autonomous corporations) in the region —CORPOCALDAS, CRQ, and CARDER— as well as two farmers' associations: the Coffee Growers Committee of Quindío and the Colombian Horticultural Association (Asohofrucol). Additionally, a representative from the Quindío Department's Secretariat of Agriculture was interviewed. This information provided a better understanding of the regional context that helped to validate and refine the questionnaire administered to farmers. The questionnaire was pre-tested at a village in the Quindío department and then adjusted accordingly. The village visits occurred between November 2022 and February 2023.

Each farmer was visited at their farm. The questionnaire was used to collect information from the farmers through individual interviews. The questionnaire consisted of six sections. The first two sections collected general socio-demographic information about the farmer and farm characteristics. The third section gathered information on the farmers' perceptions of climate change, using the frameworks of PMT from Rogers (1975, 1983): perceived severity, perceived vulnerability, and perceived costs; and psychological distance from Liberman and Trope (1998, 2014): spatial, temporal, social, and hypothetical. The fourth section covers the adaptation measures they implement, including loans as a response to weather events. The fifth section corresponded to the sociodemographic characteristics of the farmer that are particularly sensitive, such as their level of education, income, and indebtedness. The final section addressed the farmers' financial knowledge. For this, we used the financial literacy measures from the LitFin Survey—developed by Standard & Poor's Ratings Services, Gallup, Inc., the World Bank Development Research Group, and the Global Financial Literacy Excellence Center in 2014.

Finally, in-depth interviews were conducted with eleven farmers to explore aspects not covered in the questionnaire, providing richer insights into specific contexts and enhancing the robustness of the cumulative thesis' findings. During these in-depth interviews, the farmers were asked about their experiences in the rural sector of the region and how it has changed over time. They were also questioned about any observed changes in the climate and how these changes have affected them, both positively and negatively. This allowed the farmers to provide more in-depth insights into the extreme weather events they have experienced in their local villages, and how these events have impacted their farm operations and personal lives. Additionally, the farmers elaborated on the various measures they have taken to protect themselves or mitigate the effects of these climatic shocks, delving into the reasons behind each measure.

1.4.3. Overview of Methods

This cumulative thesis uses four main empirical methods to examine factors influencing farmers' climate adaptation behaviors, borrowing decisions, and climate change perceptions as outlined in the research questions and objectives in section 1.2. To address the first objective, an SLR was conducted, applying content analysis to identify the drivers of adaptive behavior to climate change, and develop a conceptual framework for analysis. The second objective uses a mixed-methods approach, combining quantitative logit models with qualitative content analysis of interviews to gain insights into decision-making processes and preferences for funding sources. For the final objective, PSM assesses how direct exposure to extreme events, such as landslides and droughts, shapes farmers' perceptions of climate change. A detailed explanation of each methodology can be found in each article.

1.4.3.1. Systematic Literature Review (SLR)

An SLR allows for the comprehensive identification, organization, and analysis of existing knowledge on a research topic, helping to identify gaps and develop new theoretical frameworks (Castro Campos, 2022; Paul & Criado, 2020). The review was conducted in the WoS database using the following search equation: ("Climate change" OR "Climate variability" OR "climatic change") AND (Farmers OR "rural households") AND (Behavior OR Behaviour) AND (Adaptation OR resilience OR adoption OR coping) AND (Vulnerability). This search yielded 146 articles; however, 59 articles that did not align with the research objectives were excluded, leaving 87 studies for the final analysis.

The SLR process followed the three phases outlined in the SPAR-4-SLR protocol: assembling, arranging, and assessing. The search terms were defined in the assembling phase, and the articles were gathered in WoS. Next, during the arranging phase, these articles were categorized using various codes, such as the year of publication, journal name, number of citations, country of research, theoretical framework employed, types of crops or livestock owned by farmers, climate change adaptation measures, and drivers of adaptive behavior. In the assessing phase, the drivers of farmers' adaptive behavior were identified and classified.

1.4.3.2. Content Analysis

Content analysis is a technique used to systematically analyze textual data by categorizing and identifying patterns (Krippendorff, 2004). For the first article (objective 1), this method was applied to identify and quantify the drivers related to adaptive behaviors towards climate change. For this, 179 drivers were systematized into six types: socio-demographic characteristics of the farmer, farm characteristics, financial resources, situational factors, experiential aspects, and cognitive factors. With these types, the 3F-SEC framework was constructed. It allows us to holistically address all the drivers that affect farmers' decision-making in terms of climate change adaptation measures.

For the second article (objective 2), content analysis was used to complement the quantitative analysis. For this purpose, the interviews of the same sample of farmers from the quantitative component were systematically analyzed. These interviews capture farmers' views on adverse weather events and the strategies they use to cope with them. We identified recurring themes, like their understanding of financial concepts (e.g. loan terms and interest rates), their preferences for loan sources, and the drivers of these decisions, such as ease of access, trust, and cost of loans. This mixed-methods approach allows us to triangulate data, enhancing the robustness of the conclusions and ensuring alignment with participants' lived experiences.

1.4.3.3. Logit Models

To address the second objective of the thesis (article 2), we also employed logit models. The first model evaluates the likelihood (z) of farmers borrowing money (1 = if the farmer borrowed money as a consequence of a weather shock, 0 = otherwise) where

$$z = \beta_0 + \beta_1 literate_i + \sum_i \beta_i W_i + \sum_i \beta_i X_i + \varepsilon \qquad (2)$$

The model includes the binary variable literate (0 = financially illiterate; 1 = financially literate), alongside control variables (W_i) that capture financial perceptions, such as financial constraints (whether limited funds have restricted decision-making) and risk, indicating if the farmers gave a value of 5 or higher on a 10-point scale on how much they like risk. Additional control variables (X_i) consist of demographic and farm characteristics, including age, age squared, gender, education, marital status, income, farm size, and farm altitude.

The initial logit model (Equation 2) was modified in two ways:

$$y = \beta_0 + \beta_1 literate_i + \sum_i \beta_i W_i + \sum_i \beta_i X_i + \varepsilon \qquad (3)$$

$$y = \beta_0 + \beta_1 literate_i + \beta_2 literate * age + \sum_i \beta_i W_i + \sum_i \beta_i X_i + \varepsilon \qquad (4)$$

First, in Equation 3, the model was adjusted to focus exclusively on loans from non-financial sources, changing the dependent variable to indicate whether a farmer borrowed specifically from a non-financial source or not (y). In the second modification (Equation 4), an interaction term between financial literacy and age was included to explore whether age affects borrowing from non-financial sources. To interpret these models, marginal effects were calculated, and while potential endogeneity was considered, instrumental variables were ultimately deemed unsuitable due to limitations in the available data. Therefore, we present our original results to avoid introducing greater bias or imprecision from an inadequate instrument. Instead, qualitative findings were used to gain deeper insights behind loan-making decisions.

1.4.3.4. Propensity Score Matching (PSM)

For the third article (objective 3), to compare differences in climate change perceptions based on exposure to extreme events, such as landslides and droughts, we focused on calculating the Average Treatment Effect (ATE) and the Average Treatment Effect on the Treated (ATET):

$$\tau_{ATE} = E(\tau) = E[Y(1) - Y(0)] \tag{5}$$

$$\tau_{ATET} = E[\tau|D = 1] = E[Y(1)|D = 1] - E[Y(0)|D = 1] \tag{6}$$

Equation 5 estimates the ATE across the entire sample, regardless of whether farmers receive the treatment. Meanwhile, Equation 6 examines the subset of the population that received the treatment. Our analysis considered farmers to be "treated" if they lived in a village where landslides or droughts had occurred. The treatment effect for an individual farmer reflects the difference in perceptions based on whether or not they experienced the extreme event. However, since it is impossible to observe a scenario where the same farmer both experienced and did not experience the event, we estimate the average effect for the group that did experience it, comparing their outcomes to those of a group that did not. This gives us the average treatments, demonstrating the specific impact on farmers directly exposed to these extreme climate events.

To estimate the ATE and ATET, we employed PSM (Equations 7 and 8). First, we calculated the probability that a farmer resides in an area affected by each type of event, landslide (L_i) or drought (D_i), based on observable characteristics (X_i), including age, gender, education level, income, farm attributes, and access to natural resources. This probability is known as the propensity score (PS) and enables us to match farmers who experienced the event with those who did not, based on similarities in their characteristics.

$$p(X_i) = Pr\ (L_i = 1|X_i) \tag{7}$$

$$p(X_i) = Pr\ (D_i = 1|X_i) \tag{8}$$

To ensure robust comparisons, we used two matching techniques. First, we employed nearest-neighbor matching, where each farmer affected by an extreme weather event was paired with the most similar farmer who had not experienced the event, based on their characteristics. Additionally, to avoid poor matches, we used caliper matching. In this case, we set a tolerance margin (caliper) that only allows matching between farmers whose likelihood of having experienced the event is very similar. This approach ensures that the matched pairs are as comparable as possible. By using these methods, we created groups of affected and unaffected farmers that were similar in terms of their characteristics, enabling a more accurate comparison to identify how living in affected areas influences their perceptions of climate change.

1.5. Summary of Results

This section summarizes the results of the cumulative thesis. The summary encapsulates the results from three analyses conducted on the key factors influencing farmers' adaptive behavior to climate change. The first step was an SLR conducted to identify and systematize the drivers of farmers' adaptive behavior. As a result, the 3F-SEC framework was developed, which highlights the influence of these drivers on farmers' decision-making. Building on this framework, two empirical analyses evaluated how financial, experiential, and cognitive drivers affect farmers' behavior. First, we assessed how financial literacy influences farmers' access to credit after climate shocks, considering both formal and informal lending sources. Secondly, we explored how direct exposure to droughts and landslides affects farmers' perceptions of climate change, focusing on perceived severity, vulnerability, and the dimensions of psychological distance.

1.5.1. SLR: 3F-SEC Framework

Cano, A., & Castro Campos, B. (2024). Drivers of farmers' adaptive behavior to climate change: The 3F-SEC framework. Journal of Rural Studies, 109, 103343.
https://doi.org/10.1016/j.jrurstud.2024.103343

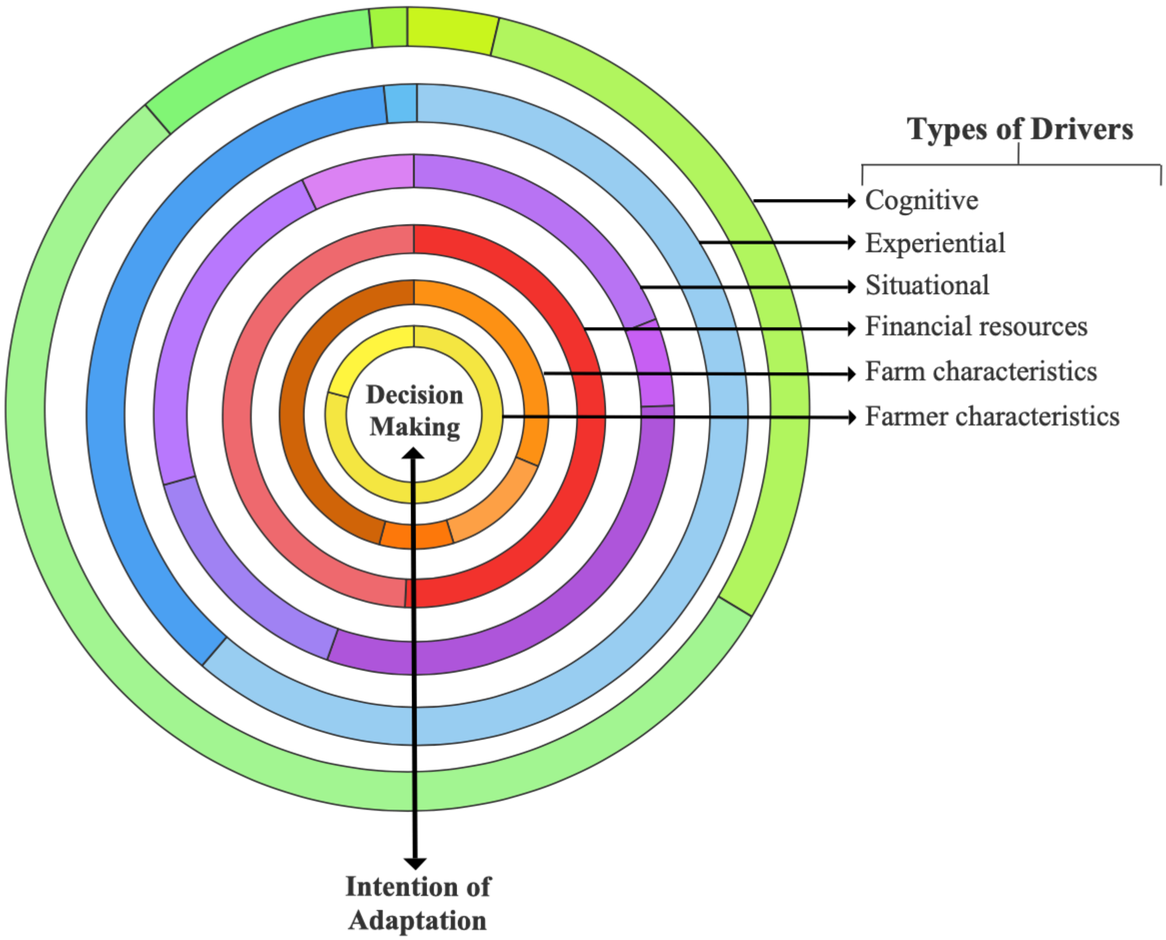
Over the years, research on how farmers adapt to climate change has increased significantly, with 58% of the reviewed articles published between 2020 and 2022. This trend highlights the growing academic interest in understanding the factors that influence farmers' adaptive strategies in response to climate variability. Geographically, most studies have focused on Asia, with Iran leading (14 studies), followed by China (11 studies). In contrast, Oceania has received minimal attention, with only one study conducted in New Zealand. Among the reviewed articles, 37 explicitly identified the climate-related phenomena to which farmers were adapting, mentioning a total of 16 different challenges. Water-related issues were the most frequently studied, with drought appearing in 17 articles as a standalone issue and in 3 additional articles in combination with other factors. Other common themes included floods and water availability.

Regarding theoretical frameworks, 34 out of the 87 reviewed studies incorporated theories to analyze farmers' adaptation decisions. The PMT by Rogers (1975) was the most commonly applied, appearing in 16 studies, followed by the Theory of Planned Behavior by Ajzen (1985), which was used in four. Other frameworks, such as the Values-Beliefs-Norms (VBN) theory by Stern (2000), and the Model of Private Proactive Adaptation to Climate Change (MPPACC) by Grothmann and Patt (2005), were each used in a limited number of studies. Additionally, adaptation strategies were categorized into multiple groups, including farming and livestock management practices, financial measures, and migration strategies. Farming techniques were the most frequently cited, with soil conservation, improved crop selection, and irrigation adjustments being the most common. Financial adaptations, particularly acquiring insurance and accessing credit, were also widely discussed, alongside diversification strategies such as off-farm employment and livestock sales. Some farmers also explored more drastic options, including reducing or quitting farming altogether, and in certain cases, maladaptive behaviors or inaction were observed.

A total of 179 behavioral drivers influencing farmers' adaptation decisions were identified, categorized, and classified by type. Among these, cognitive drivers were the most prominent, cited 348 times, with beliefs about the negative consequences of climate change being the most frequently mentioned. This highlights the crucial role of psychological processes in shaping adaptive behavior. Socio-demographic characteristics ranked as the second most influential type of driver, referenced 183 times across the studies, with age (54 mentions) and education level (51 mentions) being the most common factors.

Situational factors also played a significant role, with 46 different elements identified and cited 199 times. Farm characteristics were another major category, mentioned 179 times, with farm size being the most frequently mentioned driver (28 times). Additionally, farmers' experiences had a strong influence on adaptation decisions, with 25 different experience-related drivers cited 138 times. Financial resources were also critical, with 16 different financial drivers, such as income, expenses, and both financial and non-financial capital, cited 135 times.

Figure 5 3F-SEC Framework



Source: Cano and Castro Campos (2024)

Notes: Each circle represents a type of behavioral driver. These are organized starting with the most personal and easy to measure, which are the socio-demographic characteristics of farmers, and ending with the types of drivers related to the farmer's mental processes, which are the cognitive ones. However, the order in which they are organized has no particular meaning. The double arrow through all the circles represents the farmers' decision-making process to adapt to climate change. This double date means that this process is not unidirectional and involves all types of behavioral drivers. Likewise, the drivers can influence each other, so it is difficult to demonstrate any causality between them.

Each circle is divided according to the categories identified in each type of driver. Additionally, this division was made according to the frequency in which they were mentioned in the eighty-seven articles. The first circle is divided by the socio-demographic characteristics of the farmer (80.3%) and the characteristics of the household (19.7%). The second circle is all farm components, such as land (31.3%), irrigation (14%), livestock (8.9%), and farm characteristics (45.8%). The third circle represents the farmer's financial status, income and expenses (49.6%), and capital, both monetary and non-monetary (50.4%). The fourth circle represents the situational categories, i.e. where the farmer has little or no control. Access to different things (20.1%), the market (5.5%), society (29.1%), information (15.1%), the environment (21.6%), and institutions (8.5%). The fifth circle represents all the farmers' experiences, such as the impacts of climate change (61.6%), the adaptation measures they already use (37%), and the costs of adapting (1.4%). The last circle has different cognitive processes of farmers, such as their understanding of risk (3.7%), their perceptions (29%), their beliefs (55.7%), psychological distance (10.1%), and other cognitive processes that do not belong to any of the other categories (1.4%).

To systematize these behavioral drivers, the 3F-SEC framework was developed (Figure 5). This framework visually represents the diverse types of factors influencing farmers' adaptation decisions, illustrating their interconnected and non-linear nature. While cognitive components, such as beliefs and perceptions, exist at one end, socio-demographic and household-related characteristics lie at the other, with farm-related, financial, and experiential factors positioned in between. Importantly, adaptation decisions do not follow a straightforward, linear path but emerge from a dynamic interplay of multiple interdependent factors.

The complexity of these interactions makes isolating the impact of individual behavioral drivers challenging. For instance, financial resources can shape farmers' experiences by enabling the implementation of specific adaptation measures, while direct exposure to climate events can influence perceptions of climate risks. Likewise, a farmer's perception of climate change may determine whether they have previously adopted adaptive strategies. These interrelationships highlight the complexity of farmers' decision-making in adapting to climate change.

1.5.2. Financial Literacy and Loan Choices

Cano, A., & Castro-Campos, B. (2025). The Role of Financial Literacy in Climate Mitigation: The Case of Central Colombia. Environmental Development, 54, 101164. https://doi.org/10.1016/j.envdev.2025.101164

The analysis identifies key factors influencing farmers' borrowing decisions in response to weather shocks. The results from the logit regression model (Equation 2) highlight the significance of financial literacy, financial constraints, and risk perception in shaping farmers' loan-seeking behavior. Farmers with a stronger understanding of at least three fundamental financial concepts—risk diversification, inflation, numeracy, and compound interest—are more likely to seek loans than those with lower financial literacy levels, *ceteris paribus*. Additionally, perceived financial constraints play a crucial role, as farmers who consider themselves financially constrained show a higher propensity to apply for loans. Risk perception also influences borrowing behavior; farmers who consider themselves risk-takers are more inclined to seek financial support in response to adverse weather conditions.

Among the socio-demographic factors, age exhibits a non-linear relationship with loan uptake. While the likelihood of borrowing increases with age, this effect diminishes over time, as indicated by the negative coefficient for age squared. This suggests that younger farmers are more inclined to take loans, but this trend reverses at older ages. Education also emerges as a statistically significant factor, with a negative correlation suggesting that farmers with more years of formal education are less likely to seek loans. This finding suggests that while education typically enhances financial knowledge, other factors such as risk aversion, alternative funding sources, or financial goals may deter highly educated farmers from borrowing.

Insights from interviews provide further depth to the analysis of financial literacy and borrowing behavior. Farmers who correctly answered financial literacy questions demonstrated more strategic borrowing decisions, as illustrated by one respondent who preferred bank loans over informal lending due to lower interest rates. However, financial literacy remains low among central Colombian farmers, with only 16.7% classified as financially literate. The level of understanding varies by concept, with risk diversification being the most recognized (50.28%) and compound interest the least understood (24.44%). Regarding borrowing patterns, 20% of farmers took out loans due to weather shocks. Most (79.71%) relied on non-financial sources like family, friends, or informal lenders, while only 15.94% borrowed from financial institutions and 4.35% obtained loans from both sources. Some farmers expressed distrust toward formal financial institutions, citing high interest rates and unfavorable repayment terms. This reluctance highlights the influence of subjective factors, such as fear of debt and perceived unfairness of loan conditions.

The second logit model (Equation 3) focuses specifically on loans from non-financial sources. As in the previous model, financial literacy continues to have a positive and statistically significant effect on borrowing from informal sources. This suggests that while financially literate farmers understand basic financial principles, they still prefer borrowing from informal sources, potentially due to easier access, flexible repayment terms, or trust in personal relationships. Financial constraints and self-perceived risk-taking behavior also significantly increase the likelihood of turning to non-financial loans. A deeper exploration of the age factor reveals a significant interaction between age and financial literacy. While financially literate farmers are more likely to seek non-financial loans at younger ages, this likelihood decreases as they grow older. The highest probability of borrowing from non-financial sources occurs around 40 years of age, after which it declines. This non-linear trend suggests that as farmers age, they either accumulate more financial stability or develop alternative coping strategies, reducing their reliance on loans.

Marginal effects analysis further quantifies the impact of financial literacy on borrowing behavior. Financially literate farmers are approximately 10.7% more likely to seek loans overall and 11.6% more likely to choose non-financial sources. However, with each additional year of age, the probability of borrowing from informal lenders declines by roughly 2.4%. Financial constraints and risk perception remain significant determinants across all models, reinforcing the idea that external economic pressures and individual attitudes toward risk strongly influence borrowing decisions.

1.5.3. Extreme Weather Events and Climate Change Perceptions

Cano, A., & Castro-Campos, B. (2025). Farmers' Climate Change Perceptions in Central Colombia: A Propensity Score Matching Approach Using Protection Motivation Theory and Psychological Distance. *Submitted and under review (Climate Risk Management)*

The analysis identifies if extreme weather events influence farmers' perceptions of climate change. The first step in this process was to assess the balance of the PS between treated and control groups for farmers residing in villages affected by landslides or droughts. Treated individuals, those in affected areas, were compared to control individuals within the common support range, ensuring valid matching. We estimate the ATEs of living in villages affected by landslides and droughts on farmers' perceptions. Landslides significantly affect only two perceptions: they decrease the perceived severity of climate change on natural resources and the hypothetical distance where farmers agree that they are not sure that climate change is occurring. In contrast, droughts have a positive and significant effect on farmers' perceived severity of climate change, particularly concerning natural resources and other farmers in the village. Regarding perceived vulnerability, droughts significantly heighten farmers' concerns about climate change in the three dimensions measured (thinking about climate change, their negative impacts, and their negative effects on their farm operations). These effects are statistically significant across all three analyzed categories, with stronger impacts observed in the frequency of concerns about climate change and its consequences.

For psychological distance, droughts have negative and statistically significant effects in multiple categories, leading farmers to be less likely to agree with the following statements: for temporal distance, that the effects of climate change are happening in the future but not right now; for social distance, that climate change will affect other farmers but not themselves; and for hypothetical distance, that they are not sure climate change is happening. On the other hand, droughts had a positive and significant effect on another hypothetical distance, where farmers are more likely to agree that droughts are a consequence of climate change.

The ATET results further confirm these findings. For farmers living in villages that have experienced landslides, none of the effects were statistically significant. In contrast, for farmers in drought-affected villages, the estimated effects remained significant for the same variables as in the ATE analysis, both those of perceived severity and perceived vulnerability. Regarding psychological distance, the same variables showed statistically significant effects, along with two additional variables. In both cases, the effects were positive, indicating that farmers who live in villages that have experienced droughts are more likely to agree that the effects of climate change are happening right now (temporal distance) and that climate change is already affecting them (hypothetical distance).

1.6. Discussion

The objectives of this cumulative thesis are to identify the drivers influencing farmers' adaptive behavior to climate change and to examine the role of financial literacy and extreme weather events in shaping both borrowing decisions and climate change perceptions among farmers in central Colombia. Through a structured approach, this research contributes to the broader understanding of adaptation from multiple dimensions, providing a more comprehensive perspective on their responses to climate change. First, an SLR was conducted to identify the drivers of farmers' adaptive decisions to climate change. As a result, the 3F-SEC framework was developed. Secondly, using the framework as a reference, it investigates how financial literacy influences borrowing decisions in response to climate shocks. Third, focusing on the experiential and cognitive dimensions of the framework, it analyzes differences in climate change perceptions among farmers who have experienced extreme weather events, such as landslides and droughts.

The SLR revealed that Iran has the highest contribution to research on farmers' adaptive behavior to climate change (e.g. Azadi et al., 2019b; Zobeidi et al., 2016), while countries from Latin America are underrepresented. The review also highlighted psychological theories, such as the PMT by Rogers (1975) and the Theory of Planned Behavior by Ajzen (1985), as the most commonly used. The 3F-SEC framework was developed to organize the 179 behavioral drivers identified and to provide a comprehensive understanding of the factors shaping farmers' climate change adaptation decision-making processes. For example, a farmer's financial standing influences their access to resources and feasible adaptation options, shaping their experiences and knowledge of specific adaptation measures (Luther et al., 2020). Similarly, experiential factors, such as firsthand exposure to extreme weather events, can shape cognitive perceptions of climate change (Borick & Rabe, 2017; Dai et al., 2015). In turn, these perceptions influence the adoption of adaptation strategies based on prior experiences (Lujala et al., 2015).

Applying the 3F-SEC framework, this cumulative thesis examined how financial literacy influences borrowing decisions in response to climatic shocks. The findings indicate that financially literate farmers are more likely to obtain loans due to a better understanding of the lending process (Cheng et al., 2023; Klapper et al., 2013). Additionally, when the analysis focused solely on loans from non-financial sources, it was found that financial literacy had a positive effect on the selection of these loans. The literature suggests that financially literate farmers would prefer formal financial institutions as loan sources (Mujabi et al., 2022). However, our results suggest that financial knowledge does not necessarily lead to exclusive reliance on formal credit sources and that there are subjective perceptions that may influence these decisions, as established by Prospect Theory (Kahneman & Tversky, 1979).

As proposed in the 3F-SEC framework, financial decisions represent only one dimension of how farmers respond to climatic shocks. Another critical aspect involves examining how these extreme weather events influence farmers' perceptions of climate change. By exploring these perceptions —of severity, vulnerability, and psychological distance— we can better comprehend the cognitive mechanisms that shape adaptive behaviors in the context of increasing climate variability. The findings indicate that landslides have no statistically significant effect on the 16 perception measures assessed. Similar research has reported that increased exposure to landslide risk does not necessarily translate into an intention to mitigate or prevent such occurrences (Mertens et al., 2018; Spegel & Ek, 2022). One potential explanation is that landslide impacts tend to be more indirect, often through disruptions to the transportation network (Vranken et al., 2013; Winter et al., 2019). Similarly, given that most landslides in this region are consequences of heavy rainfall (Aristizábal & Sánchez, 2020; Garcia-Delgado et al., 2022), it is crucial to understand how farmers perceive changes in precipitation patterns. Prior research has indicated that farmers' perceptions of rainfall do not always align with meteorological data (Dhanya & Ramachandran, 2016; Guido et al., 2020).

In contrast to landslides, which tend to have localized effects, droughts have a prolonged impact on agricultural productivity, making climate risks more tangible to farmers. Empirical evidence suggests that farmers' drought perceptions significantly shape their views on climate change (Carlton et al., 2016; Kim & Ahn, 2019; Lyons et al., 2018; Panda, 2016). Our findings reinforce this evidence, as we observed statistically significant differences in 10 out of the 16 climate change perception measures among farmers living in drought-affected villages. The results are consistent with the PMT, which suggests that how individuals assess risks based on perceived severity and vulnerability is influenced by firsthand experiences of climate-related events (Truelove et al., 2015).

From a theoretical standpoint, this thesis advances the understanding of farmers' adaptation decisions by integrating financial, experiential, and cognitive drivers within the 3F-SEC framework. This comprehensive structure extends psychological models of risk perception by emphasizing the role of specific climate events in shaping adaptation intentions. Additionally, the thesis highlights the importance of financial knowledge in borrowing behavior as a response to weather shocks, which have received limited attention in adaptation research. From a policy perspective, if the objective is to better understand farmers' adaptive capacity to climate change, a more integrated approach that considers the three types of drivers previously mentioned could be beneficial and provide a more holistic perspective.

Likewise, the findings suggest policy interventions depending on the type of driver. If the goal is to improve formal credit access, strengthening financial literacy programs tailored to the needs of rural communities may help farmers navigate borrowing decisions more effectively, especially the trade-offs between financial and non-financial sources. If the aim is to foster proactive adaptation strategies, integrating localized climate data into training programs on sustainable agricultural practices could support more informed decision-making, particularly in regions vulnerable to drought. Additionally, if policymakers seek to enhance climate risk awareness, communication strategies leveraging farmers' direct experiences with extreme weather events may be useful in reinforcing the perception of climate change. In particular, awareness campaigns could target villages that have experienced landslides, as their experience alone does not have a significant effect on their perceptions of climate change.

While this cumulative thesis offers valuable insights, several limitations must be acknowledged. The focus on central Colombia may prevent making inferences about other regions in the world. Additionally, data constraints, particularly in rural areas, pose challenges for establishing causal relationships and limit the availability of instrumental variables to treat potential endogeneity issues. Furthermore, the reliance on self-reported measures, such as climate change perceptions, introduces the risk of potential recall bias and subjective interpretation. Lastly, the cross-sectional nature of the empirical analyses restricts the ability to capture long-term adaptation dynamics, preventing a deeper understanding of how farmers' responses evolve in the face of changing environmental and economic conditions.

Future research could focus on these dynamics further by conducting longitudinal studies to assess how financial literacy and climate change perceptions evolve over time. Expanding to other regions would also help test the applicability of the 3F-SEC framework in different contexts. Additionally, incorporating other types of drivers, such as the characteristics of the farmer and the farm and the situational circumstances, would provide a more comprehensive understanding of adaptation behavior.

1.7. Conclusion

Overall, this cumulative thesis contributes to the understanding of farmers' adaptive behavior to climate change. Our 3F-SEC framework provides a comprehensive approach to these drivers, helping to understand their interconnections, and emphasizing how socio-demographic, farm characteristics, financial, situational, experiential, and cognitive factors jointly shape farmers' adaptive decisions. The two empirical analyses highlight the relationship between three types of drivers from the 3F-SEC framework: financial, experiential, and cognitive. Particularly, the role of financial literacy in loan taking as a consequence of weather shocks and extreme weather experiences in shaping climate change perceptions. The findings reveal that financial literacy plays a crucial role in determining farmers' access to credit following climate shocks, not only by improving their understanding of formal lending processes but also by shaping their preferences for different loan sources. Moreover, while landslides appear to have a limited influence on climate change perceptions, droughts significantly shape farmers' assessments of vulnerability, severity, and the immediacy of climate risks. The findings reinforce the need for a holistic approach to further research farmers' adaptation, particularly in regions highly vulnerable to climate change.

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Chapter 2: Drivers of farmers' adaptive behavior to climate change - The 3F-SEC framework

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Drivers of farmers' adaptive behavior to climate change: The 3F-SEC framework

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ABSTRACT

Climate change can have a negative impact on agriculture and lead to significant crop losses and increasing food insecurity. Despite the growing body of research on farmers' adaptive behaviors to climate change, there remains a lack of comprehensive classification of influencing factors. In our systematic literature review comprising 87 articles, we identified 179 distinct drivers, categorized into socio-demographic characteristics, farm attributes, financial resources, situational influences, experiential aspects, and cognitive elements. Notably, cognitive drivers, such as beliefs about climate change consequences, were frequently cited (348 times), along with critical socio-demographic factors like age and education. Drawing from a case study of farmers in central Colombia, we illustrate how these factors interact. Through the lens of four exemplary farmer types, we observe that older farmers were less likely to adapt due to limited exposure to climate emergencies and higher age, whereas for others community relationships drove adaptive behaviors. High-income motivated adaptation, while direct experience with climate disasters increased adaptation willingness. Finally, the framework we have developed highlights the importance of understanding the complex interplay of different factors behind farmers' adaptation decisions, paving the way for the development of more localized and context-specific climate adaptation strategies.

1. Introduction

Climate change impacts include rising global temperatures, more frequent and severe extreme weather events, disruption of ecosystems and biodiversity, and challenges to water and food security. Nonetheless, it is necessary to recognize that these effects are not uniformly manifested globally (Epanchin-Niell et al., 2017), and may vary within the same geographical region (A. K. Gupta et al., 2020). Consequently, there is a certain level of uncertainty in determining how the different communities will be specifically impacted (Jacoby et al., 2015). One of the main groups expected to be affected by climate change is farmers, especially in "developing" countries, as their economies are largely dependent on the agricultural sector (Asmare et al., 2019; de Sousa et al., 2018). For this reason, it is important to understand how farmers respond to these effects, bearing in mind that everyone may experience them differently.

Different problems associated with climate, such as changes in average temperatures, changes in weather patterns, and changes in seasons, have a direct impact on agricultural production (Gerlitz et al., 2017; Liu et al., 2022; Mulwa et al., 2016). Several studies have been conducted to show the consequences of climate change on different types of crops; and a negative correlation has been found between these climate disruptions and crop yields (Arshad et al., 2017; Chen et al., 2016; Hertel et al., 2010; Miller et al., 2021; Quaye et al., 2018). These reductions in agricultural production directly affect farmers' livelihoods, specifically their food security and income (Abid et al., 2016; Narayanan and Sahu, 2016; Wang et al., 2022). Likewise, due to international trade in agricultural products, it is expected that these local problems could have repercussions at the global level (Baldos et al., 2019).

Climate change creates pressure on farming operations and farmers are expected to adapt their practices in these scenarios of climate uncertainty. However, for a farmer to be seen as adapting, two things are needed: they must notice changes in the environment they are used to,

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and then make changes to their farming to deal with these changes (Deressa et al., 2011; Talanow et al., 2021). Many of the practices that farmers adopt are options that are already available to them, such as planting new crops; others may be more drastic, such as finding other jobs (Mulwa et al., 2016). However, in many cases, farmers need practices that rely on institutions to make them available, like heat-resistant seeds and new infrastructure (Wineman and Crawford, 2017).

Understanding the decision-making process of farmers about the adaptation measures they need on their farms is crucial for understanding adaptation success. The more severe the climate fluctuations, the greater the effects on agricultural production, so adaptation measures to mitigate these impacts will be more necessary (Asmare et al., 2019). The adaptive capacity of farmers depends not only on their available resources and assets but also on their experience with the climate and how their cognitive processes are being affected by these new environmental changes (Adger, 2003). Therefore, if farmer behavior is to be studied, it is recommended to incorporate geographic, economic, institutional, and socio-demographic characteristics, as well as characteristics of their farming operations (Castro Campos, 2022; Duffy et al., 2021). Incorporating these different dimensions into the study of adaptive behavior allows for a deeper understanding of farmers' actions in the face of climate change.

In recent years, there has been an increase in research on the behavior and decisions of farmers in relation to their adaptation to climate change. However, to the best of our knowledge, a systematic analysis of all the different types of drivers of farmers' adaptive behavior has not yet been carried out. Previous studies, such as Lyle (2015), proposed a nested multi-scale spatial hierarchy of factors influencing climate change adaptation but did not incorporate other categories, particularly situational factors like institutional and market drivers. Van Valkengoed and Steg (2019) examined motivational factors of climate change but were limited to only thirteen factors. Dessart et al. (2019) focused on factors that affect the adoption of new agricultural practices; yet the scope of this study was on the adoption of sustainable agricultural practices rather than climate change mitigation within farms. Similarly, Sok et al. (2021) reviewed farmer behavior through the Theory of Planned Behavior but did not distinguish whether these behaviors were influenced by climate change.

In contrast, some research has systematically analyzed literature related to climate change, but these studies have been limited to particular topics. For instance, Wiederkehr et al. (2018) focused solely on migration as an adaptation strategy, while Soubry et al. (2020) examined farmers' perceptions of climate change. Ricart et al. (2022) studied disparities between farmers' climate perceptions and meteorological data and Feola et al. (2015) looked at cases of adaptation to climate change without systematically organizing the factors involved. We find that these studies, although important, do not incorporate all the dimensions that influence farmers' adaptive behavior to climate change. This represents a significant knowledge gap. Therefore, a comprehensive literature review is necessary to incorporate all the factors influencing the adaptive behavior of farmers to climate change.

The objective of this study is to improve the understanding of the behavior of farmers when making decisions that allow them to adapt to climate change by systematically analyzing all the different factors that affect the decision-making process. This study aims to address the following research questions: (1) What are the drivers influencing farmers' decision-making behavior regarding climate change adaptation measures? (2) How do these influential factors interact with each other and shape individuals' adaptive behaviors? By investigating these questions, this study seeks profound insights into understanding how agricultural stakeholders respond and adjust strategies accordingly.

To accomplish these objectives, we conduct a review of 87 articles that examine farmers' adaptive behavior in response to climate change. The study utilizes the Scientific Procedures and Rationale for Systematic Literature Reviews (SPAR-4-SLR) protocol proposed by Paul et al. (2021) and applied by Castro Campos (2022) and Castro Campos and Qi (2024). As a result, we introduce the Farmer-Farm-Financial-Situational-Experiential-Cognitive (3F-SEC) framework, which provides a holistic overview of all the factors that drive farmers' adaptive behavior in response to climate change. This framework makes contributions to the existing literature in three ways. Firstly, it is the first study to categorize all the drivers of adaptive behavior based on their nature and type; secondly, it integrates various drivers that have not been collectively addressed in previous studies; lastly, it serves as a resource for future research endeavors aimed at investigating farmer behavior under changing climatic conditions.

The present article is structured in the following manner. Section 2 outlines the research methodology used, specifically the implementation of the SPAR-4-SLR protocol, explaining how articles are obtained, categorized, and assessed. Section 3 presents the bibliographic results derived from these gathered articles, introduces the 3F-SEC framework, and a sub-section for the discussion of the results. Continuing to section 4, the 3F-SEC framework is applied in a case study involving farmers in central Colombia who have faced and responded to challenges associated with climate change. Finally, concluding remarks can be found in section 5.

2. Methodology

A systematic literature review is a valuable method for effectively managing a wide range of knowledge within a specific academic domain. The primary objective of this method is to integrate, synthesize, and critically analyze findings from previous studies to provide a comprehensive understanding of the chosen research topic. Doing so, not only offers insights into existing knowledge but also helps identify gaps that require further investigation. Furthermore, a key aim is to develop new theoretical frameworks by building upon the foundational insights derived from prior research (Castro Campos, 2022; Paul and Criado, 2020; Snyder, 2019; Tranfield et al., 2003).

The methodology employed in this study follows the SPAR-4-SLR protocol proposed by Paul et al. (2021), which provides a structured approach with clear guidelines for each stage of the review process. This protocol ensures a systematic and organized method for identifying, selecting, and analyzing relevant literature. It encompasses three major stages: assembling, arranging, and assessing. Each stage is further divided into six sub-stages, including identification, acquisition, organization, purification, evaluation, and reporting (Fig. 1). By emphasizing comprehensive coverage, the SPAR-4-SLR protocol systematically assembles, arranges, and assesses literature, thereby providing a clear structure of the analysis and traceability of the results. In addition, we employ an inductive coding procedure based on Corbin and Strauss (2014), which allowed us to identify all drivers of farmers' adaptive behavior towards climate change based on the selected articles. The list of all the articles included and the codes and framework used in their systematization can be found in supplement S1 "List of Articles".

Assembling	Identification Domain: Farmers' behavior in adapting to climate change Research Question: What are the drivers of farmers' adaptive behavior to climate change? Source type: Journal articles Source Quality: Literature from Web of Science (WOS). ↓ Acquisition Search mechanism and material acquisition (n = 146) 1. WOS for literature in English: (n = 145) 2. WOS for literature in Portuguese: (n = 1) Search period: 2008–2022 Search keywords in WOS: (Climate change OR Climate variability OR climatic change) AND (Farmers OR rural households) AND (Behavior OR Behaviour) AND (Adaptation OR resilience OR adoption OR coping) AND (Vulnerability) (n = 146) ↓
Arranging	**Organization** **Organizing codes:** year, journal, citations, country, theory,

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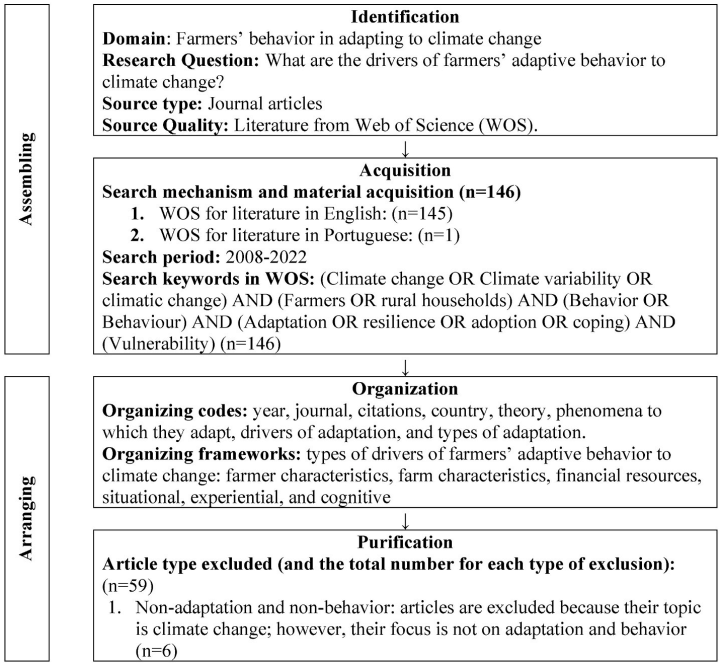

Fig. 1. Flowchart of the SPAR-4 SLR protocol.

(*continued*)

phenomena to which they adapt, drivers of adaptation, and types of adaptation.
Organizing frameworks: types of drivers of farmers' adaptive behavior to climate change: farmer characteristics, farm characteristics, financial resources, situational, experiential, and cognitive
↓
Purification
Article type excluded (and the total number for each type of exclusion): (n = 59)
1. Non-adaptation and non-behavior: articles are excluded because their topic is climate change; however, their focus is not on adaptation and behavior (n = 6)
2. Non-adaptation and behavior: articles are excluded because the topic is about behavior as a consequence of climate change; however, the focus is not adaptation (n = 1)
3. Non-adaptation: articles are excluded because their topic is climate, but the focus is not adaptation (n = 1)
4. Adaptation and non-behavior: articles are excluded because the studies do not explain the behavior of the farmers (n = 28)
5. Non-climate change: articles are excluded because the adaptation behavior studied is not related to climate change (n = 13)
6. Non-agricultural: articles are excluded because the unit studied is not farm (n = 7)
7. Literature reviews (n = 3)
Article type included (and the total number of articles included): (n=87)
This classification is made according to the different categories of drivers of adaptive behavior (organizing framework) that the authors included in their research. These can be found in detail in supplement S2 "Heat Map", where the proportion by type of drivers that the authors used in their studies can be observed.
1. Six different types of drivers of adaptive behavior: Asrari et al. (2022); Azadi et al. (2019a); Budhathoki et al. (2020); Elijah and Odiyo (2020); Guo et al. (2021); W. Li et al., 2021; Lone et al. (2022); Mu et al. (2020); Puupponen et al. (2022); Roesch-McNally et al. (2017); Savari and Shokati Amghani (2021); Shi et al. (2019); Skevas et al. (2022); Wens et al. (2022); Zobeidi et al. (2021) (n = 15)
2. Five different types of drivers of adaptive behavior: Abbas et al. (2022); Albert et al. (2021); Aliabadi et al. (2022); Arifah et al. (2022); Azadi et al. (2019b); Below et al. (2012); Benabderrazik et al. (2022); Burnham and Ma (2017); de Matos Carlos et al. (2020); Dieye and Roy (2012); Do and Ho (2022); Engler et al. (2021); Islam et al. (2021); Linder and Campbell-Arvai (2021); Li et al. (2017); Li et al. (2022); Masud et al. (2017); Messmer et al. (2021); Minh et al. (2020); Mirzaei et al. (2022); Pakmehr et al. (2020); Quiroga et al. (2020); Saroar and Routray (2012); Tetteh et al. (2020); Wale et al. (2022) (n = 25)
3. Four different types of drivers of adaptive behavior: Ayal et al. (2021); Buelow and Cradock-Henry (2018); Bulla and Steelman (2016); Campos et al. (2014); Gebrehiwot and van der Veen (2015); Goli et al. (2022); Guo et al. (2022); Jellason et al. (2020); Kirsch and Filipi (2018); Lamichhane et al. (2022); Mohammadzadeh et al. (2021); Muench et al. (2021); Niles et al. (2015); Ntim-Amo et al. (2022); Nyantakyi-Frimpong et al. (2022); Petersen-Rockney (2022); Petrescu-Mag et al. (2022); Poudyal et al. (2021); Rodríguez-Cruz and Niles (2021); Tessema et al. (2019); Van Aelst and Holvoet (2018); Zheng and Byg (2014); Zobeidi et al. (2016) (n = 23)
4. Three different types of drivers of adaptive behavior: Bagagnan et al. (2019); Brondizio and Moran (2008); Ciampi et al. (2022); Haden et al. (2012); Hailegiorgis et al. (2018); Lei et al. (2016); Neisi et al. (2020); Pauw (2013); Peng et al. (2022); Running et al. (2019); Singh et al. (2017); Tomlinson and Rhiney (2018); Wang et al. (2013) (n = 13)
5. Two different types of drivers of adaptive behavior: Arbuckle et al. (2015); Delfiyan et al. (2021); Fiorella et al. (2021); Gilbert and McLeman (2010); Keshavarz and Karami (2016); Ndlovu (2019); Orduño Torres et al. (2020) (n = 7)
6. One type of driver of adaptive behavior: Fujisawa and Kobayashi (2011); Rao et al. (2020); van Duinen et al. (2015); Yin et al. (2020) (n = 4)
↓

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2. Non-adaptation and behavior: articles are excluded because the topic is about behavior as a consequence of climate change; however, the focus is not adaptation (n=1)
3. Non-adaptation: articles are excluded because their topic is climate, but the focus is not adaptation (n=1)
4. Adaptation and non-behavior: articles are excluded because the studies do not explain the behavior of the farmers (n= 28)
5. Non-climate change: articles are excluded because the adaptation behavior studied is not related to climate change (n=13)
6. Non-agricultural: articles are excluded because the unit studied is not farm (n=7)
7. Literature reviews (n=3)

Article type included (and the total number of articles included): (n=87)

This classification is made according to the different categories of drivers of adaptive behavior (organizing framework) that the authors included in their research. These can be found in detail in supplement S2 "Heat Map", where the proportion by type of drivers that the authors used in their studies can be observed.

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2. **Five different types of drivers of adaptive behavior:** Abbas et al. (2022); Albert et al. (2021); Aliabadi et al. (2022); Arifah et al. (2022); Azadi, Yazdanpanah, Forouzani, et al. (2019); Below et al. (2012); Benabderrazik et al. (2022); Burnham and Ma (2017); de Matos Carlos et al. (2020); Dieye and Roy (2012); Do and Ho (2022); Engler et al. (2021); Islam et al. (2021); Linder and Campbell-Arvai (2021); S. Li et al. (2017); X. Li et al. (2022); Masud et al. (2017); Messmer et al. (2021); Minh et al. (2020); Mirzaei et al. (2022); Pakmehr et al. (2020); Quiroga et al. (2020); Saroar and Routray (2012); Tetteh et al. (2020); Wale et al. (2022) (n=25)

3. **Four different types of drivers of adaptive behavior:** Ayal et al., (2021); Buelow and Cradock-Henry (2018); Bulla and Steelman (2016); Campos et al. (2014); Gebrehiwot and van der Veen (2015); Goli et al. (2022); H. Guo et al. (2022); Jellason et al. (2020); Kirsch and Filipi (2018); Lamichhane et al. (2022); Mohammadzadeh et al. (2021); Muench et al. (2021); Niles et al. (2015); Ntim-Amo et al. (2022); Nyantakyi-Frimpong et al. (2022); Petersen-Rockney (2022); Petrescu-Mag et al. (2022); Poudyal et al. (2021); Rodríguez-Cruz and Niles (2021); Tessema et al. (2019); Van Aelst and Holvoet (2018); Zheng and Byg (2014); Zobeidi et al. (2016) (n=23)

4. **Three different types of drivers of adaptive behavior:** Bagagnan et al. (2019); Brondizio and Moran (2008); Ciampi et al. (2022); Haden et al. (2012); Hailegiorgis et al. (2018); Lei et al. (2016); Neisi et al. (2020);

Fig. 1. (*continued*).

(*continued*)

Assessing	**Evaluation** **Analysis method:** Content analysis on the drivers of adaptive behavior **Agenda proposal method:** A holistic understanding of the drivers that influence farmers' adaptive behavior to climate change ↓ **Reporting** **Reporting conventions:** Graphs, frequency tables, heat map, 3F-SEC framework **Limitation(s):** Only WOS articles were analyzed. **Source(s) of support:** Financial support from the German Academic Exchange Service (DAAD) under the program Development-Related Postgraduate Courses (EPOS), contract number P1401273

2.1. Assembling

In the assembling stage, we proceed with two sub-stages: identification and acquisition. During the identification process, we determine the research domain, refine our research question, and evaluate both the type of sources and their quality. Specifically for this study, only scholarly articles published are deemed suitable for inclusion. To ensure a comprehensive scope of literature review relevant to our topic, all articles in the WOS database are considered. Next is the acquisition sub-

Pauw (2013); Peng et al. (2022); Running et al. (2019); Singh et al. (2017); Tomlinson and Rhiney (2018); J. Wang et al. (2013) (n=13)

5. **Two different types of drivers of adaptive behavior:** Arbuckle et al. (2015); Delfiyan et al. (2021); Fiorella et al. (2021); Gilbert and McLeman (2010); Keshavarz and Karami (2016); Ndlovu (2019); Orduño Torres et al. (2020) (n=7)

6. **One type of driver of adaptive behavior:** Fujisawa and Kobayashi (2011); Rao et al. (2020); van Duinen et al. (2015); Yin et al. (2020) (n=4)

↓

Assessing

Evaluation

Analysis method: Content analysis on the drivers of adaptive behavior
Agenda proposal method: A holistic understanding of the drivers that influence farmers' adaptive behavior to climate change

↓

Reporting

Reporting conventions: Graphs, frequency tables, heat map, 3F-SEC framework
Limitation(s): Only WOS articles were analyzed.
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Fig. 1. (*continued*).

stage, which includes the acquisition mechanism, search period, keywords, and total number of articles.

To conduct a comprehensive systematic literature review addressing our research questions, it was essential to select keywords that capture the nature of this research. Moreover, to ensure the robustness and reliability of our results, we used a search equation to encompass a broad and complex spectrum of relevant studies (see Fig. 1, Acquisition). This includes a breakdown of the search terms and Boolean operators applied. The search equation is grounded in the definition of climate change provided by the Intergovernmental Panel on Climate Change (IPCC, 2014), which states, "Climate change refers to a change in the state of the climate that can be identified (e.g., by using statistical tests) by changes in the mean and/or the variability of its properties and that persists for an extended period, typically decades or longer" (p. 120). This definition shows the importance of examining long-term changes in climate patterns and their impacts, thereby justifying the inclusion of terms like "climate change", "climate variability", and "climatic change" in our search equation.

There is no consensus on the definition of behavior, as it varies depending on the field of study (Carman and Zint, 2020; Henriques and Michalski, 2020; Uher, 2016). However, a simple definition according to the American Psychological Association (n. d.) behavior is "an organism's activities in response to external or internal stimuli, including objectively observable activities, introspectively observable activities, and nonconscious processes". Given that the focus of our study is adaptive behavior to climate change, we complement this definition with the four principles of behavior proposed by Baum (2013): (a) only living organisms behave, (b) has a purpose, (c) takes time and, (d) involves choice. These principles help frame our research on how farmers' behaviors are directed toward adaptation to climate change impacts, emphasizing the intentional and choice-based nature of such adaptations. Similarly, building on the definition of behavior, we have systematically examined how different types of factors trigger adaptive responses in farmers, facilitating the categorization of these drivers. Additionally, we draw inspiration from the work of Castro Campos (2022), Dessart et al. (2019), and Lyle (2015) in operationalizing the components of behavior.

The inclusion of terms like "adaptation," "resilience," "adoption," and "coping" is theoretically grounded in understanding the spectrum of responses that farmers may employ in the face of climate threats and based on the definition proposed by the IPCC (2014) as "the process of adjustment to actual or expected climate and its effects. In human systems, adaptation seeks to moderate or avoid harm or exploit beneficial opportunities. In some natural systems, human intervention may facilitate adjustment to expected climate and its effects" (p. 118). Furthermore, the terms "farmers" and "rural households" were included to specifically target the population of interest. Finally, adding "vulnerability" was done to include the possibility of studies where it is measured using adaptive capacity (Alam, 2017; Baca et al., 2014; M. Gupta et al., 2020). Using these specific search terms in conjunction with Boolean operators, as shown in Fig. 1, we found 146 relevant academic articles. The range of years for the articles chosen for this study emerged organically from the literature and was not predetermined by us.

2.2. *Arranging*

This stage consists of two sub-stages: organization and purification. For the organization sub-stage, we use various organizing codes: year, journal, citations, country, theory, crop/livestock, drivers of adaptive behavior, and types of adaptation to climate change (as outlined in supplement S1 "List of Articles"). Given that the objective of this literature review is to examine the determinants of adaptive behavior, we implement a framework based on different types of drivers (including socio-demographic characteristics of farmers, farm characteristics, financial resources (incorporating the different forms of capital), situational factors, experiential aspects, and cognitive factors). These categories are further disaggregated by type and driver in supplement S3 "Drivers of Adaptive Behavior".

In the purification sub-stage, we select and exclude articles based on their alignment with our research focus, which aims to investigate farmers' adaptive behavior towards climate change. Specifically, any articles that did not directly address this topic are excluded from further analysis. The excluded articles amount to 59 in total, while 87 articles meet the criteria for inclusion and proceed to the next stage of analysis. A more comprehensive overview of this purification process is provided in Fig. 1, which lists the excluded articles, the main reasons for exclusion, and the selected articles (see also Supplement S2 "Heat Map" for an overview of the selected articles.

2.3. Assessing

Within this stage, evaluation and reporting are sub-stages. In the evaluation sub-stage, we apply content analysis techniques based on Krippendorff (2004) and Schreier (2014) to investigate the various factors that drive adaptive behavior among farmers, as well as their impact on farmers' overall intentions to adapt. For the coding, we followed the methodological steps outlined by Corbin and Strauss (2014). Firstly, we used an open coding approach to systematically identify all the different behavioral drivers, recognizing 179 in total. Subsequently, we employed axial coding to categorize the individual codes into broader groups that encompass similar drivers. Finally, all the drivers were categorized into six different types: socio-demographic characteristics, farm-specific attributes, financial resources, situational influences, experiential aspects, and cognitive elements (see supplement S3 "Drivers of Adaptive Behavior"). On the other hand, the reporting sub-stage encompasses all the graphical representations used to outline all the significant findings. Additionally, it addresses any limitations of the literature review and includes acknowledgment of funding sources related to this research (see Fig. 1).

3. Results

3.1. Main dataset information

Over the years, there has been a significant increase in studies looking at how farmers adapt to climate change (Fig. 2). Particularly in recent times, approximately 58% of the 87 reviewed articles were published between 2020 and 2022. Geographically, a significant proportion of research sites are situated in Asian and African countries (42 and 21, respectively), as depicted in Fig. 3. Among these locations, Iran is identified as having conducted the most studies, with 14 in total (e.g. Delfiyan et al., 2021; Goli et al., 2022; Pakmehr et al., 2020). China is the country with the second-highest number of investigations carried out with 11 articles (e.g. Burnham and Ma, 2017; Guo et al., 2021; Mu et al., 2020; Peng et al., 2022). The United States has ranked third in terms of the number of studies conducted with a total of eight (e.g. Bulla and Steelman, 2016; Haden et al., 2012; Petersen-Rockney, 2022). In contrast, the continent with the least investigations is Oceania with only one study being undertaken in New Zealand (see Niles et al., 2015).

Among the articles examined, only 37 articles identified particular phenomena to which the farmers were adapting, naming 16 different phenomena (Table 1). The most frequently analyzed topic was water-related in some capacity and its effects on agricultural systems. Drought appeared as a single phenomenon in 17 articles (e.g. Neisi et al., 2020; Savari and Shokati Amghani, 2021; Wens et al., 2022) and in conjunction with other phenomena in three more (see Brondizio and Moran, 2008; Petersen-Rockney, 2022; Zheng and Byg, 2014). Water availability was discussed in five articles (e.g. Haden et al., 2012; Pakmehr et al., 2020), meanwhile, floods were mentioned in six (e.g. Ntim-Amo et al., 2022; Nyantakyi-Frimpong et al., 2022; Skevas et al., 2022).

Other less common issues explored include different climate change scenarios and investigate how farmers would adapt accordingly (e.g. Hailegiorgis et al., 2018; Roesch-McNally et al., 2017), and hurricanes (e.g. Rodríguez-Cruz and Niles, 2021). Additionally, some articles investigate adaptations to various phenomena, these include changes in temperature, cold spells, droughts, floods, water availability, hailstorms, etc. (e.g. Budhathoki et al., 2020; Minh et al., 2020; Mohammadzadeh et al., 2021).

Only a fraction of the studies included in this literature review –specifically 34 out of 87– incorporated a theoretical framework in their research designs. Table 2 presents the 18 theories identified in these studies. The majority of these theories focus on understanding the drivers behind individuals' adoption of specific behaviors, particularly in response to threats. They typically include assessments of attitudes, beliefs, intentions, and stages of change. Among these, Protection Motivation Theory (PMT) was the most widely used, featured in 16 articles (e.g. Delfiyan et al., 2021; Engler et al., 2021; Neisi et al., 2020). The second most frequently used theory was the Theory of Planned Behavior, used in four (e.g. W. Li et al., 2021; Linder and Campbell-Arvai, 2021). The other theories within this group were each mentioned in only one article: the Trans-Theoretical Stage Model (TTM) theory in Gebrehiwot and van der Veen (2015), the Reasoned Action Approach in Roesch-McNally et al. (2017), the Health Belief Model (HBM) in Zobeidi et al. (2021), and the Protective Action Decision Model (PADM) in Ntim-Amo et al. (2022).

The second group of theories also focuses on factors that affect adaptive behaviors. However, these theories primarily examine how individuals or communities respond to environmental changes, particularly climate change. The Values–Beliefs–Norms (VBN) theory was used in two articles (see Arbuckle et al., 2015; Peng et al., 2022), and incorporated into pro-environmental behaviors. Another theory used is the Model of Private Proactive Adaptation to Climate Change (MPPACC), which extends the PMT and was used in a single article by Burnham and Ma (2017). The other theories in this group were each used only once: Liebig's Law of the Minimum in Niles et al. (2015), and Social Risk Management in Zheng and Byg (2014).

Grounded Theory was used in two articles (see Arifah et al., 2022; Petersen-Rockney, 2022) and focuses on developing theories grounded in data systematically gathered and analyzed. The other theories were each used in only one article. Some of these theories relate to psychological and cognitive processes, such as the Construal Level Theory in Rodríguez-Cruz and Niles (2021), the Psychological Distance Theory in

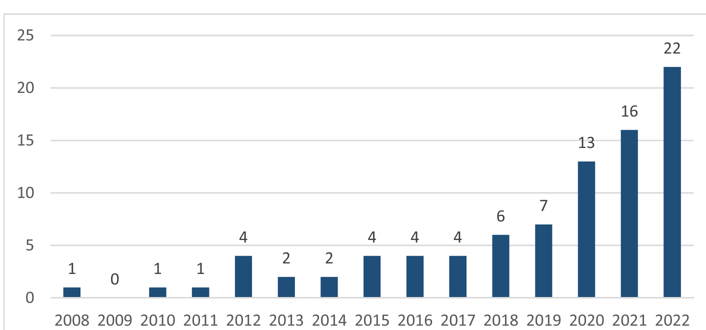

Fig. 2. Year of publication.
Source: Authors based on the systematic literature review (Supplement S1).

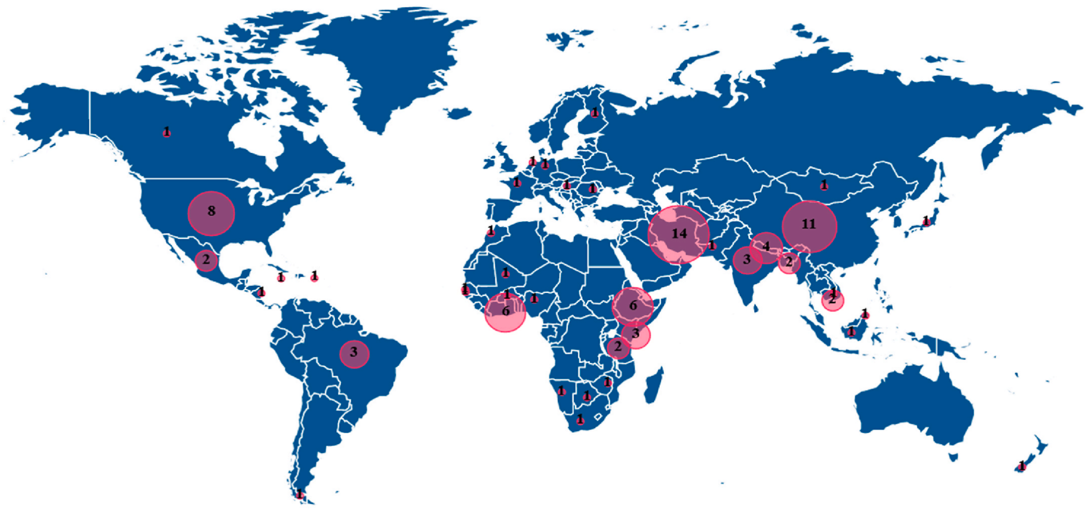

Fig. 3. Research locations.
Source: Authors based on the systematic literature review (Supplement S1).

Table 1
Phenomenon to which farmers adapt.

The phenomenon to which farmers adapt	Frequency
Drought	20
Floods	6
Water Availability	5
Changes in Temperature	4
Hurricane	3
Cold Spells	2
Climate Change Scenario	2
Sea-level Rise	1
Fires	1
Erratic Rains	1
Change in seasons	1
Pests	1
Hailstorms	1
Tropical depressions	1
Low precipitation	1
Heat waves	1
No specific event	50

Source: Authors based on the systematic literature review (Supplement S1)

Table 2
Theories.

Theory	Frequency
Protection Motivation Theory (PMT)	16
Theory of Planned Behavior	4
Grounded theory	2
Values–Beliefs–Norms	2
Construal Level Theory	1
Health Belief Model (HBM)	1
Liebig's Law of the Minimum	1
Model of private proactive adaptation to climate change (MPPACC)	1
Optimal Utility Theory	1
Protective Action Decision Model (PADM)	1
Psychological Dimensions of Climate Change	1
Psychological Distance Theory	1
Random Utility Maximization (RUM)	1
Reasoned Action Approach	1
Social Risk Management	1
Theory of Diffusion of Innovations	1
Trans-Theoretical Stage Model (TTM)	1
Unified Theory of Acceptance	1
Use of Technology Theory (UTAUT)	1
Without theory	53

Source: Authors based on the systematic literature review (Supplement S1).

Niles et al. (2015), and the Psychological Dimensions of Climate Change in Ayal et al. (2021). Others focus on innovation and technology adoption, including the Unified Theory of Acceptance and Use of Technology (UTAUT) by Asrari et al. (2022), and the Theory of Diffusion of Innovations in Muench et al. (2021). Finally, there were economic and utility-based models, such as Optimal Utility Theory in Minh et al. (2020) and Random Utility Maximization (RUM) in Wale et al. (2022).

We identify various strategies for adaptation and comprehensively categorize them (Table 3). These categories encompass a diverse range of practices, including techniques utilized in farming and livestock management, as well as the option of reducing or quitting farming. This information is detailed in supplement S4 "Types of Adaptation". The majority of the identified measures pertain to farming practices, with 30 distinct approaches being mentioned 302 times across the 87 articles reviewed. Within this category, the most frequently cited adaptive practices were soil conservation techniques, input management, the use of adapted or improved crops, adjustments in the timing of farming activities, and the adoption of new practices (e.g. Elijah and Odiyo, 2020; Guo et al., 2022; Quiroga et al., 2020; Rao et al., 2020; Tessema et al., 2019).

The second category with the highest number of cited adaptation types pertains to irrigation. Among these, improvements to irrigation systems were the most commonly mentioned practice, followed by having different sources of water for irrigation (e.g. Albert et al., 2021; Lone et al., 2022; Shi et al., 2019). On the other hand, increasing irrigation was the least used and was only mentioned once (see Peng et al., 2022). The categories encompassing financial, livestock, and income diversification adaptations include nine types of adaptations each, with financial adaptations being the most frequently mentioned, cited 53 times. Within this category, acquiring some type of insurance was the most common practice, and credits the second one (e.g. Benabderrazik et al., 2022; Zobeidi et al., 2021). For livestock-related adaptations, the most common practices were having livestock and selling it (e.g.

Table 3
Types of adaptive practices.

Category	Number of practices	Frequency
Farming	30	302
Irrigation	12	105
Livestock	10	45
Financial	9	53
Income diversification	9	38
Assets	8	36
Migration	8	33
Environmental oriented	8	35
Community-based	7	20
Information	5	12
Traditional practices	5	14
Business management oriented	4	9
Food security measures	4	6
Education/Extension	3	8
Reducing or quitting farming	2	7
No adaptation/maladaptation	2	9

Source: Authors based on the systematic literature review (Supplement S4).

Ndlovu, 2019; Tetteh et al., 2020). Regarding income diversification, obtaining jobs outside the agricultural sector was the most frequently cited practice (e.g. Budhathoki et al., 2020; Tomlinson and Rhiney, 2018).

The assets category includes eight types of adaptations, with 36 mentions across the articles. The most cited adaptation within this category was the sale or rent of land, followed by the purchase, hire, or improvement of technology as the second most cited (e.g. Campos et al., 2014; Lone et al., 2022). Similarly, the environmental-oriented category, also with eight types of adaptations, was mentioned 35 times, with reforestation or the management of forests being the most common practice (e.g. Muench et al., 2021) and prevention of environmental pollution the least cited from this category (see Keshavarz and Karami, 2016). Migration adaptations involve eight different practices, with migrating and temporal migration being the most common types (e.g. Pauw, 2013; Wang et al., 2013). Community-based adaptations, comprising six distinct practices, were mentioned 20 times, with community-based water management as the most prevalent adaptation (e.g. Niles et al., 2015). Traditional practices, including five types of adaptations, within this category, activities related to wild foods, religious practices, use of native species, and having traditional knowledge were each cited three times (e.g. Brondizio and Moran, 2008; Gilbert and McLeman, 2010; Jellason et al., 2020; Mohammadzadeh et al., 2021).

Business management-oriented adaptations include four different practices, the most common being changes in the business model (e.g. Skevas et al., 2022). The information-related category has three types of adaptations and focusing on weather forecast information is the most cited one (e.g. Azadi et al., 2019b). Within the education/extension adaptations category, education opportunities and the use of consultants were the most cited (e.g. Below et al., 2012; Campos et al., 2014). Eating different foods was the most common adaptation in the food security category (e.g. Van Aelst and Holvoet, 2018). Additionally, some farmers have also explored more drastic alternatives such as reducing farming operations or quitting farming altogether (e.g. Masud et al., 2017; Poudyal et al., 2021; Skevas et al., 2022). In some cases, certain farmers have been observed to consider non-action or engaging in maladaptive behavior as an option (e.g. Li et al., 2017; Mirzaei et al., 2022; Tomlinson and Rhiney, 2018; Zheng and Byg, 2014).

3.2. Drivers of adaptive behavior and the 3F-SEC framework

A total of 179 factors are identified, categorized, and classified by type (Table 4). For a more detailed review of each of the behavioral drivers, they are listed by category and type in supplement S3 "Drivers of Adaptive Behavior". This supplement includes an overview of all the drivers by article. Among these factors, cognitive elements are the most prominent drivers. These were cited 348 times, with particular attention to beliefs about the negative consequences associated with climate change (identified 65 times in the articles analyzed). The prominence of cognitive drivers highlights the significance placed on psychological processes in understanding farmers' adaptive behavior within the theoretical frameworks employed in the analyzed publications.

Table 4
Type and categories of drivers of adaptive behavior to climate change.

Type	Category	Number of drivers	Frequency
Farmer	Socio-demographics	14	183
Farmer	Household	8	45
Farm	Land	7	56
Farm	Irrigation	6	25
Farm	Livestock	3	16
Farm	Characteristics	10	82
Financial	Income and Expenses	9	67
Financial	Capital	7	68
Situational	Access	9	40
Situational	Market	4	11
Situational	Social	14	58
Situational	Information	7	30
Situational	Environment	7	43
Situational	Institutions	5	17
Experiential	Impacts of climate change	13	85
Experiential	Current adaptation practices	10	51
Experiential	Costs of adaptation	2	2
Cognitive	Risk	5	13
Cognitive	Perceptions	18	101
Cognitive	Beliefs	14	194
Cognitive	Psychological distance	4	35
Cognitive	Other	3	5

Source: Authors based on the systematic literature review (Supplement S3).

The socio-demographic characteristics of the farmers are in second place, these were referenced 183 times. Within these, the most common drivers were farmers' age and educational level (cited 54 and 51 times, respectively). These findings can be attributed to the frequent use of such variables in quantitative studies. Situational factors constitute another significant category of drivers, encompassing external elements beyond farmers' control such as markets and institutions. In total, 46 different situational factors are identified and mentioned 199 times throughout the reviewed articles. The most prevalent driver within this type was the social connections and affiliations that farmers have, which were counted 14 times.

The fourth most recurrent type of drivers counted during the research is the one related to the characteristics of the farm, which were cited 179. Within this, 26 different types of drivers were determined, where the size of the farm was the most prevailing of all (cited 28 times). Farmers' experiences are significant determinants in shaping their adaptive behavior. These were categorized according to their direct experiences with the effects of climate change, their experiences with the different adaptive practices they already employed on their farms, and the costs of adaptation. 25 drivers were identified within this type and were listed 138 times. The most common being impacts on agriculture, which was counted 24 times.

Additionally, the financial resources of farmers play a critical role in either motivating or impeding their willingness to adapt to climate change. In the reviewed articles, 16 different drivers, between farmers' income and expenses and their capital (which can be both financial and non-financial), were found. In total, these were mentioned 135 times: 68 related to capital along with 67 mentions of income and expenses. Among these, income and its different sources was the most common of all, which was cited 44 times.

Based on the analysis of the 87 articles studied and the systematization of the behavioral drivers, the 3F-SEC framework was developed (Fig. 4). This framework provides a comprehensive illustration of the various types and categories of drivers that have been identified. This

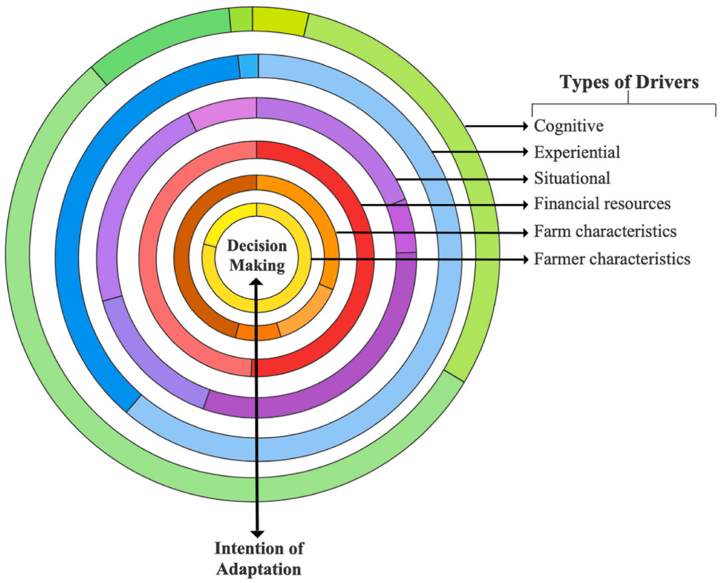

Fig. 4. 3F-SEC framework of adaptation to climate change.
Notes: Each circle represents a type of behavioral driver. These are organized starting with the most personal and easy to measure, which are the socio-demographic characteristics of farmers, and ending with the types of drivers related to the farmer's mental processes, which are the cognitive ones. However, the order in which they are organized has no particular meaning. The double arrow through all the circles represents the farmers' decision-making process to adapt to climate change. This double date means that this process is not unidirectional and involves all types of behavioral drivers. Likewise, the drivers can influence each other, so it is difficult to demonstrate any causality between them.
Source: Authors based on the systematic literature review (Supplement S3).

visual representation offers a holistic understanding of the multitude of factors that can influence a farmer's decision-making process about their intention to adapt to climate change. Each circle represents a specific type of driver, with the size of each division being proportional to its frequency in the literature review.

Each circle is divided according to the categories identified in each type of driver. Additionally, this division was made according to the frequency in which they were mentioned in the eighty-seven articles (Table 4). The first circle is divided by the socio-demographic characteristics of the farmer (80.3%) and the characteristics of the household (19.7%). The second circle is all farm components, such as land (31.3%), irrigation (14%), livestock (8.9%), and farm characteristics (45.8%). The third circle represents the farmer's financial status, income and expenses (49.6%), and capital, both monetary and non-monetary (50.4%). The fourth circle represents the situational categories, i.e. where the farmer has little or no control. Access to different things (20.1%), the market (5.5%), society (29.1%), information (15.1%), the environment (21.6%), and institutions (8.5%). The fifth circle represents all the farmers' experiences, such as the impacts of climate change (61.6%), the adaptation measures they already use (37%), and the costs of adapting (1.4%). The last circle has different cognitive processes of farmers, such as their understanding of risk (3.7%), their perceptions (29%), their beliefs (55.7%), psychological distance (10.1%), and other cognitive processes that do not belong to any of the other categories (1.4%).

The 3F-SEC framework consists at one end of the characteristics associated with farmers and their households, while at the other end lie cognitive components such as beliefs, perceptions, risks, and psychological distance. The middle section encompasses farm-related characteristics, financial resources, and experiential factors, as well as situational elements over which farmers may have limited control including access to resources or institutions and market conditions. While Fig. 4 provides a visual representation of how the circles are arranged, the decision-making process showing whether there is an intention to adapt or not to adapt to climate change is not unidirectional. The presence of an arrow connecting various types of behavioral drivers indicates that farmers' behavior does not follow a linear progression among these drivers.

Identifying a singular, linear process in which various behavioral drivers interact to influence farmers' adaptive intentions is not only challenging but also counterproductive. The interdependence and mutual nature of these behavioral drivers make it difficult to isolate their individual impact. Multiple interconnected factors come into play in shaping their decisions. For example, farmers' financial resources (including all types of capital) may influence the experiences or expertise they have, such as having a specific adaptation measure on the farm (Luther et al., 2020). Furthermore, if a farmer has directly witnessed a climate emergency event (experiential type), it can influence their perception concerning climate change (cognitive type). Similarly, how individuals perceive climate change may also determine whether they have already adopted specific adaptive measures rooted in prior experiences (Lujala et al., 2015). Hence, this complex interplay between different drivers and perceptions significantly shapes farmers' decision-making processes regarding adapting to climate change.

3.3. Discussion

The country with the highest contribution of research related to farmers' adaptive behavior to climate change was Iran. This can be attributed to the significant pressures on the country's water resources. Of the fourteen studies reviewed, nine focus specifically on particular events, especially droughts. For instance, temperature increases ranging from 2.5 °C to 5 °C have been observed in Iran between 1960 and 2005 (Azadi et al., 2019a), along with twenty-three consecutive years of reductions in rainfall (Zobeidi et al., 2016). These effects have also become visible in the agricultural regions of the country, such as Kerman province (Asrari et al., 2022).

However, this trend is evident in the rest of the studies as well, with the vast majority of adaptation phenomena being related in some way to water availability, highlighting its role as a key driver of adaptation (Adam et al., 2018; Burchfield and Poterie, 2018; Theron et al., 2022). Similarly, access to water, even when regulated by the government, significantly influences farmers' decision-making processes, including decisions to abandon agriculture (Alston et al., 2018). Furthermore, research indicates that regions with well-developed water management infrastructure are better equipped to adopt innovative agricultural practices, thereby enhancing resilience to climate change (Wu et al., 2023).

Understanding these decision-making processes is critical, and several theories can provide insights into how farmers perceive and respond to these threats. The most common theory employed in the reviewed articles was PMT, which originated in 1975 as an explanation for people's responses to fear appeals (Rogers, 1975). This theory has been used to investigate how farmers perceive climate risks and their willingness to incorporate adaptive behaviors (Grothmann and Patt, 2005; Purwanti et al., 2023; Villamor et al., 2023). The primary focus of PMT is the cognitive processes of threat appraisal and coping appraisal. Threat appraisal involves evaluating the severity of a potential threat and one's vulnerability to that threat; meanwhile, coping appraisal assesses the efficacy of the recommended preventive behavior and the individual's self-efficacy in executing that behavior (Rogers, 1983). These processes assess how individuals perceive threats and determine their intention to modify behavior accordingly based on those perceptions (Maddux and Rogers, 1983). PMT has been widely applied across various fields to understand how people respond to health risks, environmental hazards, and other threats. Comprehending how farmers process climate change risks is crucial because it relates directly to their learning and reasoning processes. Farmers' perceptions of the relative benefits, costs, and risks associated with a given practice influence their intention to adopt it or not (Castro Campos, 2022; Dessart et al., 2019). Furthermore, the impact of farmers' beliefs is not homogeneous across all types of adaptation practices, their responses to climate events vary depending on the nature of their beliefs and how they perceive the potential effects of these events (Zhang et al., 2020).

Our review has identified a wide range of adaptation strategies, demonstrating the diverse approaches farmers take to cope with climate change. The prominence of farming practices such as soil conservation, input management, and the use of adapted crops highlight a strong emphasis on sustainable agricultural techniques to maintain productivity even in challenging conditions (Fantappiè et al., 2020). Agroecological methods appear to be crucial for building resilience, as they play an essential role in enhancing soil health and optimizing resource use (Altieri and Nicholls, 2017). The frequent reference to irrigation improvements highlights the important role of efficient water management in agriculture; especially since improved irrigation practices are pivotal in mitigating water scarcity impacts (Fischer and Sanderson, 2022).

Furthermore, implementing financial measures like obtaining insurance and accessing credits demonstrate the important function of financial mechanisms in mitigating climate-related risks. These strategies offer a safety net that enables farmers to make investments in adaptive measures and recover from climatic shocks (Hirons et al., 2018). Livestock-related adjustments, such as the management and sale of livestock, provide flexibility and additional income streams that are essential for supporting livelihoods during climate variability (Amfo and Ali, 2020; Radolf et al., 2022). Diversifying income with off-farm jobs also highlights a strategic shift to decrease dependency on agriculture, ultimately improving overall household resilience (Kumar et al., 2023; Rahman et al., 2023). Migration and community-based adaptations emphasize the broader social and collective dimensions of resilience, showing the importance of social networks and community actions in climate change adaptation (Chaudhury et al., 2017; Wang et al., 2021).

The results show the interplay of different elements influencing farmers' adaptive behaviors toward climate change, emphasizing the need for a comprehensive approach to addressing these drivers. Cognitive elements, which were the most frequently cited, highlight the importance of psychological processes in farmers' decision-making. This finding is consistent with previous research suggesting that farmers' beliefs and perceptions about climate change significantly influence their willingness to adopt adaptive measures (Feola et al., 2015; Talanow et al., 2021). The significance of cognitive drivers suggests that improving farmers' comprehension and knowledge of climate risks may be a key approach to promoting adaptive behavior (Esham and Garforth, 2013; Yazdanpanah et al., 2024).

In addition to cognitive factors, socio-demographic characteristics - such as age and education level - were identified as significant drivers. This aligns with prior research suggesting that younger and more educated farmers are more likely to adopt innovative practices (Ali and Erenstein, 2017; Doherty et al., 2021). These results suggest that targeted interventions focusing on younger and more educated farmers could be more effective in promoting adaptation. Furthermore, situational drivers such as market conditions and institutional support emphasize the external influences on farmers' adaptive capacities (Kassie et al., 2013; Marie et al., 2020; Thi Lan Huong et al., 2017). Additionally, strong social connections are important and can contribute to more effective adaptive responses (Esham and Garforth, 2013; Wood et al., 2014). Farm-specific characteristics, such as size, highlight the diversity in adaptive capabilities, as larger farms typically have greater resources for implementing adaptive strategies (Jha and Gupta, 2021; Ochieng et al., 2017). These insights emphasize the need for a multifaceted approach that incorporates cognitive, socio-demographic, situational, and financial factors to effectively understand farmers' adaptive behaviors.

4. Case study of Colombia

The 3F-SEC framework illustrates and summarizes the different drivers that influence farmers' decision-making process to adapt to climate change (Fig. 5). These factors have a complex interaction in which there is no single unidirectional effect. The reciprocity and complexity of these interactions result in a network of relationships that translate into diverse impacts on farmers, depending on their specific circumstances. To illustrate this, we include the cases of four different farmers in central Colombia and how they adapt to climate change. These types of farmers were identified during fieldwork in the region from October 2022 to February 2023.

Farmer 1 is an eighty-year-old male living in a village where no weather emergencies have been reported. He perceives himself as less vulnerable to climate change and does not see it as a threat to him or his farm operations. Consequently, he has not taken any steps to adapt his farming practices and reports no intention to do so. This mindset can be attributed to his limited exposure to emergencies attributed to climate change, which affects his perception and reduces his motivation for adaptation. However, younger farmers in the same village who have had similar experiences show a greater tendency to adapt their farming practices, so his advanced age may be another crucial factor in his low willingness to adapt.

Within the decision-making process, different authors have studied how age influences it (Huang et al., 2015; Josef et al., 2016; Rolison et al., 2013; Tymula et al., 2013; S. Wood et al., 2005). Similarly, older adults are more risk-averse than younger people when in uncertainty scenarios (Zamarian et al., 2008). However, people often manifest this risk aversion by simply avoiding making a decision (Blanchard-Fields et al., 2007; Mather, 2006). This can be directly associated with elderly

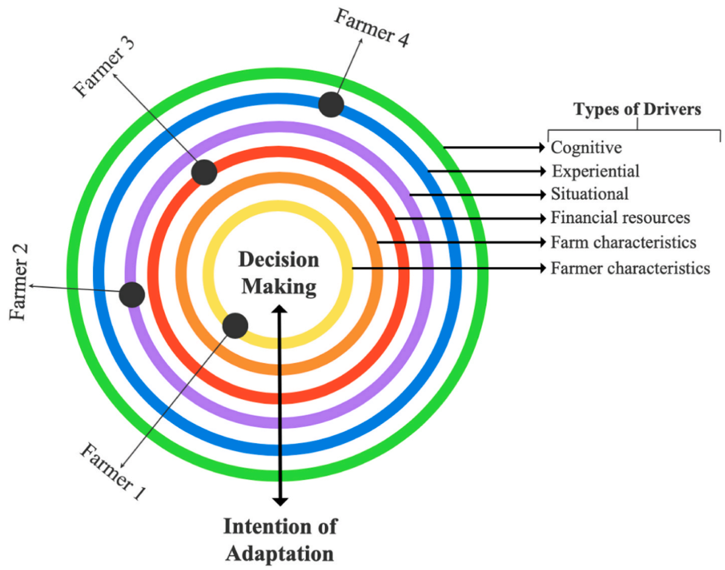

Fig. 5. 3F-SEC Framework for the case of Central Colombia.

farmers avoiding the decision of whether or not to adapt their farming operations to climate change.

The decision-making process of elderly adults differs significantly from that of younger adults (Sproten et al., 2018). Older adults have been found to involve emotions and affective processes within their decision-making, which results in postponing decisions (Zamarian et al., 2008). Research shows that they tend to rely more on their emotional processes than on analytical thinking; similarly, they also tend to remember their past choices more favorably, ignoring any negative aspects they may have encountered while making decisions (Mather and Johnson, 2000). Consequently, this aversion to decision-making among elderly adults may lead them to refrain from taking appropriate measures, such as adapting to climate change.

Other studies have analyzed other variables in addition to age. For instance, it has been found that although age has a negative correlation with the adoption of measures, participation in groups, such as cooperatives, has a positive correlation (M. Li et al., 2021). An example is the case of Farmer 2, a woman in her sixties who experienced two droughts in 2013 and 2016 that were considered emergencies. Thanks to her active participation in a farmers' association in the municipality, she learned to use agroforestry practices to mitigate the impacts of droughts on her farm.

Community relationships are responsible for influencing farmers' decision-making processes. For example, research has shown how these relationships promote social resilience within communities (Tompkins and Adger, 2004). Similarly, the influence of associations, such as cooperatives, on farmer behavior and decision-making has been studied before (Abebaw and Haile, 2013; Hao et al., 2018; Manda et al., 2020; Wossen et al., 2017). Since there is an interrelationship between institutions and people in adaptive processes (Adger, 2003), it is to be expected that associations influence the adaptive measures that farmers choose. Moreover, when people have had experiences that affect the whole community, such as droughts, they are important in forming the collective memory of the community, as it influences the formation of social networks and collaborative efforts to overcome similar situations in the future (Folke et al., 2005).

Farmer associations play a crucial role in influencing the adoption of measures by farmers through the active sharing of information (Abdulai, 2016). Farmers often rely more on their respective associations for advice and support than on extension services (Al Zadjali et al., 2013). This is even more evident when the main role of the associations is to promote innovation and provide more access to technologies and inputs (Chagwiza et al., 2016). For this reason, it is more likely that one of the recommended measures will be adopted when belonging to an association (Abdulai and Huffman, 2014; Ji et al., 2019). These results highlight the importance of agricultural association membership in the decision-making process.

On the other hand, it has been shown that people from lower socioeconomic backgrounds and women tend to have a lower capacity to adapt to climate change (Ranasinghe et al., 2023). Likewise, it has been found that there is a positive correlation between indicators of financial status, such as per capita income, and the adoption of new agricultural practices (Andaregie and Astatkie, 2021; Kisaka-Lwayo, 2008; Singh et al., 2018; Tompkins and Adger, 2004). Farmer 3, who is a seventy-two-year-old woman with a high income, exhibits this behavior. Although she has not had any direct experience with climatic emergencies on her farm, she sees her farming operations as being threatened by climate change and feels that her farm is under threat. Based on her perception, she is determined to adapt her practices to counteract the effects of climate change, such as the use of organic fertilizers and agroforestry practices.

Although income is discussed as a driver of farmer behavior, it is not only limited to farm income; non-farm income has also been found to be positively correlated with adopting new farming practices (Boulay et al., 2012). The same is true for proxy variables for wealth, such as farm size (Luther et al., 2020). Similarly, income and experience have been found to significantly influence preferences for adaptive practices (Ayanlade et al., 2018). Income serves as a bridge between several factors in this context. For example, farmers with higher incomes have better access to credit and tend to participate more in agricultural associations; this in turn translates into greater access to extension services and inputs from these associations, such as improved seeds (Mugumaarhahama et al., 2021).

Financial aspects, thus, play an important role in decision-making.

Farmers are often constrained by their income level, as their financial status limits the possibility of adopting certain measures. This is because, in many cases, adapting requires an initial investment that farmers do not have access to (Pye et al., 2020). As a result, those who do adapt tend to have higher incomes than those who do not (Alidu et al., 2022). Moreover, some authors have even suggested that to incentivize adoption, per capita income should be increased (Borchers et al., 2014). It is evident, then, that financial considerations strongly influence decision-making in farming communities.

Weather emergencies impose additional pressures on farmers, underscoring the necessity for them to adapt to these altered conditions at both individual and community levels (Budhathoki et al., 2020). Numerous research studies have explored how encounters with climate emergencies influence farmers' decision-making processes regarding the adoption of adaptive measures on their farms (Brügger et al., 2021; Marlon et al., 2019; Myers et al., 2013; Ogunbode et al., 2019). Farmer 4 is a man in his forties who lives in a village where several landslides have been experienced because of heavy rains. The geographic proximity of these events has reduced his psychological distance from climate change. This means that he believes that climate change is already occurring in his village and will affect farmers like him. As a consequence, this farmer has a high intention to adapt to climate change. For example, he commented on diversifying his production and a particular interest in planting more trees on his farm and the possible construction of a retaining wall.

When farmers experience climate emergencies, emotional reactions can be triggered that prompt them to take direct action to mitigate potential effects within their farming operations (Demski et al., 2017). Given this, it is necessary to understand these experiences, as they significantly influence farmers' decisions regarding climate change adaptation (Boissière et al., 2013). Furthermore, these individual experiences and their perceived spatial distance to the effects of climate change play an important role in farmers' behavior (Asuero et al., 2012; Lujala et al., 2015). Further understanding how individual factors contribute to farmers' responses is, therefore, essential for effective planning and implementation strategies aimed at enhancing climate change adaptation among agricultural communities.

When individuals encounter a situation, they engage in a process of comparative analysis between their present circumstances and previous experiences. This process facilitates the examination and assessment of the current situation (Marx et al., 2007). When farmers perceive differences between current conditions and their experiences, they attribute these changes to the impact of climate change on their farming operations. In addition, the frequency with which these climate changes occur influences the farmer's decision-making process. First, it helps them determine whether climate change is occurring (Weber, 2010). Second, the more frequent the climate anomalies, the more skillful farmers will be in selecting the most appropriate measure for each event they experience (Enete et al., 2016).

Our research results reveal the complex interplay of drivers influencing farmers' decision-making on climate change adaptation. Farmer 1's reluctance to adapt, despite advanced age, reflects the combination of perceived vulnerability and exposure to climate-related emergencies. In contrast, Farmer 2's active involvement in a local farmers' association highlights how community relationships promote adaptive behaviors; for example, adopting agroforestry practices during droughts. Additionally, financial considerations influence Farmer 3's willingness to adapt due to her high income, underscoring the link between socioeconomic status and adaptation behaviors. Furthermore, Farmer 4's increased desire to adapt after experiencing events like landslides emphasizes how direct experience shapes these behaviors. Recognizing these dynamics can aid policymakers in devising tailored strategies for encouraging climate change adaptation within agricultural communities.

5. Conclusions

Growing concern about the potential effects of climate change on the agricultural sector has led to an increase in research on farmers' behavior and decision-making on adaptation. In light of this, the present study has set forth two key objectives. This study aimed to identify the multitude of factors that significantly influence farmers' decisions regarding the adoption of climate change adaptation strategies, and to shed light on the complex interrelationships of these drivers amid uncertainties related to climate change. Based on a systematic literature review of 87 articles on farmer adaptation to climate change, we propose the 3F-SEC framework to provide a holistic view of all factors influencing farmer behavior. We identify 179 factors categorized into cognitive elements, situational factors, socio-demographic characteristics, and farm-specific attributes as prominent drivers influencing farmers' adaptive behavior.

Cognitive drivers, including beliefs about climate change consequences, are particularly significant, underscoring the role of psychological processes in adaptation. Socio-demographic characteristics such as age and educational level, as well as situational factors like market conditions and institutional support, also play critical roles. The complex interdependence of these factors highlights the need for integrated approaches to understanding and supporting farmers' adaptation intentions. The cases of four farmers in central Colombia illustrate how these factors interact in diverse contexts, reinforcing the necessity of context-specific interventions. This highlights that farmers' decision-making processes are influenced by a complex interplay of these factors, creating diverse impacts depending on individual circumstances.

Although the study is based on 87 articles from the WOS database, future research could expand the scope to include systematic literature reviews from other databases such as Scopus. Additionally, integrating supplementary case studies from different regions would facilitate a more comprehensive comparison and extension of insights from the 3F-SEC framework. This approach would contribute to a deeper understanding of the multifaceted drivers influencing farmers' adaptive behavior in response to climate change.

Policymakers need to prioritize strategies that address the complex nature of farmers' adaptive behavior as outlined in the 3F-SEC framework. If the goal is to strengthen cognitive involvement, then customized educational initiatives and improved access to financial support, such as credit and insurance, could be facilitated. Additionally, enhancing situational factors by developing robust water management infrastructure to address both droughts and flooding, along with facilitating market access will significantly impact farmers' adaptive capacities. By addressing these key areas, policymakers can create an environment that enables farmers to make informed and effective adaptation decisions, potentially enhancing the sustainability of agricultural practices in the face of climate change.

CRediT authorship contribution statement

Alexander Cano: Writing – original draft, Investigation, Formal analysis, Data curation. **Bente Castro Campos:** Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Alexander Cano reports financial support was provided by German Academic Exchange Service. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jrurstud.2024.103343.

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Chapter 3: The Role of Financial Literacy in Climate Mitigation - The Case of Central Colombia

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The role of financial literacy in climate mitigation: The case of central Colombia

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A R T I C L E I N F O

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A B S T R A C T

Understanding how financial literacy shapes borrowing decisions in the face of climate shocks is crucial for enhancing farmers' resilience, ensuring food security, and reducing rural poverty. This study investigates how financial literacy influences the borrowing behavior of farmers in central Colombia when facing adverse weather events such as landslides and droughts. Using a mixed-methods approach, we analyze survey data from 360 farms through logit regressions, assessing financial literacy across four key components and examining loan sources. Qualitative interviews with the same sample complement the analysis, providing deeper insights into farmers' decision-making processes. Drawing on prospect theory, we incorporate perceived risks into our framework to better explain borrowing behavior. The results show that financially literate farmers are more likely to take loans, including those from non-financial sources. However, among financially literate farmers, older individuals are less likely to borrow from non-financial lenders. Additional factors, such as risk attitude and financial constraints, also play a significant role. Interviews reveal that farmers prioritize subjective perceptions, such as convenience, trust, and speed, when choosing non-financial lenders. These findings underscore the importance of financial literacy programs tailored to farmers' risk perceptions and borrowing preferences, offering valuable insights for policymakers seeking to improve credit access and climate resilience in rural communities.

1. Introduction

Given that agriculture relies on weather patterns and natural resources, it is considered highly vulnerable to weather shocks (Muench et al., 2021; Skevas et al., 2022). The significant threats placed on agriculture by climate include crop failures, reduced yields, and soil degradation (Skevas et al., 2022). This has led to a growing recognition of the need for adaptation in the agricultural sector to address the social, economic, and ecological repercussions of climate (Papaioannou and de Haas, 2017). Researchers are increasingly studying the role of adaptation in mitigating these impacts on farmers' livelihoods (Ayal et al., 2021; Burnham and Ma, 2017; Wang et al., 2013).

Adaptation plays a crucial role as it helps to assess whether social systems are becoming more resilient to weather shocks (Campos

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et al., 2014). Within the range of adaptation strategies, financial resilience is essential for farmers to minimize their vulnerability to climate and overcome the associated challenges. Accessing financial support, such as obtaining loans, can help offset the negative impacts of climate and alleviate financial constraints, enabling them to invest in necessary resources (Azadi et al., 2019; Fenton et al., 2017; Möllmann et al., 2020; Ndlovu, 2019). Conversely, limited access to loans presents a major barrier to farmers' ability to adapt (Opiyo et al., 2016; Piya et al., 2013; Zobeidi et al., 2021). This study examines the impact of financial literacy on farmers' borrowing behavior in central Colombia amid adverse weather events like landslides and droughts.

Financial literacy plays a pivotal role in financial behavior. The Organization for Economic Co-operation and Development (OECD, 2020, p. 6) defines it as a "combination of financial awareness, knowledge, skills, attitudes and behaviors necessary to make sound financial decisions and ultimately achieve financial well-being". Moreover, financially literate people can compare financial products and services from different sources, enabling them to make the best decisions for their needs (OECD, 2023). Low levels of comprehension regarding financial concepts are reflected in a limited awareness and adoption of new financial products (Berry et al., 2018; Sarfo et al., 2023), as well as low involvement in the financial system as a whole (Grohmann et al., 2018). Research also indicates that individuals with low financial literacy are more prone to incurring higher costs associated with credit, such as payday loans and home-collected credit (Disney and Gathergood, 2013). Many people exhibit challenges in fully grasping the concept of risk and its relationship with return, thus jeopardizing the financial well-being of households (Lusardi, 2015; Sekita, 2011). Likewise, those who are financially literate tend to avoid high-risk investment products (Gui et al., 2021; Schicks, 2014) and tend to seek more information and engage in economic discussions, so their behavior can adapt according to the situation (Xu et al., 2022).

A comprehensive understanding of finance plays a crucial role in guiding individuals toward making optimal financial decisions (Klapper and Lusardi, 2020). Without a solid grasp of basic financial principles, people may struggle to make well-informed choices, especially when it comes to selecting loans. Consequently, those with limited financial literacy are more likely to seek loans from non-financial sources such as family and friends (van Rooij et al., 2011). Building on this idea, Klapper and Lusardi (2020) highlight the positive correlation between financial knowledge and financial resilience; suggesting that individuals with higher levels of financial literacy are better equipped to navigate through various financial challenges. This is consistent with findings suggesting that individuals with improved financial literacy tend to make smarter and more effective financial decisions and financial well-being (Fong et al., 2021; Hwang and Park, 2023).

The literature on financial literacy is mainly dominated by business management and accounting (Idris et al., 2023). For instance, studies by Adomako et al. (2016), Hossain et al. (2023), and Owusu et al. (2019) have examined how financial literacy contributes to business growth. Similarly, Brownhilder Ngek (2016) and Li and Qian (2019) have explored how financial literacy impacts firms' performance. Additionally, many studies investigate the relationship between financial literacy and financial inclusion, as seen in the works of Mindra and Moya (2017) and Rastogi et al. (2021). While financial knowledge has been extensively studied, its role in shaping farmers' financial behavior during climate shocks remains unexplored. Investigating this relationship is essential to understanding how financial literacy affects farmers' ability to navigate financial challenges, access resources, and build long-term resilience in the face of environmental uncertainties. To fill this knowledge gap, we analyze the following research questions (1) To what extent does the financial literacy of farmers affect their decision to borrow money when facing operational and financial challenges due to weather shocks affecting their farm operations? (2) How does financial literacy influence farmers' selection of loans from non-financial alternatives like friends, family, and moneylenders? (3) In what ways does the interplay between financial literacy and age impact the choice of loans from non-financial sources for farmers?

To address these questions, our primary aim is to acquire a comprehensive understanding of individuals' decision-making processes. To achieve this, we draw upon prospect theory, which explains how subjective assessments influence financial decisions. When it comes to weather events, prospect theory suggests that farmers may evaluate the risks related to crop damage or yield losses by considering potential losses and the costs of risk management options (Rajeev and Nagendran, 2023). This suggests that individuals may be more sensitive to losses during adverse weather events, leading to changes in risk preferences and decision-making strategies (Haer et al., 2017; Ihli et al., 2022).

To delve deeper into the determinants of loan acquisition and the specific mechanisms underlying decisions concerning non-financial sources, we employ mixed methods. This entails a quantitative component utilizing logit regression models, complemented by a qualitative aspect involving content analysis of interviews conducted with the study population in central Colombia. The expected new insights gained by applying this mixed method approach include a better understanding of the complex nature of farmers' borrowing decisions. Specifically, the quantitative analysis identifies the significant relationships between financial literacy, demographic factors, and loan choices during weather shocks. Meanwhile, the qualitative component delves into the subjective perceptions and reasoning processes of farmers, capturing elements that cannot be fully explained by the econometric models alone. This methodological integration provides a deeper, more holistic perspective on how financial literacy shapes borrowing behavior, and uncovers the underlying mechanisms that influence these decisions. Additionally, we incorporate a segment addressing the potential endogeneity of our models and the inadequacy of instrumental variables to rectify it, alongside a robustness check of our findings.

The contributions of our study lie in providing a novel perspective on the role of financial literacy in farmers' borrowing decisions. While the literature has extensively examined financial literacy in the context of business management and financial inclusion, its specific impact on loan acquisition in agricultural settings under adverse climatic conditions remains an underexplored area. By addressing this gap, our study not only enhances the understanding of financial decision-making in rural economies but also provides empirical evidence that can inform policies aimed at strengthening farmers' financial resilience. Moreover, by integrating quantitative and qualitative approaches, we offer a more comprehensive perspective that goes beyond statistical associations, allowing us to identify the underlying mechanisms influencing farmers' financial choices. These findings can contribute to the design of targeted interventions that improve financial literacy and access to credit, ultimately supporting farmers in building resilience to climate shocks.

This article is structured as follows. Section 2 provides the theoretical background of prospect theory and its application to financial literacy used in this research. In sections 3 and 4, we detail the quantitative and qualitative methods, respectively. Section 5 presents the results of the proposed models, mechanisms, and interviews. Following this, in section 6, we discuss the effects of financial literacy on the borrowing decisions of farmers in central Colombia. Finally, we draw conclusions in section 7.

2. Theoretical background

When individuals are faced with the decision of whether to take out a loan and, if so, which lender to choose, the complexity of this decision-making process often challenges traditional notions of rational behavior (Tversky and Kahneman, 1986). The prospect theory provides a framework for understanding human behavior in financial decision-making (Kahneman and Tversky, 1979). It explains that individuals' choices in financial matters are not strictly guided by rationality but rather influenced by their subjective assessments, which are not necessarily aligned with the framework of expected utility theory (De Martino et al., 2006; Ruggeri et al., 2020). However, financial literacy plays a crucial role in shaping these subjective assessments, influencing whether individuals rely on cognitive biases or make more informed financial decisions. Integrating prospect theory with financial literacy explains borrowing behavior by showing how individuals perceive financial risks and how their knowledge influences decision-making. Prospect theory highlights that borrowers evaluate gains and losses relative to a reference point, often leading to risk-averse or risk-seeking behaviors. Financial literacy moderates these biases by enabling better debt evaluation and reducing irrational choices.

According to Kahneman and Tversky (2000), decisions under risk are a choice between prospects, which is a contract that yields an outcome x_i with a probability p_i, where the sum of all the probabilities is equal to 1. The authors explain that the overall utility of a prospect is the expected utility of its outcomes

$$U(x_1, p_1; \ldots; x_n, p_n) = p_1 u(x_1) + p_n u(x_n) \tag{1}$$

In addition, the expected utility theory assumes risk aversion and that the utility function is concave $u''(x) < 0$. In contrast, in prospect theory, the value function captures the idea that people evaluate outcomes relative to a reference point and exhibit diminishing sensitivity to gains and losses:

$$V(x, p; y, q) = \pi(p)\nu(x) + \pi(q)\nu(y) \tag{2}$$

Where π and ν are two scales, p, and q are the probabilities, and x and y are the outcomes. π is associated with every probability and reflects the impact of p on the overall value of the prospect. Meanwhile, ν assigns to each outcome x a number representing the subjective value of that outcome. According to this, attitudes towards risk are determined jointly by π and p, and not solely by the utility function (Kahneman and Tversky, 2000).

Understanding the impact of these deviations from the expected utility theory on financial decisions becomes apparent when examining individuals' preferences for loan types. For instance, individuals might assign more weight to the potential risks of default or fluctuations in interest rates when comparing types of loans (Kushawaha and Sharma, 2024). Examining decision weighting through the perspective of prospect theory helps elucidate how perceived risks influence individuals' preferences among various loan options (Brick and Visser, 2015; Mori et al., 2009). Moreover, loss aversion and the imbalance between gains are significant in influencing people's preferences (Visser et al., 2020). Individuals often exhibit more risk aversion towards potential losses, such as high-interest payments or default risk, compared to their desire for an equivalent gain (Bylander, 2015; van Winsen et al., 2016). While prospect theory explains how subjective risk affects borrowing behavior, financial literacy plays a crucial role in determining those assessments. For example, individuals with higher financial literacy are better equipped to weigh financial risks (Akhtar and Malik, 2023; Bateman et al., 2015; Harahap et al., 2022).

Financial literacy moderates how individuals interpret the subjective risk assessments outlined in prospect theory. Individuals with higher financial literacy are more likely to accurately assess the benefits and risks associated with different credit sources and to understand loan conditions, repayment structures, and the implications of interest rates (Markle, 2019; Sol Murta and Miguel Gama, 2022; Su et al., 2024). For example, financially literate individuals may recognize the advantages of structured repayment plans in formal loans, while those with lower financial literacy might avoid them due to concerns about penalties, even if informal credit options present higher risks and cumulative costs (Huston, 2012; Kim and Lee, 2018; Sol Murta and Miguel Gama, 2022).

By incorporating prospect theory into our framework, we gain a deeper understanding of how farmers perceive and respond to borrowing decisions. Prospect theory suggests that people do not evaluate risks purely rationally; instead, their decisions are influenced by loss aversion and probability weighting. Those with lower financial literacy may be more susceptible to distortions in risk perception, whereas financially literate individuals can better contextualize financial risks and opportunities. This perspective helps explain variations in borrowing behavior and credit preferences, leading to distinct preferences for financial versus non-financial credit sources.

3. Quantitative methods

To comprehensively analyze the relationship between financial literacy, borrowing decisions, and loan source selection among farmers, we employ a mixed methods design that integrates quantitative and qualitative approaches (Creswell and Plano Clark, 2017; Vogl, 2023). This approach allows us to capture both statistical patterns and contextual insights, providing a more nuanced understanding of farmers' financial decision-making in response to weather shocks.

Specifically, our study addresses the following research questions (1) To what extent does the financial literacy of farmers affect their decision to borrow money when facing operational and financial challenges due to weather shocks affecting their farm operations? (2) How does financial literacy influence farmers' selection of loans from non-financial alternatives like friends, family, and moneylenders? (3) In what ways does the interplay between financial literacy and age impact the choice of loans from non-financial sources for farmers? Fig. 1 outlines the methodological framework, which integrates these research questions into a structured analysis. The subsequent sections provide a detailed explanation of the analytical components of our study, and the qualitative approach is explained in section 4.

3.1. Data

To address the research questions, data were collected through a survey and interviews with farmers in the central region of Colombia, focusing on their experiences with extreme weather events and borrowing behavior. Initially, a list of all the villages in the three departments that make up the central region of Colombia was obtained from public records. Using information from the *Gestion del Riesgo de Desastres de Colombia* (UNGRD by its name in Spanish), all the villages that had experienced landslides and droughts from 2005 to 2021 were identified. Villages that had experienced three or more landslides and two or more droughts were pre-selected to ensure a sample representing areas where extreme climatic events are recurrent. From this pre-selection, four villages with landslide experience, four villages with drought experience, and four villages where none of these events occurred were randomly selected (Fig. 2). Furthermore, a random selection process was used to choose 30 farmers in each village.

Between November 2022 and February 2023, a total of 360 farmers were visited and surveyed across the 12 villages. The purpose of the survey was to collect information on the practices and actions taken by farmers to cope with weather shocks on their farms (see Fig. 3), including their financial decisions. Additionally, participants provided information on their socio-demographic characteristics and details regarding their farm operations. Furthermore, the survey included open-ended questions aimed at capturing farmers' experiences and their intentions regarding the utilization of loans for adapting to weather events. Within this, they were asked how they have been affected, both negatively and positively, by the climate. They were also asked what kind of things limit their decision-making within their farms, and mainly why they decide to borrow or not to borrow money from financial and non-financial sources when they were affected by weather shocks.

Farmers were surveyed about their financial responses to the effects of weather effects on their farm operations. The survey focused on whether they had needed to borrow money due to climate-related events. This information was also disaggregated into the different sources of these loans, categorizing them into two groups. The first is loans from financial institutions, such as commercial banks, second-tier banks, agricultural banks, or cooperatives which are regulated by the government through the "*Superintendencia Financiera de Colombia*" (Ley 510, 1999). The second group is loans from non-financial sources, such as relatives, friends, and moneylenders. The latter are not subject to any institutional regulation. Given that only 11 farmers took loans from financial sources, we are focusing our analysis on the loans from non-financial sources. However, while the number is not statistically significant, it holds significant importance due to the underlying reasoning explored through the interviews, which will be discussed in the results sections. The descriptive statistics of the main variables used are summarized in Table 1, along with the socio-demographic and farm characteristics used in the study.

In the context of financial knowledge, we employed the measures proposed in the S&P Global FinLit Survey, which was developed by the Standard & Poor's Ratings Services, Gallup, Inc., the World Bank Development Research Group, and the Global Financial Literacy Excellence Center in 2014.[1] These included a single question for each financial concept: risk diversification, inflation, numeracy, and two questions on compounded interest. If the farmer responds correctly to at least three questions, they are deemed financially literate. In our study, we incorporated not two but only one question concerning compounded interest and adapted the questions to the local context using Colombian pesos (Table 2).

The use of these financial concepts as tools for measuring financial literacy and its subsequent impacts is well-established. These concepts have been applied in previous studies, especially in assessing their impact on the financial well-being of households (Clark et al., 2021; Sekita, 2011; Yakoboski et al., 2020). Furthermore, researchers have employed these financial metrics to investigate how individuals respond financially to specific shocks within their households (Lusardi et al., 2021). Moreover, financial literacy has been recognized as a contributing factor in shaping people's financial behavior (Allgood and Walstad, 2016; Goedde-Menke et al., 2017) and their attitudes toward borrowing (Almenberg et al., 2021).

Finally, the control variables linked to socio-demographic information in Table 1 show that 16.7% of farmers are considered financially literate, with the average age being approximately 50 years old, and almost half (48.3%) selected women as their gender. Most of the farmers have not completed high school, with an average formal education period lasting 6.42 years. In terms of farm characteristics, the average property size is 6.7 ha. We use the altitudes of the farms' locations as a regional control measure since the villages were selected based on their experience with extreme weather events such as droughts and landslides (see Fig. 2). About 42.2% of the farms are located at altitudes higher than 1500 m above sea level.

[1] Source: https://gflec.org/initiatives/sp-global-finlit-survey/(accessed on 01 March 2024).

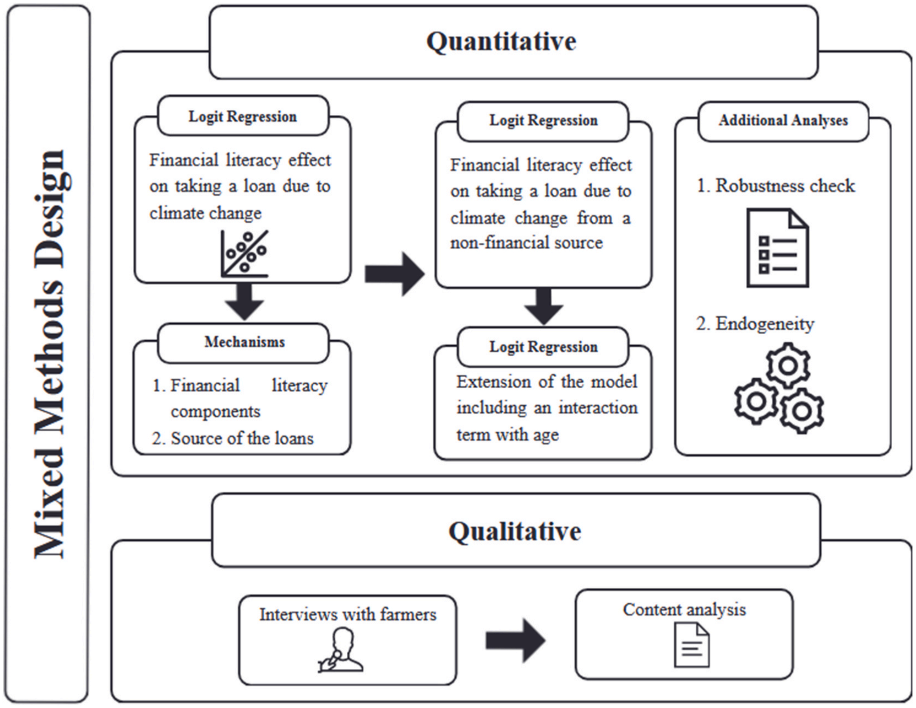

Fig. 1. Methodological framework overview.
Source: Authors.

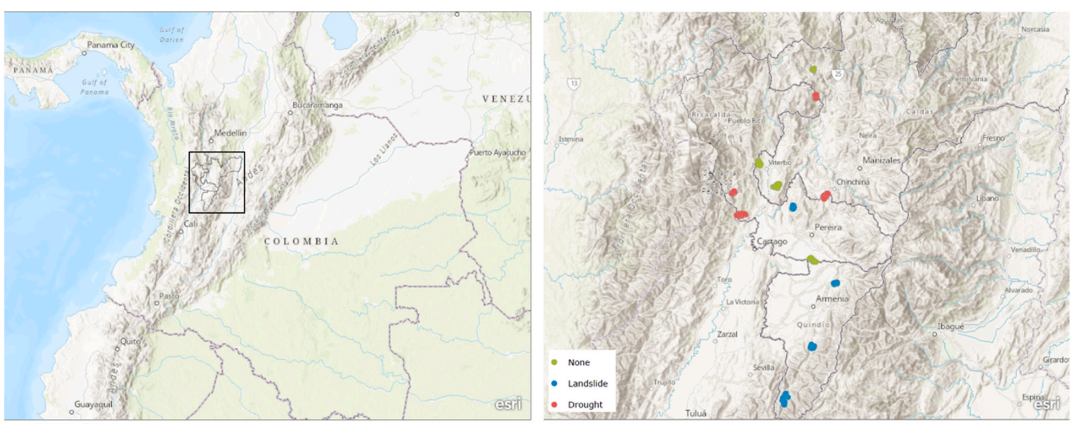

Fig. 2. Research Locations in central Colombia.
Source: Authors.

3.2. Logit models

The logit model is characterized by a binary dependent variable y, taking only two values. In our first model, this variable represents the occurrence of a loan, where a value of 1 means that the farmer i borrowed money as a consequence of a weather shock, while a value of 0 indicates that they did not. To estimate the probabilities, the logit model establishes

Fig. 3. Landslide in central Colombia.
Note: Photo taken during the data collection process for this research in 2022. Location: municipality of Génova, Quindío.
Source: Authors.

$$\Pr(y_i = 1 | x_i) = \Lambda\left(x_i'\beta\right) \tag{3}$$

where Λ is the logistic cumulative distribution function of

$$\Lambda(z) = \frac{1}{(1 + e^z)} \tag{4}$$

where

$$z = \beta_0 + \beta_1 literate_i + \sum_i \beta_i W_i + \sum_i \beta_i X_i + \varepsilon \tag{5}$$

Literate is a binary variable that represents whether farmer *i* is (0) *financially illiterate* and (1) *financially literate*. For a farmer to be considered financially literate, they must have correctly answered at least three of the questions on financial concepts (risk diversification, inflation, numeracy, and compound interest). This benchmark for financial literacy has been previously recognized as a determinant of financial behavior (Allgood and Walstad, 2016; Almenberg et al., 2021; Goedde-Menke et al., 2017).

W_i is the set of control variables regarding their financial perceptions about themselves. The first one is financial constraint which represents if the farmers consider that their lack of money has limited their decision-making. From the perspective of prospect theory,

Table 1
Description and summary statistics of variables.

Variables	Description	Total Sample Mean/Proportion	Total Sample SD	Loans Mean/Proportion	Loans SD	Loan from a Non-Financial Source Mean/Proportion	Loan from a Non-Financial Source SD
Adaptation Measure							
Loan	1 if the farmer obtained a loan as a result of the weather; otherwise 0	0.200	0.421				
Non-Financial	1 if the farmer obtained a loan from a non-financial source as a result of the weather; otherwise 0	0.161	0.368				
Financial							
Literate	1 if the farmer answered 3 or more correct financial literacy questions; otherwise 0	0.167	0.373	0.246	0.434	0.276	0.451
Financial constraint	1 if the farmer considers that their decision-making is constrained by money; otherwise 0	0.497	0.501	0.710	0.457	0.672	0.473
Risk	1 if the farmer responded 5 or more on a scale (1–10) of liking risk; otherwise 0	0.369	0.483	0.493	0.504	0.500	0.504
Mechanism							
Risk Diversification	1 if the farmer answered the question correctly; 0 otherwise	0.503	0.501	0.594	0.495	0.603	0.493
Inflation	1 if the farmer answered the question correctly; 0 otherwise	0.319	0.467	0.377	0.488	0.414	0.497
Numeracy	1 if the farmer answered the question correctly; 0 otherwise	0.325	0.469	0.348	0.480	0.379	0.489
Compound interest	1 if the farmer answered the question correctly; 0 otherwise	0.244	0.430	0.319	0.469	0.328	0.473
Control Variables							
Age	Age of farmer (years)	51.619	16.328	53.493	14.231	51.828	14.021
Age squared	Age square of the farmer (years)	2930.442	1673.890	3061.058	1492.865	2879.310	1433.447
Female	1 if the farmer identifies herself as a female; 0 otherwise	0.483	0.500	0.478	0.503	0.466	0.503
Education	Number of years of formal education	6.425	5.030	5.696	4.081	5.948	4.194
Marital status	1 if the farmer lives together with their partner; 0 otherwise	0.375	0.485	0.319	0.469	0.293	0.459
Income	1 if their income is less than one national monthly wage; 0 otherwise	0.656	0.476	0.667	0.475	0.690	0.467
Farm Size	Size of the farm in hectares	6.742	18.900	5.916	9.381	6.491	10.088
Altitude	1 if the farm is more than 1500 m above sea level; 0 otherwise	0.422	0.495	0.406	0.495	0.379	0.489
Observations		360		69		58	

Source: Authors.

Table 2
Financial literacy concepts.

Financial Concept	Question & Answers
Risk diversification	Suppose you have some money. Is it safer to put your money into one business or investment, or to put your money into multiple businesses or investments? [one business or investment; **multiple businesses or investments**; don't know; refused to answer]
Inflation	Suppose over the next 10 years the prices of the things you buy double. If your income also doubles, will you be able to buy less than you can buy today, the same as you can buy today, or more than you can buy today? [less; **the same**; more; don't know; refused to answer]
Numeracy	Suppose you need to borrow 100,000 Colombian pesos. Which is the lower amount to pay back: 105,000 Colombian pesos or 100,000 Colombian pesos plus three percent? [105,000 Colombian pesos; **100,000 Colombian pesos plus three percent**; don't know; refused to answer]
Compound interest	Suppose you put money in the bank for two years and the bank agrees to add 15 percent per year to your account. Will the bank add more money to your account the second year than it did the first year, or will it add the same amount of money both years? [**more**; the same; don't know; refused to answer]

Source: Authors based on the S&P Global FinLit Survey.

financial constraints may influence risk behavior, leading some individuals to avoid borrowing due to loss aversion, while others take greater risks in an attempt to overcome financial hardship (Kahneman and Tversky, 1979). The second variable is risk, indicating if the farmers gave a value of 5 or higher on a scale of 1–10 on how much they like risk. This variable represents the farmers' risk attitudes, which, according to prospect theory (see Section 2), deviate from the expected utility theory framework (Ruggeri et al., 2020). Specifically, individuals may exhibit loss aversion, overweight small probabilities, and underweight large probabilities, leading to risk-averse or risk-seeking behavior depending on how loan-related decisions are framed as potential gains or losses (Kushawaha and Sharma, 2024; Mori et al., 2009; van Winsen et al., 2016). X_i is the set of control variables for individual characteristics (age, age square, gender, education, marital status, and income), and farm controls (farm size and location altitude of the farm).

In order to get a deeper understanding on the role of financial literacy in borrowing, we include two mechanisms. The first is a summary of the concepts that make up financial literacy (risk diversification, inflation, numeracy, and compound interest) and the degree of farmers' knowledge of each of them. The second is a summary of the amount of loans farmers have obtained as a result of a weather shock and the source of each loan.

As a continuation of the first model, we want to focus on the effect of financial literacy only on loans from non-financial sources. For this, we modify the dependent variable z in equation (5) for y

$$y = \beta_0 + \beta_1 literate_i + \sum_i \beta_i W_i + \sum_i \beta_i X_i + \varepsilon \tag{6}$$

Where y takes a value of (0) *if farmer i did not borrow money* or (1) *if farmer i borrowed money from a non-financial source due to a weather shock*. For the third research question where we study the interplay between financial literacy and farmers' age, we include in equation (6) an interaction term between these two variables

$$y = \beta_0 + \beta_1 literate_i + \beta_2 literate^{*}\ age + \sum_i \beta_i W_i + \sum_i \beta_i X_i + \varepsilon \tag{7}$$

Since it is not possible to directly interpret a logit model's parameters, it is necessary to estimate the marginal effects (Greene, 2012). The marginal effect represents the change in the probability of the ith regressor

$$ME_i = \frac{\partial \Pr(y = 1|x)}{\partial x_i} = \phi(x'\beta)\beta_i \tag{8}$$

Where ϕ denotes the probability density function of the logistic distribution. This calculation clarifies how a one-unit change in the regressor x_i affects the probability of the outcome, holding all other variables constant.

We conducted various tests to assess the validity and robustness of our models. A Wald test was performed both individually and jointly for the key predictors —financial literacy, financial constraint, and risk— confirming that these variables significantly influence loan uptake ($p < 0.05$). In the final model, we also tested the interaction between financial literacy and age, which exhibited borderline significance ($p \approx 0.059$), suggesting that the effect of financial literacy may vary by age. Additionally, the Hosmer-Lemeshow test yielded p-values higher than 0.05, indicating a good model fit and that the estimated probabilities align well with actual loan uptakes. Lastly, the Pregibon-Link test showed no evidence of model misspecification, as the p-values for the squared predicted values were consistently greater than 0.05, confirming that the functional form of the model was correctly specified.

3.3. *Potential endogeneity*

Endogeneity arises when an independent variable is correlated with the error term of the model. According to Lal et al. (2024), there may be different reasons for this, such as (1) there are omitted variables in the model that are correlated to both the dependent and independent variables, (2) measurement error in the independent variable, or (3) simultaneity or reverse causality between independent and dependent variables. As a result, the parameters are potentially inconsistent and biased. One of the ways to deal with endogeneity is by incorporating Instrumental Variables (IVs); these are by default correlated with the endogenous explanatory variable but not with the error term.

One method to correct potential endogeneity using IVs is the control function approach. Wooldridge (2015) proposes a first stage where these instruments and other exogenous variables are used to regress the endogenous variable. The residuals from this regression capture the endogenous component correlated with the error term. These residuals, serving as control functions, are included in the second stage regression, where the dependent variable is regressed on all explanatory variables, including the endogenous variable, and the residuals obtained from the first stage. By incorporating the control functions in the second stage, the endogenous explanatory variables effectively become exogenous, leading to more accurate and unbiased estimates in the main equation.

However, it is important to acknowledge a limitation of our study regarding the potential endogeneity of financial literacy in our model. For instance, previous research used the entire population's financial literacy as an IV; if relatives and neighbors know these concepts and use them appropriately when borrowing, the rest of the population may imitate these choices (Xu et al., 2022). Unfortunately, such data is not available in our study area. Klapper et al. (2013) suggest exposure to financial information as an IV for financial literacy. Following this suggestion, we first use the distance of the farms to the nearest agricultural bank. Nonetheless, this variable was not correlated with financial literacy. Using the financial inclusion database of the "*Superintendencia Financiera de Colombia*" we incorporate other municipal variables that might expose the population to financial information such as the number of banks, total loans - for consumption and housing -, and total savings accounts. Likewise, these variables were evaluated by taking into account the municipal, rural, and educated population totals. Unfortunately, none were suitable IVs.

A recent systematic review of instrumental variable studies highlights similar challenges faced across various disciplines in identifying suitable instruments, establishing that IVs are rare and difficult to find (Lal et al., 2024). Given our situation, we prefer to present our original results rather than attempt to treat endogeneity with inadequate instruments, as doing so could lead to more biased or imprecise parameter estimates, thereby compromising the validity of our analysis. Alternatively, we employ a mixed method approach, incorporating qualitative findings from interviews to elucidate the specific reasons behind loan-making decisions. This offers a deeper understanding of the underlying decision dynamics.

4. Qualitative methods

To complement the quantitative analysis, we collected qualitative data from the same sample of individuals used in the logit regressions. The qualitative component involved semi-structured interviews designed to capture participants' perspectives regarding weather conditions and their effects on their farm operations. The main questions asked during the interviews were whether the farmers had been affected by climate shocks, how they were affected, and what coping strategies they employed. They were also asked if they had ever had to take out a loan as a result of one of these climate shocks, and whether the loan was obtained from a financial institution or informal sources such as friends, relatives, neighbors, or moneylenders. Furthermore, participants were asked to explain

Table 3
Logit estimates: Loan as a response to the weather shocks.

Variable	Loan
Literate	0.761***
	(0.28)
Financial constraint	1.075***
	(0.20)
Risk	0.733**
	(0.30)
Control variables	
Age	0.117*
	(0.07)
Age squared	−0.001*
	(0.00)
Female	0.043
	(0.20)
Education	−0.056**
	(0.03)
Marital status	−0.111
	(0.35)
Income	−0.025
	(0.23)
Farm Size	−0.004
	(0.01)
Altitude	−0.036
	(0.29)
Constant	−4.945**
	(2.01)
N	360
Pseudo R2	0.095
AIC	340.4857
BIC	383.2329

Robust standard errors (clustered on village) are in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
Note: Efforts were made to address endogeneity concerns related to financial literacy in the analysis. Various instrumental variables were explored, including distance to the nearest agrarian bank from each farm, the number of bank offices in the municipality, the number of consumption and house loans, and the amount of savings accounts in each municipality. Additionally, these variables were examined at per capita levels for the entire population, rural population, as well as literate and illiterate subgroups. However, none of these instrumental variables demonstrated a significant effect in addressing the potential endogeneity issue. As a result, the estimates presented in this table should be interpreted with caution due to potential endogeneity bias.
Source: Authors

the main reason for choosing this source of financing.

Through content analysis, we systematically examined the interview transcripts to identify recurring themes related to their preferences for loans and their sources. Specifically, we focus on their understanding and knowledge of financial concepts, such as interest rates and loan terms, as well as preferences for loan sources (financial institutions versus informal lenders) and non-financial sources like family and friends. Additionally, we explored factors influencing their loan decisions, including ease of access, trust in lenders, and the cost of loans. This approach allowed for a better understanding of the underlying factors and contextual influences that may impact the quantitative findings, thereby enhancing the overall validity and robustness of our research (Elo and Kyngäs, 2008; Hsieh and Shannon, 2005).

Content analysis of the qualitative data serves to triangulate and validate the results obtained from the logit regressions. By comparing and contrasting the qualitative insights with the quantitative outcomes, we aim to identify convergences that can provide deeper explanations for the observed statistical relationships (Creswell and Plano Clark, 2017; Vogl, 2023). This mixed-methods strategy ensures that our conclusions are not only statistically significant but also grounded in the lived experiences and realities of the participants, thereby offering a more comprehensive and credible understanding of the research problem.

5. Results

The results are presented in four parts. The first part shows the role of financial literacy and the determinants of farmers' loan taking due to weather events on their farms, including the mechanism that determines financial literacy. In the second part, we show the influence of financial literacy on the choice of loan with a focus on non-financial sources. We detail how the interplay between farmers' age and financial literacy influences their choice of loans from this source. The third part focuses on the comparison of the average marginal effects. Finally, a robustness check is conducted. Throughout the results section, qualitative findings are integrated, supported by direct quotes from interviews. This approach not only enhances comprehension of the statistical results but also serves as a robust strategy for mitigating potential endogeneity bias, thereby strengthening the overall analysis.

5.1. Determinants of loan-taking

Table 3 presents the results from the logit regression model. The dependent variable indicates whether farmers chose to secure or not loans in response to weather shocks. It can be observed that financial literacy is statistically significant. This suggests that farmers who understand at least three of the basic financial concepts (risk diversification, inflation, numeracy, and compound interest) are more inclined to seek a monetary loan in response to weather effects on their farms than do farmers who know less than three of the financial concepts, *ceteris paribus*. Financial constraints, representing whether a farmer considers their decision-making to be constrained by lack of money, is a determinant that increases the likelihood of a farmer applying for a loan. Furthermore, if the farmers in central Colombia consider themselves risk-takers they are more likely to increase their likelihood of applying for a loan.

Among the socio-demographic characteristics of farmers, age and age squared are significant but with different signs. This indicates that the effect of age on the likelihood of taking a loan is initially positive, as indicated by the statistically significant coefficient of 0.117 (with a standard error of 0.07). However, this effect diminishes over time, as shown by the negative coefficient for age squared. This suggests that while older farmers are more likely to take loans up to a certain age, the likelihood decreases as they continue to age. Education is the other only statistically significant variable that affects the likelihood of farmers borrowing money in response to weather shocks. Given the negative correlation, the more years of formal education a farmer has, the less likely they are to apply for a loan. This finding suggests that there may be factors beyond education influencing farmers' decisions to apply for loans. While higher education levels might typically imply better financial knowledge and access to credit, other factors such as risk aversion, alternative

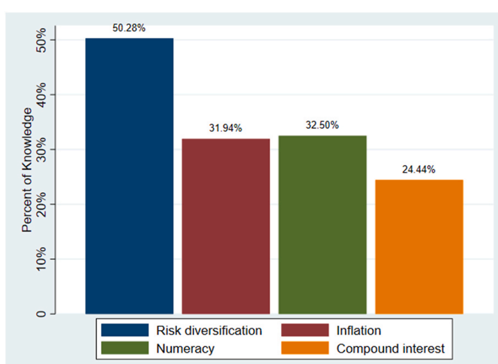

Fig. 4. Proportion of knowledge of basic financial concepts.
Source: Authors.

sources of funding, or differences in financial goals could be at play (Cheng et al., 2023). Additionally, it is possible that highly educated farmers may perceive lower risks associated with borrowing or may have alternative strategies for managing financial needs, leading to a decreased likelihood of seeking loans (Brewer et al., 2019).

For a deeper understanding, let us examine the financial literacy based on the information from the open interviews. Farmers who correctly answer the financial concepts questions, shown in Table 2, are anticipated to make more informed decisions when it comes to lending. This is demonstrated by a farmer's testimony, who correctly responded to all four questions and is considered financially literate. He states:

> "[…] when you ask for money from a third party, the interest rates are much higher than from a bank. If I am thinking of asking for money, I ask a bank, so I go to the Agrarian Bank, where the interest rates are more affordable for the rural sector than going to my aunt and asking her to lend me 20 million and she charges me 5% […]"
>
> [Farmer 103, own translation from Spanish]

Nonetheless, when we take a look at the whole sample, as seen in Table 1, only 16.7% are considered financially literate, and the answers for each concept differ from each other. Fig. 4 presents the results for this mechanism, the proportions of correct answers among respondents for the four basic financial concepts, which serve as indicators of financial literacy. When asked about risk diversification, 50.28% of respondents correctly recognized that it is safer to spread money across multiple businesses or investments rather than focusing on a single one. In the context of inflation, 31.94% of farmers accurately understood that if prices and income increase proportionally, purchasing power remains unchanged. In terms of numeracy skills, 32.5% recognized that repaying 100,000 Colombian pesos plus 3% is less than repaying 105,000 Colombian pesos. The concept with the lowest correct response rate was compound interest at 24.44%, indicating varying levels in understanding whether a bank adding an annual interest rate would contribute more money to an account in its second year compared to the first year.

In total, 20% ($n = 69$) of the farmers obtained loans due to the impact of weather conditions. To gain a deeper understanding of borrowing trends among central Colombian farmers, it is important to examine the sources of these loans. Fig. 5, shows that of the total loans made by farmers in central Colombia, only 15.94% ($n = 11$) accessed funds from financial institutions. In contrast, 79.71% ($n = 55$) were made through non-financial sources, indicating a variety of borrowing options that go beyond official financial institutions. Moreover, there is an overlap in the sources of 4.35% (n- = 3), where farmers obtained loans from both sources.

Regardless of financial literacy, only 11 farmers decided solely to borrow from formal financial sources. This implies that there are other reasons why farmers in central Colombia choose non-formal sources of credit. In many cases, it has been observed that farmers only borrow from financial institutions as a last resort. This viewpoint was reaffirmed by some of the farmers:

> "[…] my husband had a loan and he had to pay it back like twice, and since then I've panicked about loans […]"
>
> [Farmer 246, own translation from Spanish]

> "[…] I would not do it because of the interest, because […] there was an incentive for us farmers, for small coffee growers, so, I went and got a loan of 10 million pesos and now I owe 17 million, so that is unfair to the farmer […]"
>
> [Farmer 67, own translation from Spanish]

Since the sample of farmers who borrowed from financial sources is only 3.88%, our regression analysis will only focus on loans from non-financial sources. The next section aims to determine whether financial literacy influences the selection of this type of loan among farmers in central Colombia.

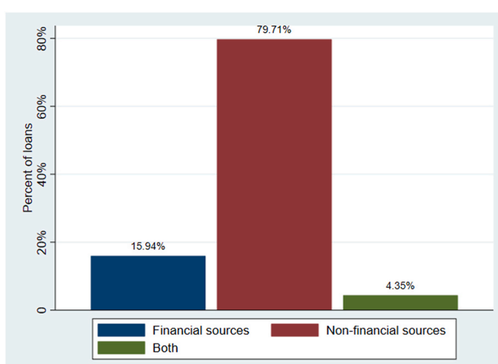

Fig. 5. Loans and its Sources.
Source: Authors.

5.2. Determinants of loan taking from non-financial sources

Table 4 presents the results of the logit model for loans from non-financial sources, with (0) *no borrowing money* and (1) *borrowing money from a non-financial source*. When it comes to financial literacy, the results show that it is statistically significant and positive for farmers who decided to take out a loan from a non-financial source. This suggests that while farmers have knowledge of basic financial concepts, they still choose to borrow from sources outside of the official financial sector. These alternative sources may include friends or relatives, as well as moneylenders with a payday scheme. However, based on the available data, it is not possible to confirm precisely where they obtained their loans from.

Additionally, when farmers perceive their decision-making is limited due to monetary constraints is statistically significant and positive; in such cases, there is an increased likelihood of borrowing. Furthermore, farmers who perceive themselves as risk-takers are more likely to resort to borrowing from this type of source. Moreover, there are statistically significant negative relationships with age square and years of education as the only socio-demographic factors. In addition, the decision to opt for loans outside the formal financial system may be determined by factors that are subjective to individuals, as established by prospect theory in the weighting of decisions in their loan preferences. In some cases, farmers give more weight to the cost of the loan through the interest rate, as in the case of this farmer:

> "[…] sometimes it's a bit difficult for me to pay the bills, but I'm very consistent and I have a very good rating. And above all, it is the *Banco Agrario,* and it does not charge high-interest rates […]"
>
> [Farmer 173, own translation from Spanish]

However, there are cases where farmers give greater weight to other factors, such as the ease of access to non-financial sources and trust with friends than to the higher cost of borrowing from financial institutions, as noted by the following farmers:

> "[…] if I take a loan from a neighbor or relative, the costs are higher for me, in terms of interest […], let's say that financial institutions, in a way, give you more guarantees for the form of payment in order to mitigate costs. If I ask a neighbor for money, it would be a quick loan that I would have to pay back quickly because otherwise it does not involve paying a large amount of money, with interest and so on […]"
>
> [Farmer 25, own translation from Spanish]

Table 4
Loans from non-financial sources.

Variables	Loans from Non-Financial Sources
Literate	0.918***
	(0.25)
Financial constraint	0.850***
	(0.23)
Risk	0.757**
	(0.33)
Control variables	
Age	0.134
	(0.08)
Age squared	−0.001*
	(0.00)
Female	−0.015
	(0.21)
Education	−0.053*
	(0.03)
Marital status	−0.343
	(0.44)
Income	0.147
	(0.29)
Farm Size	−0.003
	(0.01)
Altitude	−0.156
	(0.27)
Constant	−5.137**
	(2.42)
N	349
Pseudo R2	0.093
AIC	306.8616
BIC	349.2674

Robust standard errors (clustered on village) are in parentheses.
***p < 0.01, **p < 0.05, *p < 0.1.
See note Table 3.
Source: Authors.

"[…] I think that if you needed one, you would have to ask for help. That's what friends are for, to help you and to help them […]"

[Farmer 76, own translation from Spanish]

As we detect a non-linear relationship with the variable age, which stands out as the most crucial socio-demographic characteristic in both models, we introduce an interaction term for age and financial literacy to gain deeper insight into their combined effect. The corresponding results are presented in Table 5.

The results show that the interaction term holds statistical significance and that the variables that were found to be significant in Table 4 are still significant in this model with the same magnitudes. The interaction effect of being financially literate and age on taking out non-financial loans is negative and statistically significant at the 10% level. This suggests that while farmers may possess fundamental financial knowledge, as they grow older, they become less inclined to obtain loans from non-financial sources. Fig. 6 illustrates the non-linear relationship between age and its impact on the probability of financially literate farmers obtaining loans from non-financial sources. The highest probability of literate farmers securing a loan from a non-financial source occurs at approximately 40 years of age, after which their likelihood of doing so decreases with each passing year, *ceteris paribus*.

5.3. Comparative analysis of average marginal effects

Table 6 presents the marginal effects from the logit regression for whether farmers chose to secure or not loans (1), secure loans from non-financial sources (2), and loans from non-financial sources including the interaction term between financial literacy and age (3). Evaluating the impact of financial literacy on farmers' decisions to borrow money in response to adverse weather conditions affecting their farms, the findings indicate statistically significant positive effects. This suggests that financially literate farmers are approximately 10.7% more inclined to borrow money compared to farmers who are not financially literate, *ceteris paribus*. With respect to loans from non-financial sources, financially literate farmers are approximately 11.6% more likely to look for funding sources outside of traditional financial institutions, such as family, friends, and informal lenders. Additionally, the interaction between financial literacy and age indicates that financially literate farmers become roughly 2.4% more likely to choose non-financial sources

Table 5
Extended logit estimates: Interaction term.

Variables	(1) Financial Source
Financially Literate	3.736**
	(1.64)
Financially Literate x Age	−0.060*
	(0.03)
Financial constraint	0.919***
	(0.25)
Risk	0.763**
	(0.34)
Control variables	
Age	0.208**
	(0.10)
Age squared	−0.002**
	(0.00)
Female	−0.081
	(0.22)
Education	−0.042
	(0.03)
Marital status	−0.216
	(0.42)
Income	0.182
	(0.28)
Farm Size	−0.004
	(0.01)
Altitude	−0.129
	(0.26)
Constant	−7.565**
	(3.11)
N	349
Pseudo R2	0.107
AIC	302.4495
BIC	344.8552

Robust standard errors (clustered on village) are in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
See note Table 3.
Source: Authors.

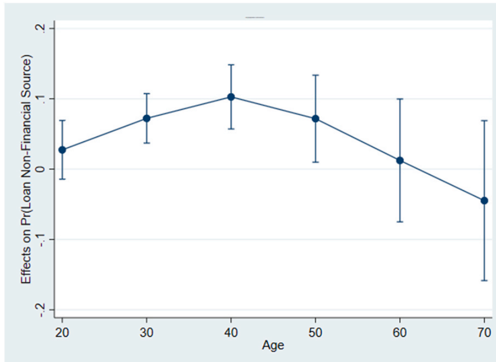

Fig. 6. Average marginal effects - interaction term.
Source: Authors.

Table 6
Marginal effects for all models.

	(1) Loan	(2) Loan from Non-Financial Sources	(3) Loan from Non-Financial Sources
Financially Literate	0.107***	0.116***	0.093***
	(0.04)	(0.03)	(0.03)
Financially Literate = 1 x Age			0.024*
			(0.013)
Financially Literate = 0 x Age			0.023**
			(0.013)
Financial constraint	0.151***	0.107***	0.115***
	(0.03)	(0.03)	(0.03)
Risk	0.103**	0.096**	0.095**
	(0.04)	(0.04)	(0.04)
Control variables			
Age	0.016*	0.017*	0.024**
	(0.01)	(0.01)	(0.01)
Age squared	−0.000*	−0.000**	−0.000**
	(0.00)	(0.00)	(0.00)
Female	0.006	−0.002	−0.010
	(0.03)	(0.03)	(0.03)
Education	−0.008**	−0.007*	−0.005
	(0.00)	(0.00)	(0.00)
Marital status	−0.016	−0.043	−0.027
	(0.05)	(0.06)	(0.05)
Income	−0.003	0.019	0.023
	(0.03)	(0.04)	(0.03)
Farm Size	−0.001	−0.000	−0.001
	(0.00)	(0.00)	(0.00)
Altitude	−0.005	−0.020	−0.016
	(0.04)	(0.03)	(0.03)

Robust standard errors (clustered on village) are in parentheses.
***p < 0.01, **p < 0.05, *p < 0.1.
Source: Authors.

with each passing year, though there is a non-linear effect as shown in Fig. 6.

For the financial control variables, both financial constraint and self-perceived risk, have a significant and positive relationship in all three models. This means that farmers who consider that their decision-making is constrained by a lack of money are more likely to take a loan as a consequence of adverse weather events. Likewise, farmers who consider themselves risk-takers are also more likely to borrow due to climate shocks in their farm operations.

5.4. Robustness check

In the initial robustness check, we attempted to consider the three departments that constitute the sample. However, due to the limited number of observations in each subgroup, the models failed to converge. Similarly, efforts to incorporate the altitude of farm locations as a regional control yielded the same issue. Consequently, we opted to conduct the analysis based on gender, as approximately 48.3% of the sample identified as women and the remainder as men, resulting in two nearly equally sized groups. Table 7 presents the marginal effects of the extended models by gender. Notably, the findings exhibit variations between the two groups. Among females, financial literacy and certain financial control variables demonstrate statistical significance. Conversely, for males, financial literacy lacks significance. Only the financial constraint variable emerges as statistically significant among the financial control variables. Moreover, age and education variables remain statistically significant for the male regressions, contrasting with the female regressions where they do not hold significance.

These results suggest that the robustness of the model depends on gender, with significant variations observed between male and female groups. While financial literacy and certain financial control variables exhibit statistical significance for females, the same variables do not hold significance for males. This divergence underscores the importance of considering gender-specific factors in understanding the determinants of loan uptake in response to weather shocks.

6. Discussion

The motivation of this study is to analyze the financial behavior of farmers from central Colombia in the face of adverse weather conditions because understanding their decision-making processes under stress can provide critical insights into their resilience and adaptability. Utilizing prospect theory, which suggests that people value gains and losses differently and often make decisions based on perceived gains rather than actual outcomes, this study aims to uncover how farmers perceive and respond to financial risks and uncertainties brought about by adverse weather. This understanding is essential for developing targeted support mechanisms, such as financial aid, insurance products, and policy interventions, that can help mitigate the economic impact of climate variability. By applying prospect theory, the study can also reveal cognitive biases and risk preferences that influence financial behavior, contributing to broader discussions on sustainable agricultural practices and rural development in regions vulnerable to climate change.

In our study, we incorporated financial literacy into a logit model where the dependent variable is borrowing in response to a weather shock affecting farm operations. We included two key mechanisms: the farmers' understanding of the four concepts of financial literacy and their risk behavior. A second logit model examined loans from non-financial sources, such as family, friends, and moneylenders, which lack governmental oversight. Given the significant and non-linear relationship between age and financial behavior found in previous models, we included an interaction term between age and financial literacy. Additionally, open interviews with the 360 farmers in our sample provided further depth and validation for our analysis, specifically addressing potential endogeneity challenges.

Our results indicate that financial literacy has a positive effect on loan taking. It is expected that farmers who have an understanding of financial concepts are more likely to secure loans due to their enhanced understanding of the lending process (Cheng et al., 2023; Klapper et al., 2013). In our sample, however, we observed relatively low levels of financial literacy among farmers, with only 16.7% demonstrating an understanding of at least three assessed financial concepts. This result aligns with previous research indicating disparities in financial literacy across different segments of the population (Lusardi and Mitchell, 2014), particularly within the rural population where low levels of financial literacy have been documented (Das and Maji, 2023; Maji and Laha, 2023).

From prospect theory, we analyze how farmers face the possibility of a weather shock that could result in significant losses. To protect themselves, farmers may consider borrowing from financial institutions or non-financial sources. Financial institutions typically offer lower interest rates than non-financial sources as said by Farmer 103. This reflects how farmers value the financial security and stability these loans provide against the risk of loss due to climate shock. Whereas non-financial sources can offer speed in obtaining money and a personalized relationship that builds trust. In this case, this reflects the valuation of speed and interpersonal trust, although interest rates can often be higher. This acknowledges the individual weighing on decisions proposed by Kahneman and Tversky (2000).

Our findings reveal a differentiated outcome despite the expectation that financially literate farmers would prefer formal financial institutions (Mujabi et al., 2022). Although financial literacy does influence farmers' borrowing decisions, we find that farmers often choose non-financial sources such as friends, family, and informal lenders. This suggests that factors beyond financial literacy, such as trust, flexibility, access, and convenience may influence their choice of borrowing sources (Layaoen and Takahashi, 2022; Sandhu et al., 2015; Shinta et al., 2018). Our findings support prospect theory by demonstrating that farmers' decisions to borrow are not solely based on rational calculations but are influenced by subjective assessments of potential gains and losses that are outside of the expected utility theory framework (Ruggeri et al., 2020). The research also highlights the effect of age, showing that older farmers with financial literacy are less likely to take a loan from a non-financial source. This aligns with previous research, where older farmers are less likely to add non-traditional lenders to their debt portfolio (Brewer et al., 2019).

A notable finding is the influence of age on the relationship between financial literacy and the choice of loan sources. It is interesting to note that literate younger farmers have more probability of choosing a loan from a non-financial source than their older counterparts (Pham and Lensink, 2007). This behavior of young people borrowing from non-financial sources, such as moneylenders, is expected of people with less financial literacy (Li, 2022). In contrast, the preference of older farmers may stem from their risk-averse nature and a desire for more secure options for financing sources and the security provided by conventional financial systems (Fong et al., 2021). The asymmetry in risk perception, as explained by prospect theory, could be a contributing factor (Kahneman and Tversky, 2000; Levy and Levy, 2021).

An additional factor that significantly contributes to increasing the likelihood of farmers securing loans from non-financial providers, is the presence of financial constraints. Farmers who perceive themselves as constrained by a lack of funds often exhibit a heightened motivation to pursue a loan, particularly given the prevalent low incomes within the agricultural sector in central

Table 7
Robustness check: Logit estimates and extended model by gender.

	(1) Loans		(2) Loans from non-financial sources		(3) Loans from non-financial sources	
	Female	Male	Female	Male	Female	Male
Financially Literate	1.006***	0.625	1.150***	0.815*	3.779***	4.221
	(0.29)	(0.47)	(0.34)	(0.43)	(1.31)	(2.66)
Financially Literate x Age					−0.063*	−0.067
					(0.03)	(0.05)
Financial constraint	0.940**	1.198***	0.573	1.069**	0.590	1.170**
	(0.41)	(0.40)	(0.44)	(0.46)	(0.44)	(0.47)
Risk	0.995**	0.557	0.920**	0.623	0.888*	0.649
	(0.45)	(0.42)	(0.47)	(0.43)	(0.47)	(0.41)
Control variables						
Age	0.075	0.162**	0.099	0.168**	0.173	0.269**
	(0.11)	(0.07)	(0.14)	(0.08)	(0.15)	(0.12)
Age squared	−0.001	−0.002***	−0.001	−0.002***	−0.002	−0.002***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Education	−0.040	−0.073*	−0.029	−0.077**	−0.013	−0.066
	(0.06)	(0.04)	(0.07)	(0.04)	(0.07)	(0.04)
Marital status	0.145	−0.345	−0.183	−0.530	−0.075	−0.386
	(0.51)	(0.60)	(0.59)	(0.68)	(0.57)	(0.66)
Income	−0.195	0.128	0.118	0.188	0.152	0.220
	(0.49)	(0.34)	(0.57)	(0.38)	(0.62)	(0.40)
Farm Size	−0.025	−0.001	−0.019	−0.001	−0.017	−0.003
	(0.03)	(0.01)	(0.03)	(0.01)	(0.03)	(0.01)
Altitude	−0.389	0.220	−0.547	0.098	−0.524	0.137
	(0.42)	(0.31)	(0.44)	(0.30)	(0.43)	(0.29)
Constant	−4.118	−5.877**	−4.459	−5.841**	−6.740	−9.201**
	(3.26)	(2.29)	(3.86)	(2.35)	(4.15)	(3.65)
N	174	186	168	181	168	181
Pseudo R2	0.110	0.107	0.095	0.111	0.105	0.129
AIC	172.4803	185.1468	156.0682	169.3286	154.5393	166.3899
BIC	207.2299	220.63	190.4318	204.512	188.9029	201.5733

Robust standard errors (clustered on village) are in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
Source: Authors.

Colombia. For example, 65.6% of our sample indicated that their monthly income is less than one legal minimum monthly salary (for the year 2021 this was around $212 US dollars[2]). The weight of these financial constraints emerges as an important factor driving farmers to seek financial support (Falola et al., 2022; Oboh and Kushwaha, 2009; Ouattara et al., 2022; Widaninggar et al., 2023).

Moreover, it is crucial to recognize that farmers, due to the nature of their work, encounter daily risky decisions (Chauke et al., 2013; Thompson et al., 2019). Furthermore, their income is usually tied to agricultural cycles which determine payment schedules. As a result, they often need access to long-term payment systems which increases their exposure to risks (Shinta et al., 2018). Likewise, the decision to take out loans is influenced by farmers' perceived risk (Attanasio et al., 2019), as demonstrated in our case where those who take loans consider themselves risk-takers. Conversely, those preferring informal borrowing might underestimate these risks due to a familiarity bias or immediate needs, which overshadow long-term considerations (Layaoen and Takahashi, 2022).

Regarding policy implications, if the goal is to improve the financial literacy of farmers in central Colombia, policymakers could prioritize and implement targeted financial education programs tailored to the specific needs of the farming community. As Agarwalla et al. (2015) and Hwang and Park (2023) suggest, improving financial literacy not only impacts financial behavior but also overall financial well-being. These initiatives aim at enhancing understanding of basic financial concepts and their practical application within the agricultural sector, including specialized financial products offered by local institutions for the farming sector. If the financial literacy of the farmers is improved, this may promote the participation of farmers in credit activities that regulate their lending behavior, enhancing the environment of the rural credit market (Cheng et al., 2023). If the official financial channels offered rural communities more stability, trust in these institutions and access to these loans could be improved.

The impact of financial literacy on farmers varies among different age groups, affecting their choices regarding loan sources. If the aim is to strategically formulate and execute public policies, it becomes crucial to acknowledge and rectify these discrepancies across diverse age groups. For example, in the case of programs directed at younger farmers, enhancing awareness of financial concepts, and diversifying their financial sources could be pivotal. Conversely, initiatives for older farmers might be more effective if they focus on instilling confidence in formal financial institutions. Tailored programs for specific groups may improve the inclusion and financial well-being of the farmers (Choudhary and Jain, 2023).

[2] The minimum monthly salary for the year 2021 was $908,526.00 Colombian pesos (Decreto 1785, 2020). The exchange rate for this date was USD$1 = COP $4278.88.

7. Conclusions

This study provides valuable insights into the role of financial literacy, age, and subjective assessments in shaping farmers' borrowing decisions during weather shocks in the rural area of central Colombia. The findings emphasize that financial literacy significantly influences financial behavior, especially when farmers face climate-related shocks in their farm operations. Moreover, the role of age and subjective assessments—such as trust and ease of access—are crucial in determining the sources of financing farmers rely on, including non-financial alternatives like loans from family, friends, or moneylenders. However, our study is not without limitations. The scarcity of information from rural areas restricted our ability to incorporate adequate instrumental variables that could address potential endogeneity of our models. Additionally, as a case study focused on a specific region of Colombia, the findings may not be generalized to other areas. The absence of panel data also prevents us from conducting a comprehensive long-term assessment. Establishing a mechanism for recurring surveys would be beneficial, enabling systematic monitoring of climate adaptation and financial behavior over time. This approach would not only address current data limitations but also provide insights into the dynamic changes of these critical factors.

Future studies can address these limitations by collecting more comprehensive rural data and developing panel data through recurring surveys for long-term assessments. Additionally, gender differences in financial behavior, highlighted by our robustness checks, need deeper exploration. Addressing these gaps will improve the accuracy and inclusivity of future policy recommendations.

CRediT authorship contribution statement

Alexander Cano: Writing – review & editing, Writing – original draft, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization, Software, Visualization. **Bente Castro-Campos:** Writing – review & editing, Validation, Supervision, Methodology, Formal analysis, Data curation, Conceptualization, Funding acquisition, Project administration, Software, Visualization, Writing – original draft.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used AI to edit and improve the fluency of the text. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Alexander Cano reports financial support was provided by German Academic Exchange Service. Alexander Cano reports financial support was provided by Alianza EFI. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Chapter 4: Farmers' Climate Change Perceptions in Central Colombia: A Propensity Score Matching Approach Using Protection Motivation Theory and Psychological Distance

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Farmers' climate change perceptions in central Colombia: A propensity score matching approach using protection motivation theory and psychological distance

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A R T I C L E I N F O

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A B S T R A C T

This study investigates how farmers' experiences with extreme weather events, specifically landslides and droughts, shape their perceptions of climate change in central Colombia, and their implications for climate risk management. Using Protection Motivation Theory and psychological distance as frameworks, we surveyed 360 farmers in 2022–2023 to assess their perceptions of climate change severity, vulnerability, and proximity. To control for confounding factors, we employed propensity score matching, comparing farmers in villages affected by landslides and droughts with those in unaffected villages. Our findings reveal that while landslides do not significantly alter farmers' perceptions, droughts heighten awareness of climate change, with statistically significant differences observed in 10 out of 16 perception categories. This suggests that the nature of extreme weather events plays a crucial role in shaping climate change perceptions. Notably, farmers affected by drought perceive climate change as more severe, feel more vulnerable, and report closer psychological distance to its impacts compared to those in landslide-affected areas. These results imply that climate risk management strategies should be tailored to the specific types of extreme weather events affecting a region. Furthermore, by comparing drought and landslide events, this study provides new insight into how different climatic shocks shape farmers' perceptions, contributing to a more nuanced understanding of climate change adaptation. This research highlights how propensity score matching, by better balancing groups and reducing bias from confounding, offers a methodological improvement over conventional approaches in climate perception studies.

1. Introduction

Farmers are particularly vulnerable to the impacts of climate change due to their reliance on weather patterns and natural resources (Miller et al., 2021; Quaye et al., 2018; Skevas et al., 2022). This vulnerability is characterized by an increase in both the frequency and intensity of extreme weather events (Muench et al., 2021). Furthermore, farmers' experiences with these types of events are strongly correlated with their beliefs about climate change (Dai et al., 2015). However, the effects of climate change are not uniform, with

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variations observed even within the same geographic region (Epanchin-Niell et al., 2017; Gupta et al., 2020).

Climate change is often perceived as an abstract, distant, and gradual phenomenon, making it less likely to elicit immediate concern or prompt action (Ricart et al., 2023). In contrast, extreme weather events provide tangible evidence of climate change's impacts (Bergquist et al., 2019). These firsthand experiences can significantly shape farmers' beliefs. It has been found that farmers in regions where different extreme weather events have occurred tend to have a stronger belief in climate change (Borick & Rabe, 2017; Dai et al., 2015). Moreover, farmers' perceptions of threats strongly influence their adaptive behaviors (Mosavian et al., 2023), making it essential to understand how different environments affect climate change perceptions.

The connection between personal experience and perception is pivotal in addressing the impacts of climate change, particularly in agricultural contexts. This underscores the need for strategies that bring climate change closer and more tangible to farmers (Yazdanpanah et al., 2023). As climate change continues to accelerate, it is essential to conduct spatial assessments of its impacts to facilitate better-informed decision-making that can preemptively mitigate its damages (Venkatappa et al., 2021). Understanding farmers' perceptions of climate change and extreme weather events is crucial for designing effective climate change measures (Fahad et al., 2020).

The central region of Colombia, located between the central and western Andean mountain ranges, serves as an ideal setting to examine the intersection of climate change impacts and agricultural practices. This region is particularly susceptible to extreme weather events, such as landslides and droughts, due to its diverse topography and resulting climatic variations, which pose significant challenges for agricultural activities. Rainfall is the main trigger for landslides in the area, accounting for 87 % of such events and being one of the main causes of socio-economic losses (Aristizábal & Sánchez, 2020; Garcia-Delgado et al., 2022). On the other hand, droughts, characterized by prolonged periods of low precipitation, exacerbate agricultural vulnerability by leading to crop failure and diminished water resources (Freire-González et al., 2017).

We use Protection Motivation Theory (PMT) and the concept of psychological distance as theoretical frameworks, given their significance in the climate adaptation literature (Cano & Castro Campos, 2024). PMT suggests that individuals' responses to threats are shaped by their perceptions of severity, vulnerability, and efficacy (Rogers, 1983). Additionally, the concept of psychological distance refers to how far away a threat feels across temporal, spatial, social, and hypothetical dimensions (Liberman et al., 2007). These theoretical constructs allow us to examine how farmers perceive and respond to climate-related risks based on both internal (perceptions) and external (observed weather shocks) factors. While previous studies have examined farmers' perceptions using these theories, they typically focus on a single type of event (see Bergquist et al., 2019; Li et al., 2023; Rodríguez-Cruz & Niles, 2021), few studies have directly compared the influence of distinct types of extreme weather events on perceptional outcomes through a quasi-experimental approach.

To address this gap, we employ Propensity Score Matching (PSM) to reduce selection bias and create comparable groups of farmers exposed to different climate shocks. This methodological choice strengthens the causal interpretation of the results, which is often limited in perception studies due to confounding factors (Austin, 2011a; Caliendo & Kopeinig, 2008; Stuart, 2010). By combining these theoretical constructs with a quasi-experimental design, this study offers new evidence on how specific weather experiences –landslides and droughts- shape farmers' perceptions of climate change severity, vulnerability, and distance.

The study makes three key contributions. First, it enhances our understanding of how different types of extreme weather experiences influence climate change perceptions across psychological constructs. Second, it applies a matching methodology rarely used in this context, improving the internal validity of results. Third, it provides empirical evidence from a climate-vulnerable region in the so-called Global South, which remains underrepresented in the behavioral adaptation literature (Cano & Castro Campos, 2024).

This study has two main objectives: (1) to examine differences in climate change perceptions between farmers in villages affected by extreme weather events (landslides and droughts) and those in unaffected villages, and (2) to compare climate change perceptions between farmers in landslide-affected villages and those in drought-affected villages. To achieve these objectives, PSM is used to control for confounding variables and isolate the effect of extreme weather events.

This article is structured as follows. Section 2 provides the theoretical background of the PMT and psychological distance used in this research. In section 3, we detail the methods, variables, and propensity score matches employed. Section 4 presents the results, followed by the discussion in section 5. We draw conclusions in section 6.

2. Theoretical background

Previous research in Colombia has examined how different populations perceive climate change and respond to its effects. These studies highlight the importance of contextual factors, including geography, livelihoods, and access to information, in shaping local interpretations of climate-related risks. For example, in Bogotá, Pardo Martínez et al. (2018) found widespread public awareness of climate change, with droughts and floods identified as major threats to health, water access, and food security. Similarly, Rodríguez Pacheco et al. (2022) analyzed perceptions among university students in the Caribbean region and found that, while students generally understood the causes and global implications of climate change, many struggled to relate these processes to their local realities.

In rural areas, climate change perceptions are often shaped by their context. Botero et al. (2021), for example, used latent class analysis to identify heterogeneous perception profiles among bean farmers in Santander. They found that farmers located at lower altitudes and farther from urban centers expressed greater concern about the future economic consequences of climate change and were more likely to seek out climate information, suggesting higher receptivity to adaptive measures such as drought-resistant seeds. In Manizales, Barrucand et al. (2017) studied coffee growers and observed that although many had limited prior knowledge of climate change, they had experienced noticeable changes in rainfall and temperature patterns and were adapting using a combination of traditional knowledge, such as placing rocks to slow the flow of running water and reduce soil erosion, and institutional support, including agricultural extension services provided by government agencies and coffee grower associations.

In the Sierra Nevada del Cocuy-Güicán, Alcántara Rodríguez et al. (2018) reported that farmers were concerned about the degradation of páramo vegetation and attributed environmental threats to both climate variability and unsustainable land use practices. Meanwhile, in rural Eastern Andes communities, Murtinho et al. (2013) found that Water User Associations primarily attributed water scarcity to deforestation rather than climate change. Notably, this perception diverged from meteorological data, highlighting how subjective interpretations of environmental change may differ from technical diagnoses.

Taken together, these studies illustrate the diversity of climate change perceptions across both urban and rural Colombia. However, few have systematically applied theoretical frameworks to explain how these perceptions emerge from individuals' lived experiences. Our study directly addresses this gap by integrating Protection Motivation Theory and psychological distance to analyze how farmers' exposure to droughts and landslides shapes their climate change perceptions. By combining these complementary theoretical frameworks, our approach advances a more robust and theoretically grounded understanding of the psychological processes driving climate perception in rural contexts.

2.1. Protection motivation theory (PMT)

This theory, originally proposed by Rogers (1975), suggests that individuals' attitudes change when they face fear-inducing events. Fear appeals have three main components: (1) the magnitude or severity of an event; (2) the likelihood of this event occurring; and (3) the effectiveness of the protective response to this event. Information about these components serves as a stimulus, prompting cognitive processes that motivate individuals to take action to avoid the threat. Essentially, fear appeals communicate the negative consequences of not following the recommended actions, encouraging individuals to adopt behaviors that mitigate the perceived danger.

The theory was updated by Rogers (1983), including different sources of information that can initiate the cognitive processes. These sources are either environmental or intrapersonal. In environmental sources, learning is observational, which implies that individuals observe their surroundings and what happens to others; it also includes verbal persuasion from other people. Intrapersonal sources consist of personal variables or past experiences with similar events that pose a comparable threat. Regardless of the information source, two key appraisal processes are initiated: threat appraisal and coping appraisal. The threat appraisal involves evaluating the severity of the threat and one's vulnerability to it. The coping appraisal assesses the ability to manage and avoid the threat, including the belief in the effectiveness of the recommended response and the associated costs. Additionally, self-efficacy, or the belief in one's capacity to successfully adopt the protective measure, was incorporated into the theory by Maddux and Rogers (1983).

According to PMT, an individual's protective motivation is determined by the combined effects of their threat and coping appraisal processes. Protective motivation, as measured through behavioral intention, is assumed to be a positive linear function of four key factors: (1) the severity of the threat, (2) personal vulnerability to the threat, (3) the ability to perform the coping response, and (4) the effectiveness of the coping response in avoiding the threat (Rogers, 1983). This linear function is a major assumption of the theory. Furthermore, an additive model applies within each appraisal process (threat appraisal and coping appraisal). However, when combining the two processes, second-order interaction effects occur. This means that the elements of one appraisal can influence how the components of the other appraisal affect motivation.

This theory has been widely used to explain climate change adaptation behaviors, particularly in agricultural settings, revealing that constructs such as perceived severity and perceived vulnerability are positively associated with farmers' intentions to adopt protective measures. For instance, empirical evidence shows that exposure to drought conditions increases both risk perception and behavioral intentions (Gebrehiwot & van der Veen, 2021), while perceptions of risk and adaptation efficacy jointly shape intentions to adopt technologies (Dang et al., 2014). Other studies highlight that the way farmers receive and process risk information, such as drought communications, can strengthen adaptation appraisal more than risk appraisal itself (Sutcliffe et al., 2024), and that socio-cognitive factors also influence adaptation intentions (Rodríguez-Barillas et al., 2024). Our study builds on this literature by operationalizing key PMT constructs in a context where different climate shocks—specifically droughts and landslides—are analyzed separately. This approach allows for a more nuanced understanding of how severity and vulnerability appraisals are shaped by the specific nature of each threat.

2.2. Psychological distance

Liberman and Trope (2014, p. 365) define psychological distance as "the extent of divergence from direct experience of me, here and now along the dimensions of time, space, social perspective, or hypotheticality". According to them, individuals use mental representations of different events or situations. These representations are categorized into high-level construals, which are abstract and focus on the most important, general aspects of an event, and low-level construals, which are concrete and focus on specific details (Liberman & Trope, 1998). Additionally, Trope and Liberman (2003) propose that temporal distance (how close or far in the future individuals see the event) changes how individuals mentally represent these events. The greater the temporal distance, the more likely to be represented in high-level construals rather than low-level construals.

Besides the temporal distance, other types of distances affect how individuals interpret an event based on their perceived divergence from it (Bar-Anan et al., 2006). For example, the closer the spatial proximity (spatial distance) of an event, the more specific and concrete the mental representation of the event (Trope et al., 2007). Social distance refers to the perceived similarity between individuals; the more similar people feel to others, the less socially distant they feel, leading to a more specific and concrete interpretation (Liberman et al., 2007). Finally, hypothetical distance pertains to the likelihood of an event occurring. Improbable or hypothetical events are perceived more abstractly, whereas certain events are viewed more concretely (Bar-Anan et al., 2006). Individuals anchor their interpretations in their actual experiences and then extend to more abstract, hypothetical scenarios.

In the context of extreme weather events, these psychological distances play a significant role in shaping how farmers perceive and respond to climate change (Azadi et al., 2019). Farmers who have directly experienced events like droughts or landslides tend to view climate change more concretely and immediately. Their interpretation is shaped by a close, immediate perspective due to the spatial and temporal distance of these events. This proximity may lead to heightened awareness and concern, influencing their decision-making and adaptive behaviors (Liberman et al., 2007). On the other hand, farmers who have not personally experienced such events may see climate change as a distant, abstract concept, focusing on big-picture ideas rather than specific, immediate details. This psychological distance can result in less urgency in their responses to climate-related risks, affecting their engagement in mitigation or adaptation strategies. Understanding these dynamics is essential for designing effective interventions that consider farmers' differing perceptions and psychological distances, both of which shape the collective reality within affected communities.

This study contributes to the literature by applying the concept of psychological distance in a rural setting highly exposed to climate variability. While prior research has explored the role of psychological distance in shaping climate change perceptions, much of it has focused on broader national samples or urban populations. Some studies have shown that reduced psychological distance increases the perceived relevance of climate threats and can trigger stronger emotional responses, while greater distance tends to elicit weaker engagement (Chu & Yang, 2019). Others suggest that exposure to locally relevant stimuli can reduce perceived socio-spatial distance and enhance personal relevance, particularly among individuals already concerned about climate change (Halperin & Walton, 2018). Additionally, while reducing distance can enhance personal engagement, the effectiveness of such strategies may vary depending on individuals' prior beliefs or global identity salience (Loy & Spence, 2020). Most existing studies address general perceptions of climate change without explicitly comparing how different types of extreme weather experiences, such as droughts and landslides, affect psychological distance across multiple dimensions (Keller et al., 2022). By examining farmers' perceptions in communities affected by different climate shocks, our study offers new insights into how spatial, temporal, social, and hypothetical dimensions of psychological distance may shift depending on the nature of the environmental threat. This focus enhances the understanding of how specific experiences shape mental representations of climate change, which is critical for designing context-sensitive adaptation strategies.

3. Methods

3.1. Average treatment effect on the treated

We consider farmers living in villages where different extreme weather events (landslides and droughts) have been experienced. Our objective is to measure how residing in these places affects their perceptions of climate change. To measure this effect, we define treatment $T_i = 1$ if farmer i receives the treatment and zero otherwise, and $Y_i(T_i)$ corresponds to their outcomes under each treatment condition for each farmer. The effect that the treatment has on a given farmer can be written as

$$\tau_i = Y_i(1) - Y_i(0) \tag{1}$$

Since causal effects are estimated based on the response after receiving a treatment, it is not possible to observe the response of the same farmer would have had if they had not received the treatment, creating a lack of a counterfactual. As a result, estimating causality is a missing data problem (Rosenbaum & Rubin, 1983). Due to the absence of a counterfactual for each farmer, the treatment effect cannot be estimated at the individual level (τ_i), and is often estimated as the average effect across a group or population (Caliendo & Kopeinig, 2008). One way to assess this is by calculating the difference in the expected values of outcomes between those who received the treatment and those who did not. This is known as the Average Treatment Effect (ATE).

$$\tau_{ATE} = E(\tau) = E[Y(1) - Y(0)] \tag{2}$$

The ATE estimates the average effect across the entire sample, regardless of whether individuals receive the treatment. However, since our focus is understanding specifically how extreme weather events have affected the climate change perceptions of the farmers who have directly experienced them, we estimate the Average Treatment Effect on the Treated (ATET), which specifically examines the subset of the population that received the treatment—in this case, those farmers residing in a village where landslides or droughts have occurred.

$$\tau_{ATET} = E[\tau|D = 1] = E[Y(1)|D = 1] - E[Y(0)|D = 1] \tag{3}$$

The expected value of the ATET is the difference between expected outcome values with and without treatment for those who received the treatment. By focusing specifically on individuals who received the treatment, this parameter reveals the direct impact on the outcome variable (Caliendo & Kopeinig, 2008; Heckman et al., 1999).

3.2. Propensity score matching (PSM)

To estimate the ATET we employ PSM, as it allows us to make inferences about treatment effects using observational data. The first step is to calculate the propensity score (PS), which is the probability of a farmer living in a village affected by extreme weather events. The PS is calculated as a probit model of a set of observable covariates that can influence both exposures to the treatment and their perceptions of climate change. In our study, we have two mutually exclusive treatments due to the characteristics of our sample, as detailed in section 3.4. For this reason, we estimate two different PSs for each event. The first is that farmers live in a village where three or more landslides have occurred (Equation (4). The second is that farmers live in villages where two or more droughts have occurred (Equation (5).

$$p(X_i) = Pr(L_i = 1|X_i) \tag{4}$$

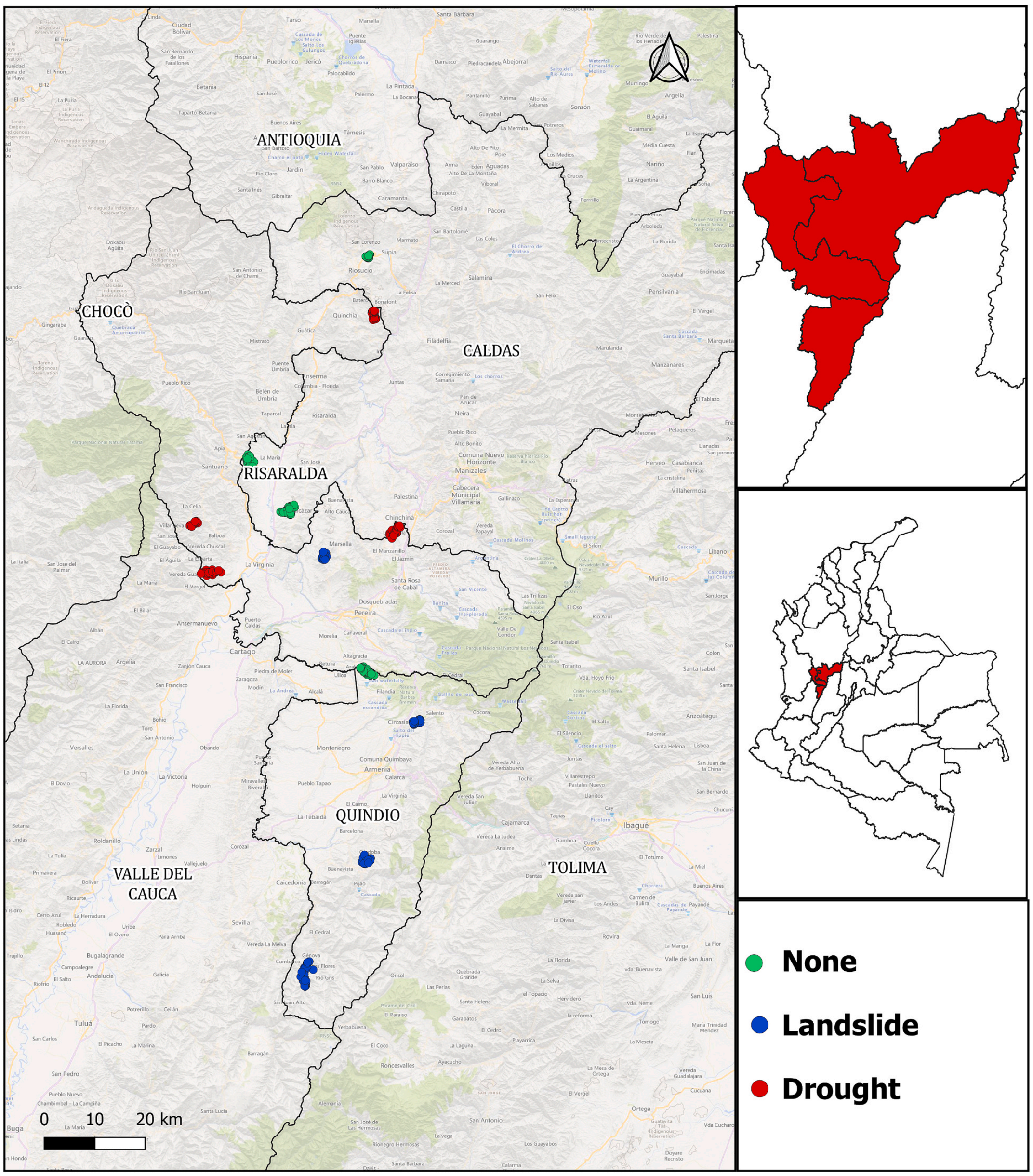

Fig. 1. Research Locations in Central Colombia. .
Source: Authors based on fieldwork conducted by Cano from Nov 2022 to Feb 2023.

$$p(X_i) = Pr(D_i = 1|X_i) \tag{5}$$

Where L_i represents whether the farmer lives in a village where landslides have occurred and D_i if they reside in a village where droughts have happened. X_i are the observable characteristics of the farmers, which include demographic variables (such as age, gender, education level, and income), farm characteristics (size and number of workers), and the natural resource endowment on their farm (e.g., having a water source on the farm or access to a water source, and having forest or part of a forest on their land).

Once the PS is estimated, matching is performed. This process consists of matching farmers who have been exposed to extreme weather events with those who have not, based on the similarity of their observable characteristics. Since we have not considered villages where both extreme events have occurred, farmers who live in villages affected by landslides have not been affected by drought, so they are used as a control group for those who have experienced drought, and vice versa. The goal of matching is to create a control group comparable to the treated group, thus minimizing bias in the estimation of causal effects (Cameron & Trivedi, 2005). By matching individuals with similar PS, the distribution of covariates between the groups is balanced (Caliendo & Kopeinig, 2008), which facilitates a more accurate comparison of the impact of the treatment, i.e., living in a landslide or drought-affected village, on perceptions of climate change.

We employed two matching techniques to ensure robust comparisons. The first is nearest-neighbor matching, where each farmer who has experienced an extreme weather event is matched with the closest untreated farmer in terms of their PS. This approach helps ensure that the pairs are as comparable as possible. The second technique is caliper matching. This method introduces an additional constraint by allowing matches only if the difference between the PS of the matched pairs falls within a predefined range, known as the caliper, minimizing the risk of mismatching by excluding pairs with overly disparate PS (Caliendo & Kopeinig, 2008). Following the usual procedure of estimating the caliper as 0.2 times the standard deviation of the PS (Austin, 2011b; Garrido et al., 2014; Harder et al., 2010), we set the caliper at 0.010 for the landslides group and 0.020 for the droughts given their different standard deviations.

3.3. Hypotheses

Based on this matching process, we aim to test the following hypotheses as explained in sections 3.1. and 3.2., respectively:

H1: There is no significant difference in climate change perceptions (perceived severity, perceived vulnerability, psychological distance) between farmers residing in villages that have experienced extreme weather events and those in villages that have not.

H2: There is no significant difference in climate change perceptions between farmers residing in villages affected by landslides and those affected by droughts.

Estimating these hypotheses can reveal whether direct experience with extreme weather events, such as droughts or landslides, influences farmers' perceptions of climate change severity, vulnerability, and psychological distance. It can also show if the type of extreme event (landslide vs. drought) leads to different perceptions, potentially guiding more targeted communication and intervention strategies.

3.4. Data

All villages in the region where extreme weather events were reported between 2005 and 2021 were identified using public data from Colombia's *Unidad Nacional para la Gestión del Riesgo de Desastres* (UNGRD). Some villages experienced up to six landslides and others up to three droughts. To ensure that only locations with significant and recurrent exposure to climatic shocks were included, thus increasing the likelihood of perceptual differences, we combined proximity to events (Funderburg et al., 2010) with an additional criterion based on event frequency (Pinto et al., 2014). Specifically, we applied a minimum threshold of three landslides and two droughts. This criterion balances empirical and practical considerations: villages with fewer events were considered less likely to show measurable differences in climate risk perceptions, while setting a higher threshold would have drastically reduced the eligible sample. Based on this criterion, four villages with landslide experience, four with drought experience, and four where neither of these events had occurred were randomly selected (Fig. 1). To confirm the classification and coordinate fieldwork, we contacted the municipal agricultural secretariat to verify event exposure and obtain contact information for local leaders. The leaders then confirmed the presence or absence of events, helped schedule the visits, and informed the community about our study.

This design constitutes a quasi-experimental design approach, where farmers are not randomly assigned to treatment or control conditions, but where PSM is later applied to statistically adjust for pre-treatment differences and strengthen causal inference (Dehejia & Wahba, 2002; Estifanos et al., 2020; Goldfarb et al., 2022; Rosenbaum & Rubin, 1983). To preserve internal validity, we excluded villages affected by both types of events to avoid confounding effects and to create three mutually exclusive comparison groups: (1) 120 farmers living in villages where landslides have been experienced, (2) 120 farmers living in villages where droughts have occurred, and (3) 120 farmers living in villages where none of these events have happened. Because the two treatment categories are mutually exclusive, farmers exposed to one type of shock also serve as potential controls for the other. For example, when analyzing the effect of drought exposure, the control group includes both farmers from unaffected villages and those from landslide-affected villages, totaling 240 individuals. The same logic applies when evaluating the effect of landslide exposure. This design maximizes the comparability between treatment and control groups while maintaining internal validity in estimating perceived impacts.

A random sampling approach was used to choose 30 farmers from each of the selected villages, and between 2022 and 2023, a total of 360 farmers were visited and surveyed. This sampling strategy resulted in 120 farmers in each treated group and 240 in the control group for each treatment, achieving a 1:2 ratio that is well-suited for PSM (Kolar & Steiner, 2021; Pirracchio et al., 2012). To further assess the adequacy of the sample size, we conducted a power analysis assuming a moderate effect size of 0.4 standard deviations, a standard deviation of 1, and a significance level of 0.05. The estimated power for detecting group differences is 0.946, which exceeds the conventional 0.8 threshold, indicating that the sample provides sufficient statistical power to detect meaningful effects with 95 % confidence. The decision to survey 30 farmers per village was also based on logistical considerations in rural areas, such as the limited number of active farms per village, and the need to ensure feasibility and balance across comparison groups.

The survey[1] included information on the farmers' perceptions of climate change, incorporating their assessments of the severity, their sense of vulnerability, and their psychological distance. Additionally, it collected socio-demographic data and details about their farm operations. The design of the perceived severity and vulnerability indicators was based on methodological approaches developed by Delfiyan et al. (2021) and Pakmehr et al. (2020). Table 1 provides variable definitions and descriptive statistics. Perceived severity was assessed through three categories: (1) the impact on their farms, (2) the village's natural resources, and (3) other farmers in the village. Each of these was evaluated using a 5-point Likert scale, where 1 = not at all serious and 5 = very serious. Perceived vulnerability was evaluated by asking farmers how frequently they worry weekly about climate change, its impacts, and the effects on their farm operations. Each item was rated on a 5-point Likert scale, where 1 = very little and 5 = a lot.

To assess the psychological distance of climate change, we followed the frameworks proposed by Peng et al. (2022) and Rodríguez-Cruz and Niles (2021), evaluating four dimensions: spatial, temporal, social, and hypothetical. Each was measured using a 5-point Likert scale where farmers indicated their level of agreement with each statement (1 = completely disagree, 5 = completely agree) to capture their perceived distance from climate change. Each dimension was measured with two items that asked respondents whether they view the effects of climate change as near (low psychological distance) or far (high psychological distance). Before full implementation, the survey instrument was pre-tested with 15 farmers from a non-sampled village to assess clarity and contextual relevance. Feedback from the pilot informed minor adjustments in language and ordering of questions. All enumerators had prior experience conducting surveys in rural settings, which facilitated communication and trust with respondents. Nevertheless, they received two days of training specifically focused on the survey protocol, theoretical constructs, and ethical procedures. Surveys were conducted face-to-face, and data entry included double-checking procedures to minimize human error. The internal consistency of the Likert-based indices was tested using Cronbach's alpha. The alpha for the perceived severity variables was 0.815, for the perceived vulnerability was 0.882, and for the psychological distance was 0.843. These values support the reliability of the variables representing each perception type.

The overall sample shows a mean perception of 3.998 (SD 1.241) for how serious the consequences of climate change are for their farm operations. Similarly, for the perceived severity of the impact on the village's natural resources, the mean is 3.768 (SD 1.418); and for the impacts on other farmers, the mean is 4.026 (SD 1.236). When it comes to perceived vulnerability, the mean perception of weekly concern about climate change is 4.046 (SD 1.307). The average perception of concern about the impacts of climate change is 4.085 (SD 1.341). Finally, when it comes to concerns about the negative effects of climate change on agricultural activities, the mean is 3.998 (SD 1.397).

Regarding the psychological distance, the belief that climate change is affecting their village (Spatial 1) has a mean of 4.072 (SD 1.393). In contrast, the perception that climate change affects other villages but not their own (Spatial 2) has a mean of 1.672 (SD 1.293). For the temporal distance, the mean perception that the effects of climate change will occur in the future but are not happening now (Temporal 1) is 1.650 (SD 1.266). Conversely, the belief that the effects of climate change are happening now (Temporal 2) has a mean of 4.354 (SD 1.246). Within the social distance, the belief that climate change is going to affect farmers like them (Social 1) has a mean of 4.619 (SD 0.898). On the other hand, the belief that climate change will affect other farmers but not themselves (Social 2) shows a mean of 1.301 (SD 0.862). For the hypothetical distance, the mean value for the uncertainty about whether climate change is really happening (Hypothetical 1) is 1.662 (SD 1.239). The belief that climate change is already affecting them (Hypothetical 2) has a mean of 4.291 (SD 1.299). The perception that landslides are a consequence of climate change (Hypothetical 3) has a mean of 4.563 (SD 0.972), while the belief that droughts are a consequence of climate change (Hypothetical 4) has a mean of 4.379 (SD 1.193).

The variables used for the PS include several demographic and farm-related factors. On average, the majority of participants (64.2 %) are under 60 years old (SD 0.480) and nearly half of them (48.3 %) were female (SD 0.500). Single farmers accounted for 19.2 % of the sample (SD 0.394). In terms of education, 38.9 % of the sample had attained an elementary education (SD 0.488) and 65.6 % reported earnings below the national monthly wage (SD 0.476). The average number of workers (including family members) per farm is 2.939 (SD 3.352) and 73.30 % of farms are smaller than 5 ha (SD 0.468). Regarding their natural resources endowment, two-thirds (66.1 %) of farmers reported having a natural spring or access to a river, creek, or stream on their farms (SD 0.474). Lastly, 65.6 % of farmers reported that their farms include a forest or bamboo forest, either in whole or in part (SD 0.476).

4. Results

4.1. Balance and test of the PSM

Fig. 2 shows the distribution of PS between the treated and untreated (control) groups for the PS balance analysis of the group of farmers residing in villages where landslides have occurred. Likewise, Fig. 3 shows the distribution, but for the group of farmers living in villages where drought has been experienced. It can be observed that the PS for landslides ranges between approximately 0.1 and 0.5, while that for droughts is between 0.1 and 0.8. The green bars show the distribution of individuals who received the treatment, i.

[1] The survey used in this research is available upon request.

Table 1
Description and Summary Statistics of Variables.

Variables	Description	Pooled		No Event		Landslide		Drought	
		mean	sd	mean	sd	mean	sd	mean	sd
Treatments									
Landslide	1 if the farm is located in a village with 3 or more landslides since 2005; otherwise 0	0.333	0.472						
Drought	1 if the farm is located in a village with 2 or more droughts since 2005; otherwise 0	0.333	0.472						
Perceived Severity	*How negative the consequences of climate change are (1 is "not at all serious" and 5 is "very serious"):*								
Farm	Your farm's agricultural operations	3.998	1.241	3.894	1.312	4.046	1.136	4.054	1.273
Natural Resources	The natural resources of the village	3.768	1.418	3.850	1.359	3.554	1.445	3.900	1.436
Farmers	Other farmers in the village	4.026	1.236	4.067	1.202	3.817	1.230	4.196	1.256
Perceived Vulnerability	*How much do these concern you on a weekly basis (1 is "very little" and 5 is "a lot"):*								
Climate Change	Thinking about climate change	4.046	1.307	3.860	1.386	3.983	1.372	4.296	1.118
Impacts of Climate Change	Being affected by the negative effects of climate change	4.085	1.341	3.925	1.452	3.992	1.405	4.338	1.114
Operation of the Farm	Negative effects on their agricultural activities	3.998	1.397	3.944	1.445	3.888	1.450	4.162	1.285
Psychological Distance	*How much do you agree with the following statements (1 is "completely disagree" and 5 is "completely agree")*								
Spatial 1	Climate change is affecting this village	4.072	1.393	3.948	1.449	4.263	1.228	4.005	1.481
Temporal 2	The effects of climate change are happening right now	4.354	1.246	4.204	1.356	4.412	1.200	4.446	1.172
Social 1	Climate change is going to affect farmers like me	4.619	0.898	4.542	1.042	4.632	0.816	4.683	0.820
Hypothetical 2	Climate change is already affecting me	4.291	1.299	4.096	1.403	4.386	1.209	4.392	1.266
Hypothetical 3	Landslides are a consequence of climate change	4.563	0.972	4.475	1.079	4.633	0.857	4.579	0.968
Hypothetical 4	Droughts are a consequence of climate change	4.379	1.193	4.283	1.270	4.215	1.343	4.638	0.882
Spatial 2	Climate change is affecting other villages, but NOT this village	1.672	1.293	1.742	1.262	1.533	1.161	1.742	1.441
Temporal 1	The effects of climate change are going to happen in the future, but they are NOT happening right now	1.650	1.266	1.796	1.360	1.692	1.289	1.462	1.125
Social 2	Climate change is going to affect other farmers but NOT me	1.301	0.862	1.396	0.881	1.300	0.863	1.208	0.839
Hypothetical 1	I am not sure that climate change is really happening	1.662	1.239	1.608	1.192	1.878	1.386	1.500	1.100
PS Control Variables									
Less than 60 years	1 if the farmer is less than 60 years old; 0 otherwise	0.642	0.480	0.633	0.484	0.633	0.484	0.658	0.476
Female	1 if the farmer identifies herself as a female; 0 otherwise	0.483	0.500	0.508	0.502	0.492	0.502	0.450	0.500
Marital status	1 if the farmer is single; 0 otherwise	0.192	0.394	0.183	0.389	0.200	0.402	0.192	0.395
Education	1 if the maximum level of education attained is elementary education; 0 otherwise	0.389	0.488	0.425	0.496	0.383	0.488	0.358	0.482
Income	1 if their income is less than one national monthly wage; 0 otherwise	0.656	0.476	0.550	0.500	0.692	0.464	0.725	0.448
Workers	Number of workers	2.939	3.352	2.850	3.436	2.767	2.053	3.200	4.216
Farm Size	1 if the size of the farm is less than 5 ha; 0 otherwise	0.733	0.443	0.767	0.425	0.708	0.456	0.725	0.448
Water	1 if the farm has a natural spring or access to a river, creek, stream, etc.; 0 otherwise	0.661	0.474	0.583	0.495	0.708	0.456	0.692	0.464
Forest	1 if the farm has a forest or a bamboo forest, or part of it; 0 otherwise	0.656	0.476	0.733	0.444	0.658	0.476	0.575	0.496
Observations		360		120		120		120	

Source: Authors.

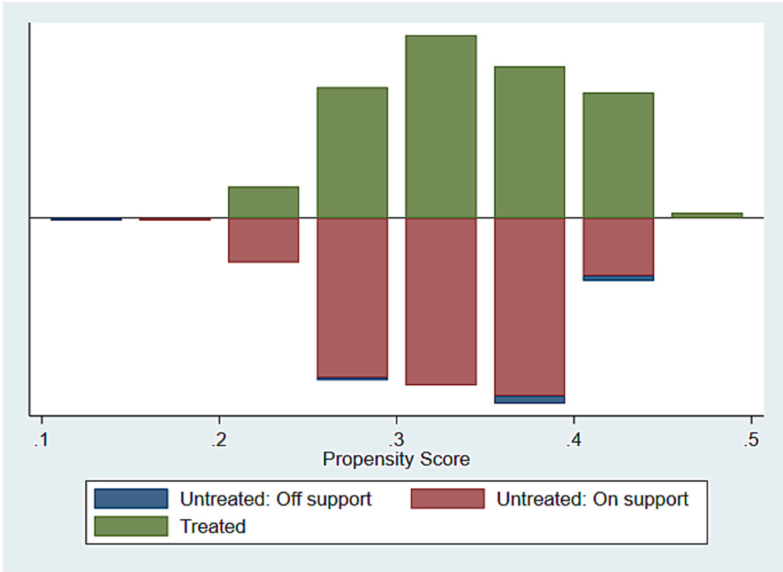

Fig. 2. Propensity Score Balance – Landslides. .
Source: Authors

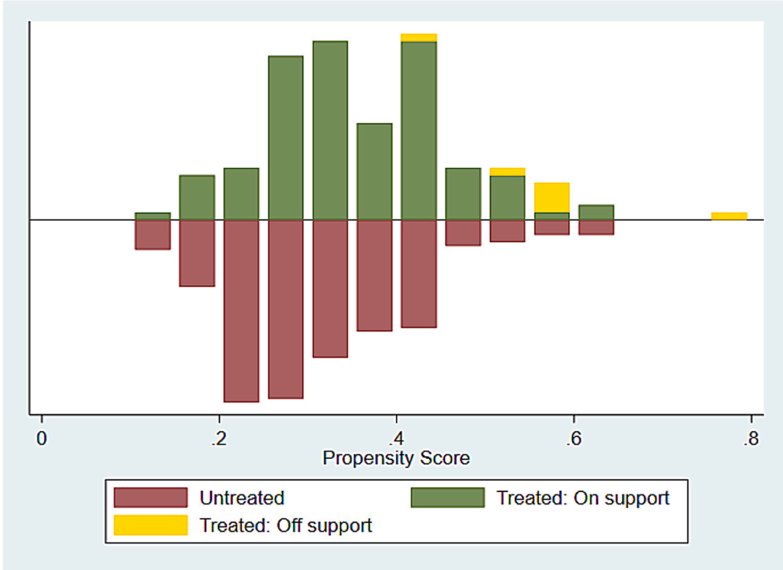

Fig. 3. Propensity Score Balance – Droughts. .
Source: Authors

e., those living in areas affected by landslides or drought. The height of each green bar indicates the number of treated individuals with a given PS range. On the other hand, the red bars represent the distribution of untreated individuals (those not living in landslide- or drought-affected areas) that are within the common support range with treated individuals. These are the control units that have PS comparable to those of the treated, thus allowing for valid matching.

In Fig. 2 the blue bars show the distribution of untreated farmers who are outside the range of common support. Likewise, in Fig. 3, the yellow bars show the distribution of treated farmers who are outside of this range. These farmers have such different PS that they have no comparable counterparts, so it is not considered appropriate to match them. Therefore, they are "out of support" and are not included in the matching analysis. The figures show that in both cases, the presence of red and green bars of similar size within the common support suggests an acceptable balance between the covariates of the matched groups.

Table 2 presents the results of a covariate balance analysis before and after applying PSM for the landslide group and Table 3 for the drought group. This analysis aims to determine if the characteristics (covariates) of farmers living in areas affected by landslides are similar to those of farmers in unaffected areas. We compare these characteristics before matching (unmatched, 'U') and after matching (matched, 'M') to check for balance between the two groups. The bias for all variables is reduced to below 10 %, which aligns with recommended standards for achieving sufficient balance between groups (Austin, 2009). Additionally, most covariates show a significant reduction in bias (%reduct |bias|), indicating better balance. Before matching (unmatched), the "Income" variable showed a bias of 11.5 % in Table 2 **and 22.3** % in Table 3. Bias here means the initial difference in "Income" between the treated group (those in landslide-affected areas) and the control group (those in unaffected areas). After matching, the bias for "Income" reduced to −5.4 % in Table 2 and −5.7 % in Table 3. This reduction means that the "Income" levels between the treated and control groups have become much closer to each other after matching.

The p-values for all covariates after matching are greater than 0.05, indicating that there are no statistically significant differences between the treated and control groups, which is desirable. Likewise, the ratio of variances (V(T)/V(C)) is within the acceptable range for all covariates, suggesting that matching has also balanced the variability between groups. The analysis suggests PSM has been effective in balancing the covariates between the treated and untreated groups. This is crucial to reduce bias in the estimation of the effect of living in a village where extreme weather events have occurred, ensuring that observed differences in outcomes between groups are not due to differences in these covariates.

4.2. *Perceived severity*

Fig. 4 compares ATEs and ATETs of farmers living in villages where landslides and droughts have been experienced. Regarding the ATEs, it can be seen that landslides are only significant in one perception in both matching methods, the severity of climate change on natural resources. However, it has a negative sign (−0.34 with nearest neighbor and −0.38 with caliper). This implies that living in a village where three or more landslides have been experienced reduces farmers' perception that climate change negatively affects

Table 2
Balance of Covariates for Landslide PSM.

Variables	Unmatched Matched	Mean			%reduct |bias|	*t*-test		V(T)/V(C)
		Treated	Control	%bias		t	p > t	
Less than 60 years	U	0.63333	0.64583	−2.6		−0.23	0.816	
	M	0.62712	0.58475	8.7	−239.0	0.66	0.507	
Female	U	0.49167	0.47917	2.5		0.22	0.824	
	M	0.49153	0.51695	−5.1	−103.4	−0.39	0.698	
Marital status	U	0.20000	0.18750	3.2		0.28	0.777	
	M	0.19492	0.16949	6.4	−103.4	0.5	0.615	
Education	U	0.38333	0.39167	−1.7		−0.15	0.879	
	M	0.38983	0.35593	6.9	−306.8	0.54	0.592	
Income	U	0.69167	0.63750	11.5		1.02	0.309	
	M	0.68644	0.71186	−5.4	53.1	−0.42	0.672	
Workers	U	2.7667	3.0250	−8.4		−0.69	0.491	0.29*
	M	2.7797	2.8644	−2.8	67.2	−0.26	0.797	0.50*
Farm Size	U	0.70833	0.74583	−8.4		−0.76	0.450	
	M	0.71186	0.70339	1.9	77.4	0.14	0.887	
Water	U	0.70833	0.63750	15.1		1.34	0.182	
	M	0.70339	0.70339	0.0	100.0	0.00	1.000	
Forest	U	0.65833	0.65417	0.9		0.08	0.938	
	M	0.66949	0.67797	−1.8	−103.4	−0.14	0.890	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.
B Statistic < 16.1 %.
Balancing property satisfied: YES.
Common support imposed: YES.
Source: Authors.

Table 3
Balance of Covariates for Drought PSM.

Variables	Unmatched Matched	Mean			%reduct |bias|	*t*-test		V(T)/V(C)
		Treated	Control	%bias		t	p > t	
Less than 60 years	U	0.65833	0.63333	5.2		0.47	0.642	
	M	0.66372	0.65487	1.8	64.6	0.14	0.889	
Female	U	0.45000	0.50000	−10.0		−0.89	0.372	
	M	0.46903	0.47788	−1.8	82.3	−0.13	0.895	
Marital status	U	0.19167	0.19167	0.0		0.00	1.000	
	M	0.19469	0.19469	0.0	.	0.00	1.000	
Education	U	0.35833	0.40417	−9.4		−0.84	0.402	
	M	0.37168	0.35398	3.6	61.4	0.28	0.783	
Income	U	0.72500	0.62083	22.3		1.97	0.050	
	M	0.70496	0.73451	−5.7	74.5	−0.44	0.658	
Workers	U	3.20000	2.80830	10.9		1.05	0.297	2.23*
	M	2.86730	2.70800	4.4	59.3	0.42	0.671	0.71
Farm Size	U	0.72500	0.73750	−2.8		−0.25	0.801	
	M	0.73451	0.77876	−10.0	254.0	0.77	0.441	
Water	U	0.69167	0.64583	9.7		0.86	0.388	
	M	0.68142	0.69912	−3.8	61.4	−0.29	0.775	
Forest	U	0.57500	0.69583	−25.2		−2.28	0.023	
	M	0.59292	0.60177	−1.8	92.7	−0.14	0.893	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.
B Statistic: 14.6%.
Balancing property satisfied: YES.
Common support imposed: YES.
Source: Authors.

natural resources compared to farmers living in villages where landslides have not been experienced. Moreover, landslide was also significant in the severity of climate change in other farmers, but only in one matching technique (−0.27 with caliper). This suggests that exposure to landslides may lead some farmers to downplay the severity of climate change impacts on others.

Regarding droughts, residing in villages that have experienced two or more droughts shows a positive and significant effect on how farmers perceive the severity of the impacts of climate change, particularly on the village's natural resources and the other farmers. The ATEs on the perceived severity of natural resources are 0.39 using nearest neighbor matching and 0.34 using caliper matching, both statistically significant at the 5 % level. Similarly, the effects on farmers within the village show ATEs of 0.30 (nearest neighbor) at the 10 % level and 0.31 (caliper), significant at the 5 % level. These findings suggest that farmers residing in villages affected by droughts perceived a higher severity of climate change, compared to farmers living in villages where droughts have not been reported.

On the other hand, the ATETs reflect the average treatment effect among only the treated group. For landslides, none of the ATETs are statistically significant, indicating that living directly in a village where three or more landslides have occurred since 2005 does not significantly influence any of the categories of farmers' perceived severity. In contrast, droughts exhibit positive and statistically significant effects among the treated farmers. The ATETs on the perceived severity of natural resources is 0.38 using nearest neighbor matching and 0.42 using caliper matching, both statistically significant at the 5 % level. Similarly, the effects on farmers within the village show ATETs of 0.40 (nearest neighbor) and 0.42 (caliper), also significant at the 5 % level. These findings suggest that farmers' perceptions of severity increase due to their direct experience with droughts in comparison with farmers who live in villages where droughts have not been reported.

4.3. Perceived vulnerability

In terms of perceived vulnerability (Fig. 5), landslides show no statistically significant effects in any of the categories, neither in the ATEs nor in the ATETs. This indicates that living in a village where three or more landslides have occurred since 2005 does not significantly influence farmers' perceptions of their vulnerability to climate change. In contrast, droughts have positive and significant effects in all three categories analyzed for both ATEs and ATETs.

The first category indicates that living in a drought-affected village significantly increases how frequently farmers worry about climate change on a weekly basis. In this case, the ATEs are positive and significant at the 1 % level, with values of 0.47 using nearest neighbor matching and 0.44 using caliper matching. Likewise, the second category indicates how often farmers worry about being negatively impacted by climate change. Here, the ATEs are 0.53 (nearest neighbor) and 0.47 (caliper), both also significant at the 1 %

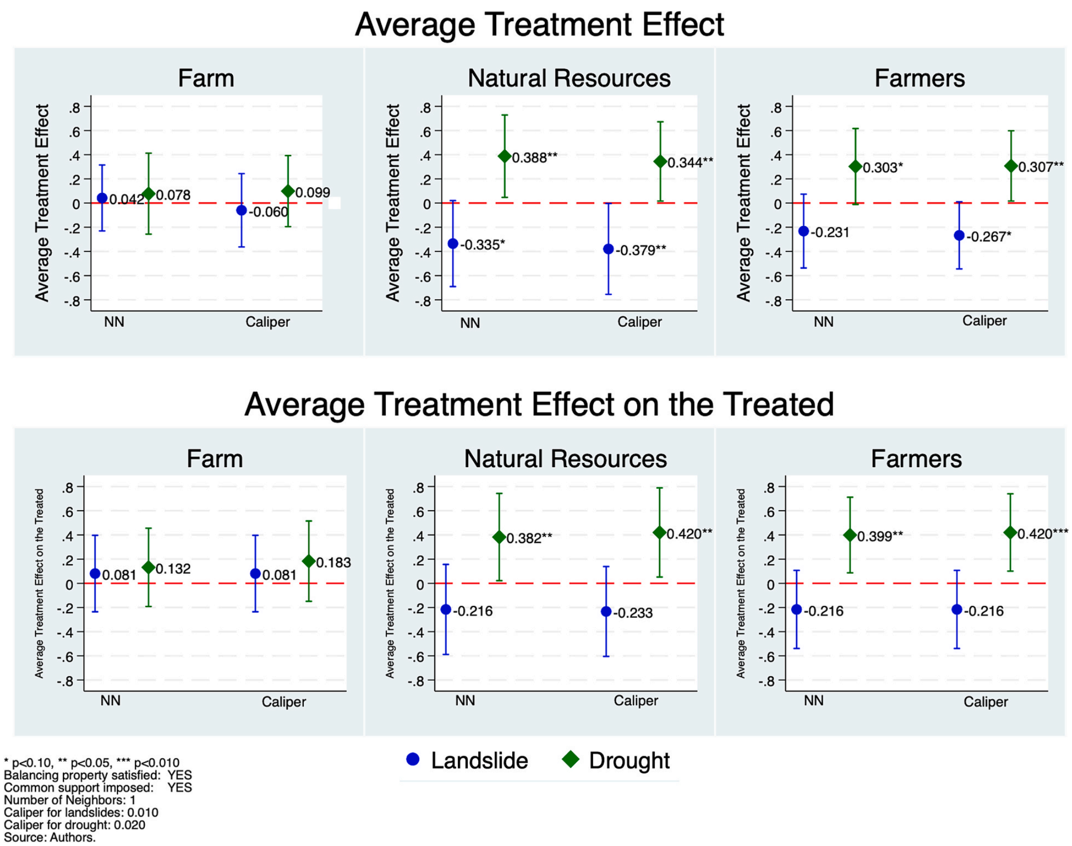

Fig. 4. Estimated ATEs and ATETs for Perceived Severity.

level. Lastly, the third category measures the concerns about the effects of climate change on their farming activities. In this case, the ATEs are 0.43 (nearest neighbor) and 0.31 (caliper), statistically significant at the 5 % and 10 % levels, respectively. These findings suggest that farmers who have experienced droughts exhibit higher perceptions of vulnerability to climate change. They worry more frequently about the potential adverse impacts on their livelihoods, in contrast to farmers residing in villages unaffected by droughts.

Regarding the ATETs, the analysis reveals that for the first category of perceived vulnerability, the effects are positive and significant at the 1 % level, with values of 0.61 using nearest neighbor matching and 0.59 using caliper matching. Similarly, the treatment effects are larger and remain positive for how often farmers worry about being negatively impacted by climate change, with ATETs of 0.70 (nearest neighbor) and 0.65 (caliper), both also significant at the 1 % level. Regarding concerns about the effects of climate change on their farming activities, drought experiences yield positive ATETs of 0.53 (nearest neighbor) and 0.54 (caliper), both statistically significant at the 5 % level. Overall, these findings imply that experiencing droughts substantially increases the perceived vulnerability among farmers, leading them to worry more frequently about climate change and its potential adverse effects on their livelihoods in comparison to farmers who live in villages where droughts have not been experienced.

4.4. Psychological distance

For the psychological distance, living in a village where three or more landslides have occurred is associated with only one statistically significant ATE (Fig. 6), specifically for hypothetical distance 2 (I am not sure that climate change is really happening). This effect is positive and significant at the 5 % level, with estimates of 0.38 using nearest neighbor and 0.32 with caliper. Also, it can be observed that the sign is positive, implying that farmers in these villages are not sure that climate change is happening, compared to farmers in villages where landslides have not been experienced. This may explain why none of the other perceptions are statistically significant.

In comparison, droughts have statistically significant effects in three categories using both matching methods. The first category is Temporal 2 (The effects of climate change are going to happen in the future, but they are NOT happening right now), where the ATEs

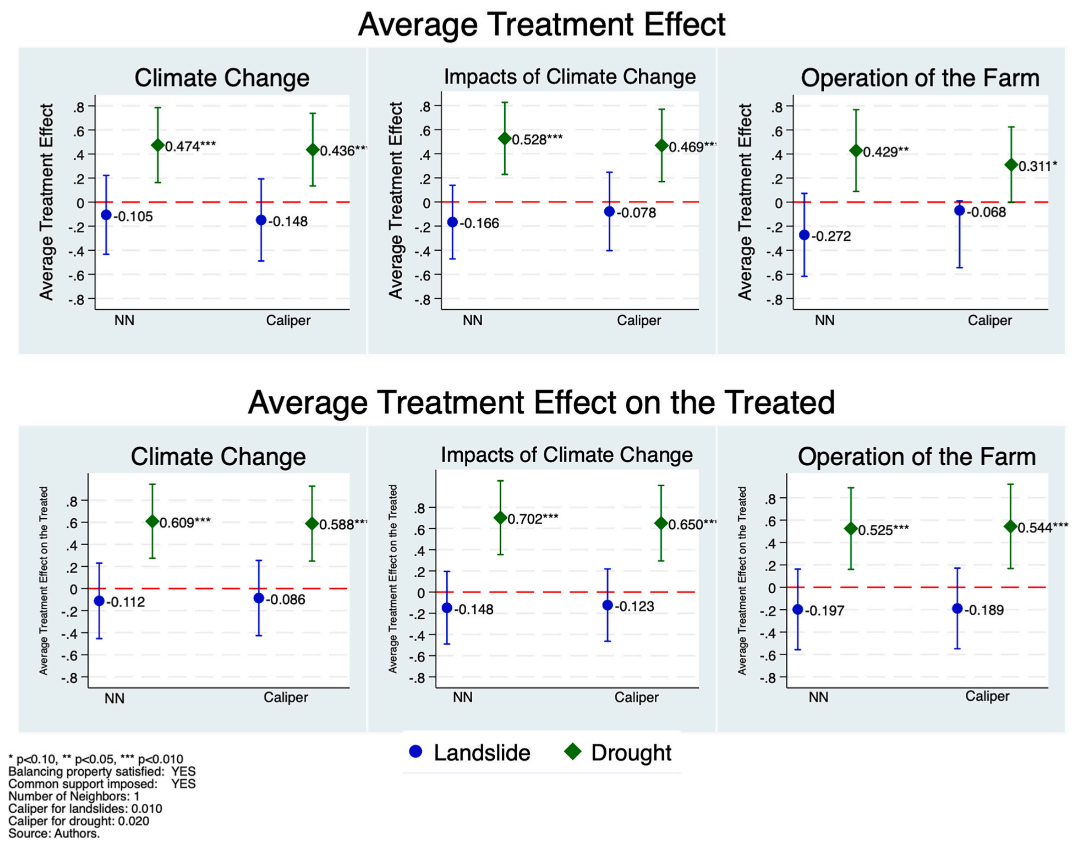

Fig. 5. Estimated ATEs and ATETs for Perceived Vulnerability.

are −0.38 (nearest neighbor) and −0.39 (caliper), significant at the 5 % and 10 % levels, respectively. This shows that living in a village affected by drought reduces farmers' psychological distance, making them perceive the effects of climate change as more immediate. The second category is hypothetical 2 (I am not sure that climate change is really happening). Unlike the landslide's ATEs, the drought showed significant negative ATEs of − 0.36 (nearest neighbor), significant at the 5 % level, and − 0.25 (caliper), significant at the 10 % level. Finally, the third category is hypothetical 4 (Droughts are a consequence of climate change), where the ATEs are positive at 0.34 (nearest neighbor) and 0.40 (caliper), both significant at the 5 % and 1 % levels, respectively. Additionally, there were two other categories where droughts showed statistically significant ATEs, but only with one matching method. For the category Social 2 (Climate change is going to affect other farmers but NOT me), the ATE with the caliper was −0.19 and significant at the 5 % level. Lastly, in the category Hypothetical 1 (Climate change is already affecting me), the ATE was 0.28 using the nearest neighbor matching method, which is significant at the 10 % level.

Fig. 7 *shows* the results from the ATET estimations. As can be seen, landslides do not have a significant impact on any of the categories studied of psychological distance. However, droughts do have significant effects in certain categories. Regarding spatial distance, neither type of event shows significant effects, indicating that experiencing these events does not significantly alter the perception of how close farmers perceive the effects of climate change in a geographical dimension. Regarding temporal distance, the first category presents the effects of climate change as an event closer in time. Here, drought has positive ATETs of 0.29 (nearest neighbor) and 0.37 (caliper), significant at the 10 % and 5 % levels, respectively. Similarly, the second category reflects the perception of climate change as a distant event in time. In this case, drought has negative ATETs of −0.44 (nearest neighbor) and −0.48 (caliper), significant at the 1 % and 10 % level, respectively. This indicates that living in a village that has experienced drought reduces the psychological distance of farmers, making them feel that the effects of climate change are less distant. Both categories suggest that these farmers perceive the impacts of climate change as more immediate on a temporal scale in comparison to farmers who live in villages with no drought experience.

In the social dimension, the first category shows positive ATETs of 0.22 (nearest neighbor) and 0.25 (caliper), both significant at the 10 % level. This category reflects the perception of climate change impacts as being closer to farmers who are similar to them. As a

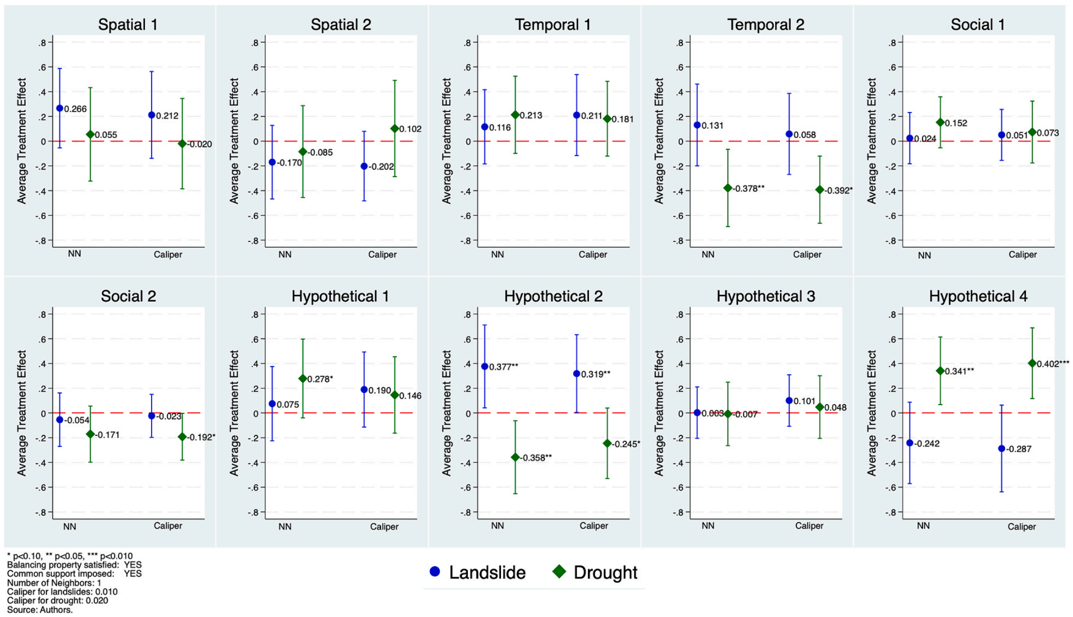

Fig. 6. Estimated ATEs for Psychological Distance.

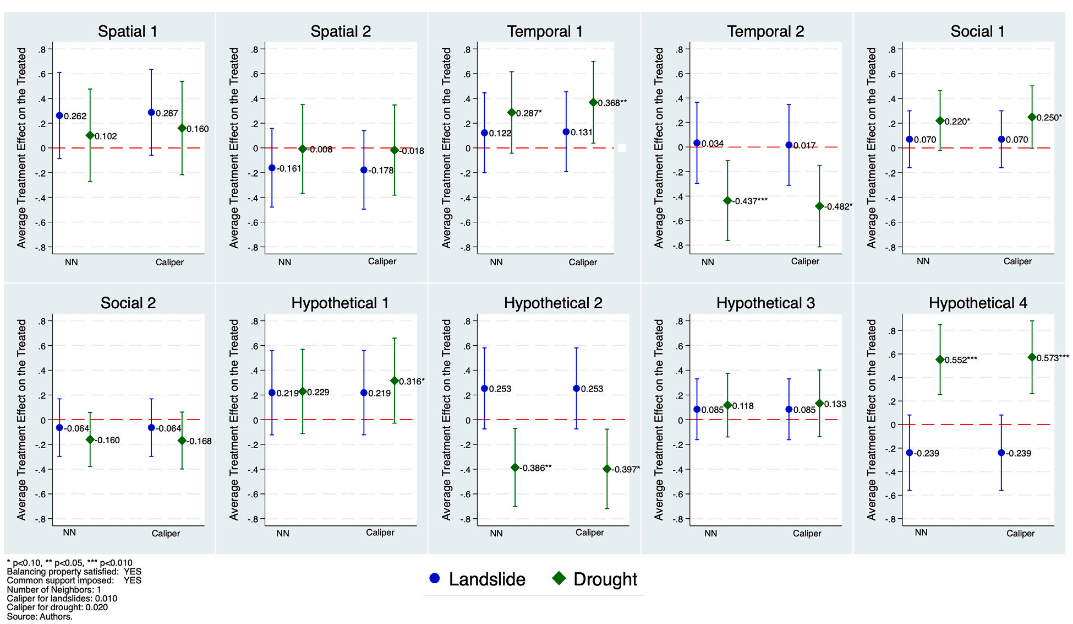

Fig. 7. Estimated ATETs for Psychological Distance.

result, farmers living in villages that have experienced drought perceive the effects of climate change as socially closer compared to those in villages where droughts have not occurred. However, the second category, which considers the effects of climate change from a more distant social perspective, is not significant. Additionally, in the hypothetical distances, only one perception, hypothetical distance 1, which frames climate change as an event already affecting farmers, was statistically significant, with only one matching technique (0.32 with caliper).

Moreover, the hypothetical distances two and four were significant in the two matching techniques. The second category frames climate change as a distant event with uncertain occurrence. In this case, droughts result in negative ATETs of − 0.39 (nearest neighbor) and − 0.40 (caliper), both significant at the 5 % level. This suggests that the experience of droughts reduces the perception of uncertainty about the occurrence of climate change, compared to villages where droughts have not occurred. The fourth category directly links droughts as a consequence of climate change. Here, the ATETs are positive at 0.55 (nearest neighbor) and 0.57 (caliper), both significant at the 1 % level, indicating that living in villages that have experienced droughts significantly increases the perception that these events are indeed a consequence of climate change compared to farmers in villages where droughts have not been experienced. A summary of all ATEs and ATETS can be found in Appendix A1.

4.5. Robustness check

To assess the robustness of our results against potential hidden biases, we calculated Rosenbaum bounds for the perception variables studied. Rosenbaum bounds are a sensitivity analysis method used in observational studies to assess the robustness of causal inference results to potential hidden biases from unobserved variables. They introduce a parameter, Gamma (Γ), which quantifies how much an unobserved variable would need to influence the odds of treatment assignment to alter the study's conclusions. For example, if $\Gamma = 1.5$, it implies that two individuals with the same observed characteristics could have up to a 50 % difference in their likelihood of receiving the treatment due to unobserved factors. By calculating Rosenbaum bounds across different values of Γ, researchers can determine how sensitive their findings are to hidden bias: if large Γ values are needed to make the effect insignificant, the results are considered robust; if small values suffice, the findings are more vulnerable to unobserved confounders.

To evaluate the potential influence of unobserved factors, we examined varying levels of gamma (Γ). We found no hidden biases ($\Gamma = 1$), as well as cases where the probability increased by 50 % ($\Gamma = 1.5$) and 100 % ($\Gamma = 2$). These results were estimated using the two matching methods previously employed: nearest neighbor and caliper. Appendix A2. shows the results of the Rosenbaum Bounds in the case of living in villages where landslides have been experienced. None of the previously estimated ATETs was significant, and when analyzing the results for Gamma 1, 1.5, and 2, no significant treatment effects were found for any of the variables, indicating that even in the presence of unobserved factors, the ATETs would still be non-significant. This suggests that living in a village where three or more landslides have occurred since 2005, does not have a statistically significant impact on the variables included for perceived severity, perceived vulnerability, and psychological distance and that this conclusion is robust to possible unobserved biases.

In Appendix A3., the results of the Rosenbaum bounds for the drought treatment are presented. For Perceived Severity, both "Natural Resources" and "Farmers" show significant ATETs at the 5 % level. The Rosenbaum bounds at Gamma level 1 remain significant at the 5 % and 1 % levels, respectively. At higher Gamma levels ($\Gamma = 1.5$ and $\Gamma = 2$), both effects remain significant at the 1 % level but only at the lower bound. This suggests that the effect is robust to biases that reduce the positive impact of drought on these perceptions but may be overestimated. Regarding Perceived Vulnerability, all three ATETs studied were significant. The Rosenbaum bounds analysis shows that the ATETs of "Climate Change" and "Climate Change Impacts" remain significant at Gamma levels of 1 and 1.5, indicating robustness to low unobserved biases. However, at Gamma 2, the effects are only significant at the lower bound, suggesting that they remain significant under moderate bias but could be overestimated. As for the variable "Operation of the Farm", it remains significant at Gamma = 1 but is only significant at the lower bound for the other two levels ($\Gamma = 1.5$ and $\Gamma = 2$), indicating the possibility of overestimation while maintaining significance.

For the psychological distance variables, the ATETs for "Temporal Distance 1" and "Hypothetical Distance 1" are significant at the 5 % level and negative. The Rosenbaum bounds show that both are significant in the absence of unobserved biases ($\Gamma = 1$). However, they are only significant at the upper bound when Gamma increases ($\Gamma = 1.5$ and $\Gamma = 2$), implying the effect is robust to biases that increase the negative effect, potentially overestimating it. For "Temporal distance 2" and "Social distance 1", the ATETs are significant and positive. Analyzing the bounds, we find that they are significant at 5 % when no unobserved biases are present ($\Gamma = 1$). However, at the higher levels ($\Gamma = 1.5$, and $\Gamma = 2$), they are only significant at the lower bound, suggesting robustness but with a risk of overestimation. Finally, for "Hypothetical Distance 4", the ATET is positive and significant at the 1 % level, with Rosenbaum bounds remaining significant across all Gamma levels tested. This suggests that, even in the presence of unobserved biases, living in a village affected by droughts maintains a significant effect on the farmers' perception that these events are a consequence of climate change.

5. Discussion

The motivation behind this study was to investigate how farmers' experiences with extreme weather events influence their perceptions of climate change, as understanding these perceptions is crucial for designing effective climate adaptation strategies. Farmers' beliefs about climate change can significantly affect their willingness to adopt adaptive practices, influence their responses to policy interventions, and shape broader community resilience. Our research was conducted in central Colombia, with fieldwork carried out between 2022 and 2023. This region has been subject to recurring landslides and droughts, which are expected to increase as a result of climate change (IPCC, 2014). We used the conceptual frameworks of PMT and psychological distance to analyze, from various dimensions, how these environmental events shape farmers' perspectives on climate change.

From a methodological perspective, we employed PSM to compare farmers residing in villages affected by landslides and droughts with those who had not experienced these events. This matching approach was essential to mitigate selection bias and ensure that the treated and control groups were comparable on various socio-economic and farm-level covariates (Ali & Erenstein, 2017; Bonfrer et al., 2016; Bravo-Ureta et al., 2012; Ham et al., 2011). Using both nearest-neighbor and caliper matching helped to improve the balance between groups further and increase the robustness of the results (Austin, 2009; Dehejia & Wahba, 2002; Jacovidis et al., 2017). This matching approach allowed us to analyze the impact of these environmental events on farmers' perceptions of climate change while accounting for potential confounding factors.

The results of the ATETs indicated no statistically significant differences in the 16 perceptions assessed for farmers who experienced landslides, suggesting that landslides may not influence how farmers perceive the threat of climate change or how psychologically distant they feel themselves from its impacts. However, we found two statistically significant ATEs, suggesting that living in a village that has experienced landslides reduces farmers' perceived severity of climate impacts on natural resources and increases the hypothetical distance, suggesting that farmers may be less certain about the reality of climate change. This uncertainty may explain why no ATETs were statistically significant for landslide experiences. In some cases, it has been found that landslides may not significantly impact farmers' behavior related to climate change. Some studies support this; for instance, there is no evidence that an increased risk of landslide exposure leads farmers to be more willing to avoid or mitigate the impacts of landslides (Lin et al., 2008; Mertens et al., 2018; Spegel & Ek, 2022). This is mainly because, in most cases, landslides do not directly impact farmers' production, unless they occur directly on a farmer's property. In our case, we focus on farmers who experienced landslides affecting their production or the village's natural resources. However, the impact tends to be more indirect, often affecting road networks rather than farming activities themselves. Consequently, vulnerability is often more extensive and determined by the state of the transport network rather than the landslide event itself (Vranken et al., 2013; Winter et al., 2019).

Additionally, the regional context of the study area must be considered. In this particular region of Colombia, landslides frequently result from heavy rainfall (Aristizábal & Sánchez, 2020; Garcia-Delgado et al., 2022). Therefore, farmers' perceptions of changes in precipitation patterns are particularly relevant to the analysis. When comparing farmers' perceptions with observed climate data, research has found that their perceptions of rainfall often do not align with actual changes in the rainfall patterns (Dhanya & Ramachandran, 2016; Guido et al., 2020; Li et al., 2022; Mahony & Cannon, 2018; Simelton et al., 2013). This mismatch between experiential and empirical evidence could help explain why landslides, which are directly linked to precipitation, do not significantly influence farmers' perceptions of climate change.

On the other hand, with their prolonged nature and direct impact on agricultural productivity, droughts seem to heighten farmers' awareness of climate change risks. Empirical evidence supports farmers' perceptions of drought are well-grounded and accurate (Marin, 2010; Slegers, 2008; West et al., 2008). Furthermore, these perceptions shape their views on the risks posed by climate change (Carlton et al., 2016; Diggs, 1991; Konisky et al., 2016; Lyons et al., 2018; Panda, 2016; Saleh Safi et al., 2012). Consequently, we found statistically significant differences in 10 out of the 16 perceptions studied among farmers in drought-affected areas, suggesting they view climate change as more severe, perceive themselves as more vulnerable, and experience a closer psychological distance to its impacts.

In analyzing the application of the PMT, our findings support existing literature suggesting that drought shapes threat appraisal (Truelove et al., 2015). This cognitive process involves how individuals assess threats based on their perceived vulnerability and severity (Keshavarz & Karami, 2016). Under drought conditions, farmers' perceptions become particularly critical, reinforcing the notion that specific extreme weather events can directly shape their understanding of climate change risks (Keshavarz & Karami, 2016; Neisi et al., 2020). Our study found all dimensions of perceived vulnerability to be significant, highlighting that farmers not only recognize the severity of drought but also increasingly feel susceptible to its impacts. This is consistent with prior research emphasizing the role of perceived vulnerability in the context of drought, suggesting that farmers' awareness of drought-related risks plays a crucial role in determining their responses to climate threats (Delfiyan et al., 2021; Gebrehiwot & van der Veen, 2015; Scarpa & Thiene, 2011; van Duinen et al., 2015).

Regarding psychological distance, the results further support the idea that drought's perceived immediacy and relevance are shaped by multiple factors. The significance of both temporal distance dimensions (The effects of climate change are happening right now or in the future) and hypothetical distance 1 (Uncertainty about climate change) represent the effect of drought in determining the perception of the immediacy of climate change. Lower temporal distances of climate change usually lead to higher perceived relevance of the event (Kim et al., 2019). Additionally, the significance of hypothetical distance 4 (Droughts are a consequence of climate change) aligns with previous research showing that people often link drought to climate change, thereby increasing their sense of risk (Deng et al., 2017; Guillard et al., 2021). The high percentage of farmers (66.1 %) with direct access to water sources, such as a spring, river, or stream (Table 1), likely reduces their perception of drought risk, as they may feel more secure in their water availability compared to farmers without such access. This sense of security can diminish the perceived relevance of spatial and social distances, as farmers with immediate water resources might not feel as affected by or concerned with broader geographical variations in drought risk or social proximity to others impacted by drought. Consequently, their access to water could lessen the significance of spatial and social factors in shaping their perceptions of climate risks, making these distances less influential in the analysis (Becker & Sparks, 2020; Craig et al., 2019).

Farmers within the same region can have different, sometimes even opposite, perceptions of climate risks because individual experiences, resources, and attitudes shape how they interpret environmental threats. Factors like access to water, past experiences with drought, and personal knowledge about climate can lead farmers to view similar conditions differently. For example, one farmer with reliable irrigation may feel less threatened by drought than another nearby farmer relying solely on rainfall. Additionally, social influences, such as community discussions or access to information, can further affect individual perceptions. This variability means that even within a shared geographic area, farmers might assess climate risks in diverse ways, reflecting a range of personal and contextual factors that influence their interpretations of climate change (Parsons & Nielsen, 2021; Yazdanpanah et al., 2023).

Overall, the Rosenbaum bounds results suggest that perceptions of severity and vulnerability to extreme events such as droughts exhibit robust effects in the face of low to moderate unobserved biases. However, in some cases, especially in the psychological distance analysis, the effects may be overestimated under a higher level of bias ($\Gamma = 2$). Despite this, the ATETs maintain their significance in most cases, suggesting that living in drought-affected villages significantly influences farmers' perceptions of climate change and its consequences.

Our findings provide only partial support for the first hypothesis (H1), which proposed a significant difference in perceptions between farmers residing in villages affected by extreme weather events and those in unaffected villages. While landslides did not appear to influence farmers' perceptions, droughts clearly did, suggesting that the type of extreme event plays a crucial role in shaping farmers' views on climate change. Regarding the second hypothesis (H2), which suggested no difference in perceptions between farmers residing in villages affected by landslides and those affected by droughts, our results lead us to reject this hypothesis. The clear contrast between the two groups—significant differences in perceptions among farmers in drought-affected areas but none among those in landslide-affected areas— indicates that the type of extreme weather event significantly influences how farmers perceive climate change.

These findings underscore the importance of considering the nature and directness of the extreme weather events when evaluating their influence on climate change perceptions. Droughts, due to their gradual onset and prolonged impact on agricultural productivity, directly interfere with farmers' livelihoods, making the consequences of climate change more tangible and salient. This direct connection helps explain why farmers affected by droughts exhibit significantly higher perceived severity and vulnerability, and experience reduced psychological distance from climate change. In contrast, landslides often result in more localized, short-term disruptions, frequently affecting infrastructure rather than agricultural output. This more indirect impact, combined with their frequent occurrence in the region and potential normalization, may reduce their salience as climate change indicators in farmers' minds. These contextual and experiential factors help justify the differentiated perceptual responses observed in our analysis and support the idea that farmers' lived experiences are critical in shaping how they internalize and react to climate risks.

6. Conclusions

This study sheds light on how extreme weather experiences, particularly droughts and landslides, shape climate change perceptions among farmers in central Colombia. Using PMT and psychological distance as frameworks, we found that while droughts increased farmers' awareness and influenced their assessments of climate risk severity and vulnerability, landslides did not have a significant effect. PSM helped control for confounding factors, enhancing the accuracy of our comparisons between affected and unaffected villages.

However, this study has limitations. First, the reliance on self-reported perceptions may introduce cognitive biases, such as over- or underestimation of risks, which are common in behavioral studies. Second, although the PSM approach is useful, it may not fully account for unobserved factors influencing farmers' beliefs. Third, to achieve covariate balance in the matching procedure, age and education had to be simplified into binary indicators. Age was coded using a 60-year threshold, and education was transformed into a dummy variable indicating whether respondents had primary education as their highest level attained, the most common educational level in our sample. While these decisions improved the performance of the matching diagnostics, they may also limit the ability to capture more nuanced differences across the population. Finally, the focus on central Colombia provides valuable context-specific insights but may limit the generalizability of the findings to other regions, where environmental, institutional, or cultural conditions may differ. Future research could incorporate longitudinal data and qualitative methods to better understand how farmers' experiences and perceptions evolve over time. From a policy perspective, it might be useful to implement targeted communication strategies. Leveraging local experiences and climate data can encourage more proactive adaptation behaviors, while training programs focused on sustainable agricultural practices can help farmers build resilience, especially in drought-affected regions.

CRediT authorship contribution statement

Alexander Cano: Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation. **Bente Castro-Campos:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A.1. Summary of results

Perceptions	Average Treatment Effect				Average Treatment Effect on the Treated			
	Landslide			Landslide	Landslide			Landslide
	NN	Caliper	NN	Caliper	NN	Caliper	NN	Caliper
Perceived Severity								
Farm	0.042	−0.06	0.042	0.042	0.081	0.08	0.132	0.183
Natural Resources	−0.335*	−0.379**	−0.335*	−0.335*	−0.216	−0.233	0.382**	0.420**
Farmers	−0.231	−0.267*	−0.231	−0.231	−0.216	−0.216	0.399**	0.420**
Perceived Vulnerability								
Climate change	−0.105	−0.148	−0.105	−0.105	−0.112	−0.086	0.609***	0.588***
Impacts of climate change	−0.166	−0.078	−0.166	−0.166	−0.148	−0.123	0.702***	0.650***
Operation of the farm	−0.272	−0.068	−0.272	−0.272	−0.197	−0.189	0.525**	0.544**
Psychological Distance								
Spatial 1	0.266	0.212	0.266	0.266	0.262	0.287	0.102	0.16
Temporal 1	0.116	0.211	0.116	0.116	0.122	0.131	0.287*	0.368**
Social 1	0.024	0.051	0.024	0.024	0.07	0.07	0.220*	0.250*
Hypothetical 1	0.075	0.19	0.075	0.075	0.219	0.219	0.229	0.316*
Hypothetical 3	0.003	0.101	0.003	0.003	0.085	0.085	0.118	0.133
Hypothetical 4	−0.242	−0.287	−0.242	−0.242	−0.239	−0.239	0.552***	0.573***
Spatial 2	−0.17	−0.202	−0.17	−0.17	−0.161	−0.178	−0.009	−0.018
Temporal 2	0.131	0.058	0.131	0.131	0.034	0.016	−0.437**	−0.482**
Social 2	−0.054	−0.023	−0.054	−0.054	−0.064	−0.064	−0.16	−0.168
Hypothetical 2	0.377**	0.319**	0.377**	0.377**	0.253	0.253	−0.386**	−0.397**
N	360	360	360	360	360	360	360	360

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.
Balancing property satisfied: YES.
Common support imposed: YES.
Number of Neighbors: 1.
Caliper for landslides: 0.010.
Caliper for drought: 0.020Source: Authors.

Appendix A.2. Rosenbaum bounds for ATET — landslides

Variables	Rosenbaum Bounds												
	Gamma (Γ)	Nearest Neighbor						Caliper					
		sig+	sig-	t-hat+	t-hat-	CI+	CI-	sig+	sig-	t-hat+	t-hat-	CI+	CI-
Perceived Severity													
Farm	1	0.3882	0.3882	0.0000	0.0000	−0.2500	0.5000	0.3882	0.3882	0.0000	0.0000	−0.2500	0.5000
	1.5	0.9290	0.0203	−0.2500	0.5000	−0.5000	0.5000	0.9290	0.0203	−0.2500	0.5000	−0.5000	0.5000
	2	0.9970	0.0004	−0.5000	0.5000	−0.5000	1.0000	0.9970	0.0004	−0.5000	0.5000	−0.5000	1.0000
Natural Resources	1	0.0642	0.0642	−0.2500	−0.2500	−0.5000	0.0000	0.0604	0.0604	−0.2500	−0.2500	−0.5000	0.0000
	1.5	0.0004	0.5967	−0.5000	0.0000	−1.0000	0.5000	0.0004	0.5842	−0.5000	0.0000	−1.0000	0.5000
	2	0.0000	0.9330	−1.0000	0.2500	−1.0000	0.7500	0.0000	0.9286	−1.0000	0.2500	−1.0000	0.7500
Farmers	1	0.0455	0.0455	0.0000	0.0000	−0.5000	0.0000	0.0499	0.0499	0.0000	0.0000	−0.5000	0.0000
	1.5	0.0003	0.4928	−0.5000	0.0000	−1.0000	0.5000	0.0004	0.5069	−0.5000	0.0000	−1.0000	0.5000
	2	0.0000	0.8777	−1.0000	0.0000	−1.0000	0.5000	0.0000	0.8837	−1.0000	0.0000	−1.0000	0.5000
Perceived Vulnerability													
Climate change	1	0.4301	0.4301	0.0000	0.0000	−0.5000	0.2500	0.4637	0.4637	0.0000	0.0000	−0.5000	0.2500
	1.5	0.0281	0.9395	−0.5000	0.2500	−1.0000	0.5000	0.0356	0.9473	−0.2500	0.2500	−0.7500	0.5000
	2	0.0007	0.9975	−0.5000	0.5000	−1.0000	1.0000	0.0011	0.9979	−0.5000	0.5000	−1.0000	1.0000
Impacts of climate change	1	0.2900	0.2900	0.0000	0.0000	−0.5000	0.0000	0.3418	0.3418	0.0000	0.0000	−0.5000	0.0000
	1.5	0.0133	0.8618	−0.5000	0.0000	−0.5000	0.5000	0.0197	0.8901	−0.2500	0.0000	−0.5000	0.5000
	2	0.0003	0.9886	−0.5000	0.5000	−1.0000	1.0000	0.0005	0.9921	−0.5000	0.5000	−1.0000	1.0000
Operation of the farm	1	0.2825	0.2825	0.0000	0.0000	−0.5000	0.0000	0.3144	0.3144	0.0000	0.0000	−0.5000	0.0000
	1.5	0.0119	0.8610	−0.5000	0.0000	−1.0000	0.5000	0.0156	0.8787	−0.5000	0.0000	−1.0000	0.5000
	2	0.0002	0.9889	−0.5000	0.5000	−1.4000	0.7500	0.0003	0.9910	−0.5000	0.5000	−1.2500	0.7500
Psychological Distance													
Spatial Distance 1	1	0.1700	0.1700	0.0000	0.0000	0.0000	0.0000	0.1289	0.1289	0.0000	0.0000	0.0000	0.0000
	1.5	0.0088	0.6651	0.0000	0.0000	−0.5000	0.0000	0.0060	0.5803	0.0000	0.0000	−0.5000	0.0000
	2	0.0003	0.9212	−0.5000	0.0000	−1.0000	0.5000	0.0002	0.8752	−0.5000	0.0000	−1.0000	0.5000
Temporal Distance 1	1	0.2451	0.2451	0.0000	0.0000	0.0000	0.0000	0.2370	0.2370	0.0000	0.0000	0.0000	0.0000
	1.5	0.7920	0.0132	0.0000	0.0000	−0.5000	1.0000	0.7770	0.0131	0.0000	0.0000	−0.5000	0.5000
	2	0.9711	0.0004	0.0000	0.5000	−0.5000	1.0000	0.9661	0.0004	0.0000	0.5000	−0.5000	1.0000

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Variables	Rosenbaum Bounds												
	Gamma (Γ)	Nearest Neighbor						Caliper					
		sig+	sig-	t-hat+	t-hat-	CI+	CI-	sig+	sig-	t-hat+	t-hat-	CI+	CI-
Social Distance 1	1	0.5611	0.5611	0.0000	0.0000	0.0000	0.0000	0.5611	0.5611	0.0000	0.0000	0.0000	0.0000
	1.5	0.9387	0.1093	0.0000	0.0000	−0.5000	0.2500	0.9387	0.1093	0.0000	0.0000	−0.5000	0.2500
	2	0.9948	0.0126	0.0000	0.0000	−0.5000	0.5000	0.9948	0.0126	0.0000	0.0000	−0.5000	0.5000
Hypothetical Distance 1	1	0.1747	0.1747	0.0000	0.0000	0.0000	0.2500	0.2229	0.2229	0.0000	0.0000	0.0000	0.0000
	1.5	0.7129	0.0067	0.0000	0.2500	−0.2500	1.0000	0.7624	0.0116	0.0000	0.0000	−0.2500	0.9000
	2	0.9490	0.0001	0.0000	0.6500	−0.5000	1.0000	0.9621	0.0003	0.0000	0.5000	−0.5000	1.0000
Spatial Distance 2	1	0.0653	0.0653	0.0000	0.0000	0.0000	0.5000	0.0443	0.0443	0.0000	0.0000	0.0000	0.5000
	1.5	0.5180	0.0009	0.0000	0.5000	−0.2500	1.0000	0.4269	0.0005	0.0000	0.5000	0.0000	1.0000
	2	0.8743	0.0000	0.0000	0.5000	−0.5000	1.0000	0.8118	0.0000	0.0000	0.5000	−0.5000	1.0000
Temporal Distance 2	1	0.3198	0.3198	0.0000	0.0000	0.0000	0.0000	0.3547	0.3547	0.0000	0.0000	0.0000	0.0000
	1.5	0.8508	0.0230	0.0000	0.0000	−0.5000	0.5000	0.8643	0.0314	0.0000	0.0000	−0.5000	0.5000
	2	0.9835	0.0009	0.0000	0.5000	−1.0000	1.0000	0.9849	0.0015	0.0000	0.2500	−1.0000	1.0000
Social Distance 2	1	0.3376	0.3376	0.0000	0.0000	0.0000	0.0000	0.3376	0.3376	0.0000	0.0000	0.0000	0.0000
	1.5	0.0534	0.7757	0.0000	0.0000	0.0000	0.0000	0.0534	0.7757	0.0000	0.0000	0.0000	0.0000
	2	0.0063	0.9461	0.0000	0.0000	−0.5000	0.0000	0.0063	0.9461	0.0000	0.0000	−0.5000	0.0000
Hypothetical Distance 2	1	0.0875	0.0875	0.0000	0.0000	0.0000	0.5000	0.0967	0.0967	0.0000	0.0000	0.0000	0.5000
	1.5	0.5767	0.0015	0.0000	0.5000	−0.5000	1.0000	0.5943	0.0019	0.0000	0.5000	−0.3000	1.0000
	2	0.9022	0.0000	0.0000	1.0000	−1.0000	1.0000	0.9087	0.0000	0.0000	1.0000	−0.7500	1.0000
Hypothetical Distance 3	1	0.2707	0.2707	0.0000	0.0000	0.0000	0.0000	0.2707	0.2707	0.0000	0.0000	0.0000	0.0000
	1.5	0.7731	0.0230	0.0000	0.0000	0.0000	0.5000	0.7731	0.0230	0.0000	0.0000	0.0000	0.5000
	2	0.9581	0.0012	0.0000	0.0000	−0.5000	0.5000	0.9581	0.0012	0.0000	0.0000	−0.5000	0.5000
Hypothetical Distance 4	1	0.0664	0.0664	0.0000	0.0000	−0.1000	0.0000	0.0664	0.0664	0.0000	0.0000	−0.1000	0.0000
	1.5	0.0014	0.4681	−0.1000	0.0000	−0.5000	0.0000	0.0014	0.4681	−0.1000	0.0000	−0.5000	0.0000
	2	0.0000	0.8223	−0.5000	0.0000	−1.0000	0.5000	0.0000	0.8223	−0.5000	0.0000	−1.0000	0.5000
N	118 matched pairs							118 matched pairs					

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.
Number of Neighbors: 1.
Caliper for landslides: 0.010.
Caliper for drought: 0.020.
Source: Authors.

Appendix A.3. Rosenbaum bounds for ATET — droughts

Variables	Rosenbaum Bounds												
	Gamma (Γ)	Nearest Neighbor						Caliper					
		sig+	sig-	t-hat+	t-hat-	CI+	CI-	sig+	sig-	t-hat+	t-hat-	CI+	CI-
Perceived Severity													
Farm	1	0.2126	0.2126	0.0000	0.0000	0.0000	0.5000	0.1439	0.1439	0.0000	0.0000	0.0000	0.5000
	1.5	0.8135	0.0059	0.0000	0.5000	−0.5000	0.5000	0.7168	0.0030	0.0000	0.5000	−0.5000	1.0000
	2	0.9824	0.0001	−0.5000	0.5000	−0.7500	1.0000	0.9595	0.0000	−0.4000	0.5000	−0.7500	1.0000
Natural Resources	1	0.0130	0.0130	0.5000	0.5000	0.0000	1.0000	0.0103	0.0103	0.5000	0.5000	0.0000	1.0000
	1.5	0.3096	0.0000	0.0000	0.7500	−0.2500	1.0000	0.2612	0.0000	0.0000	1.0000	−0.2500	1.0000
	2	0.7621	0.0000	0.0000	1.0000	−0.5000	1.5000	0.7014	0.0000	0.0000	1.0000	−0.5000	1.5000
Farmers	1	0.0035	0.0035	0.5000	0.5000	0.0000	1.0000	0.0037	0.0037	0.5000	0.5000	0.0000	1.0000
	1.5	0.1545	0.0000	0.0000	1.0000	0.0000	1.0000	0.1492	0.0000	0.0000	1.0000	0.0000	1.0000
	2	0.5581	0.0000	0.0000	1.0000	−0.5000	1.0000	0.5359	0.0000	0.0000	1.0000	−0.5000	1.2500
Perceived Vulnerability													
Climate change	1	0.0006	0.0006	0.5000	0.5000	0.0000	1.0000	0.0010	0.0010	0.5000	0.5000	0.0000	1.0000
	1.5	0.0567	0.0000	0.0000	1.0000	0.0000	1.5000	0.0744	0.0000	0.0000	1.0000	0.0000	1.5000
	2	0.3302	0.0000	0.0000	1.0000	−0.5000	1.5000	0.3725	0.0000	0.0000	1.0000	−0.5000	1.5000
Impacts of climate change	1	0.0002	0.0002	0.5000	0.5000	0.0000	1.0000	0.0004	0.0004	0.5000	0.5000	0.0000	1.0000
	1.5	0.0301	0.0000	0.0000	1.0000	0.0000	1.5000	0.0391	0.0000	0.0000	1.0000	0.0000	1.5000
	2	0.2235	0.0000	0.0000	1.5000	0.0000	1.5000	0.2453	0.0000	0.0000	1.0000	0.0000	1.5000
Operation of the farm	1	0.0098	0.0098	0.5000	0.5000	0.0000	1.0000	0.0142	0.0142	0.5000	0.5000	0.0000	1.0000
	1.5	0.2801	0.0000	0.0000	1.0000	−0.5000	1.5000	0.3120	0.0000	0.0000	1.0000	−0.5000	1.5000
	2	0.7391	0.0000	0.0000	1.0000	−0.5000	1.5000	0.7583	0.0000	0.0000	1.2500	−0.5000	1.5000
Psychological Distance													
Spatial Distance 1	1	0.3218	0.3218	0.0000	0.0000	0.0000	0.0000	0.3057	0.3057	0.0000	0.0000	0.0000	0.0000
	1.5	0.0261	0.8405	0.0000	0.0000	−0.5000	0.5000	0.0267	0.8145	0.0000	0.0000	−0.5000	0.5000
	2	0.0012	0.9800	−0.5000	0.0000	−1.0000	1.0000	0.0014	0.9719	−0.5000	0.0000	−1.0000	1.0000
Temporal Distance 1	1	0.0306	0.0306	0.0000	0.0000	0.0000	0.5000	0.0142	0.0142	0.0000	0.0000	0.0000	0.5000

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Variables	Rosenbaum Bounds												
	Gamma (Γ)	Nearest Neighbor						Caliper					
		sig+	sig-	t-hat+	t-hat-	CI+	CI-	sig+	sig-	t-hat+	t-hat-	CI+	CI-
	1.5	0.3097	0.0004	0.0000	0.5000	0.0000	1.0000	0.1854	0.0002	0.0000	0.5000	0.0000	1.0000
	2	0.6785	0.0000	0.0000	0.5000	0.0000	1.0000	0.5000	0.0000	0.0000	1.0000	0.0000	1.0000
Social Distance 1	1	0.0154	0.0154	0.0000	0.0000	0.0000	0.1000	0.0139	0.0139	0.0000	0.0000	0.0000	0.5000
	1.5	0.2073	0.0002	0.0000	0.1000	0.0000	0.5000	0.1954	0.0001	0.0000	0.5000	0.0000	0.5000
	2	0.5452	0.0000	0.0000	0.5000	0.0000	1.0000	0.5271	0.0000	0.0000	0.5000	0.0000	1.0000
Hypothetical Distance 1	1	0.0680	0.0680	0.0000	0.0000	0.0000	0.5000	0.0281	0.0281	0.0000	0.0000	0.0000	0.5000
	1.5	0.5034	0.0011	0.0000	0.5000	0.0000	1.0000	0.3098	0.0003	0.0000	0.5000	0.0000	1.0000
	2	0.8575	0.0000	0.0000	0.7500	−0.5000	1.0000	0.6881	0.0000	0.0000	1.0000	−0.5000	1.5000
Spatial Distance 2	1	0.1958	0.1958	0.0000	0.0000	0.0000	0.5000	0.1556	0.1556	0.0000	0.0000	0.0000	0.5000
	1.5	0.8042	0.0046	0.0000	0.5000	−0.5000	1.0000	0.7491	0.0031	0.0000	0.5000	−0.5000	1.0000
	2	0.9817	0.0000	−0.5000	0.5000	−1.0000	1.0000	0.9699	0.0000	−0.5000	0.5000	−1.0000	1.0000
Temporal Distance 2	1	0.0041	0.0041	0.0000	0.0000	−0.5000	0.0000	0.0019	0.0019	0.0000	0.0000	−0.5000	0.0000
	1.5	0.0000	0.1025	−0.5000	0.0000	−1.0000	0.0000	0.0000	0.0546	−0.5000	0.0000	−1.0000	0.0000
	2	0.0000	0.3714	−1.0000	0.0000	−1.5000	0.0000	0.0000	0.2343	−1.0000	0.0000	−1.5000	0.0000
Social Distance 2	1	0.0082	0.0082	0.0000	0.0000	0.0000	0.0000	0.0085	0.0085	0.0000	0.0000	0.0000	0.0000
	1.5	0.0002	0.0912	0.0000	0.0000	−0.5000	0.0000	0.0002	0.0928	0.0000	0.0000	−0.5000	0.0000
	2	0.0000	0.2698	0.0000	0.0000	−0.5000	0.0000	0.0000	0.2731	0.0000	0.0000	−1.0000	0.0000
Hypothetical Distance 2	1	0.0112	0.0112	0.0000	0.0000	−0.5000	0.0000	0.0091	0.0091	0.0000	0.0000	−0.5000	0.0000
	1.5	0.0001	0.1978	−0.5000	0.0000	−1.0000	0.0000	0.0001	0.1624	−0.5000	0.0000	−1.0000	0.0000
	2	0.0000	0.5570	−1.0000	0.0000	−1.0000	0.0000	0.0000	0.4860	−1.0000	0.0000	−1.0000	0.0000
Hypothetical Distance 3	1	0.2192	0.2192	0.0000	0.0000	0.0000	0.0000	0.2216	0.2216	0.0000	0.0000	0.0000	0.0000
	1.5	0.7424	0.0128	0.0000	0.0000	0.0000	0.5000	0.7444	0.0131	0.0000	0.0000	−0.2500	0.5000
	2	0.9531	0.0005	0.0000	0.5000	−0.5000	0.7500	0.9535	0.0005	0.0000	0.5000	−0.5000	1.0000
Hypothetical Distance 4	1	0.0000	0.0000	0.5000	0.5000	0.0000	0.7500	0.0001	0.0001	0.5000	0.5000	0.0000	1.0000
	1.5	0.0057	0.0000	0.0000	0.7500	0.0000	1.0000	0.0126	0.0000	0.0000	1.0000	0.0000	1.0000
	2	0.0554	0.0000	0.0000	1.0000	0.0000	1.0000	0.0963	0.0000	0.0000	1.0000	0.0000	1.1000
N	119 matched pairs							113 matched pairs					

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Number of Neighbors: 1.

Caliper for landslides: 0.010.

Caliper for drought: 0.020Source: Authors.

Data availability

Data will be made available on request.

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Appendix

A.1: Stata Coding for Chapter 3

```
version 15.1
clear
set more off
set matsize 11000

use "$path2\data.dta", clear

*****************************************************************************
***                 Table 1: Description and Summary Statistics of Variables                    ***
*****************************************************************************

* Total sample *
estpost summarize both_loans use7 literate money_limitation riskdummy risk_diversification inflation numeracy
compound_interest age age2 female education_years living_together less1 farm_size highaltitude
est store total_sample

* Both loans *
estpost summarize literate money_limitation riskdummy risk_diversification inflation numeracy compound_interest age age2
female education_years living_together less1 farm_size highaltitude if loans == 1
est store loans

* Loans from non-financial sources *
estpost summarize literate money_limitation riskdummy risk_diversification inflation numeracy compound_interest age age2
female education_years living_together less1 farm_size highaltitude if use7 == 1
est store non_financial

esttab total_sample loans non_financial  ///
using "$path1\excel_doc\Financial_Literacy_Table_1_Statistics.rtf", replace ///
cells ("mean(fmt(3)) sd(fmt(3))") ///
label ///
title("Table 1 Description and Summary Statistics of Variables")

*****************************************************************************
***                 Table 3: Logit Estimates: Loan as a Response to the Weather Shocks          ***
*****************************************************************************

logit loans literate money_limitation riskdummy age age2 female education_years living_together less1 farm_size highaltitude,
cluster(village)
est store mod1
estat ic

esttab mod1 ///
using "$path1\excel_doc\Financial_Literacy_Table3_Logit_Both_Loans.rtf", replace ///
cells(b(star fmt(3) label(Coef.)) se(par fmt(2) label(std.errors))) ///
label ///
star(* 0.10 ** 0.05 *** 0.01) ///
legend starlevels( * 0.10 ** 0.05 *** 0.010) stats(N r2_p, fmt(0 3 3 3)) ///
title("Table 3 Logit Estimates: Loan as a Response to the Effects of Climate Change")

* Hosmer-Lemeshow Test
qui logit loans literate money_limitation riskdummy age age2 female education_years living_together less1 farm_size
highaltitude, cluster(village)
lfit, group(10) table

* Pregibon Link Test
```

```
qui logit loans literate money_limitation riskdummy age age2 female education_years living_together less1 farm_size
highaltitude, cluster(village)
linktest

* Wald tests
qui logit loans literate money_limitation riskdummy age age2 female education_years living_together less1 farm_size
highaltitude, cluster(village)
test literate money_limitation riskdummy

qui logit loans literate money_limitation riskdummy age age2 female education_years living_together less1 farm_size
highaltitude, cluster(village)
test literate

qui logit loans literate money_limitation riskdummy age age2 female education_years living_together less1 farm_size
highaltitude, cluster(village)
test money_limitation

qui logit loans literate money_limitation riskdummy age age2 female education_years living_together less1 farm_size
highaltitude, cluster(village)
test riskdummy

*****************************************************************************
***                         Mechanism Graphs                              ***
*****************************************************************************

* Figure 4 Proportion of Knowledge of Basic Financial Concepts *
graph bar (mean) risk_diversification (mean) inflation (mean) numeracy (mean) compound_interest, showyvars bargap(10)
blabel(bar)
graph export "D:\data\iCloudDrive\Desktop\Thesis\Stata\Dissertation\pic\Financial_Literacy_Figure_4_Literacy_Concepts.png",
as(png) replace

* Figure 5 Loans and its Sources *
graph bar if type_loans>0, over(type_loans) asyvars bargap(10) blabel(total) ytitle(Percent of loans) ylabel(, valuelabel)
graph export "D:\data\iCloudDrive\Desktop\Thesis\Stata\Dissertation\pic\Financial_Literacy_Figure_5_Loans_Sources.png",
as(png) replace

*****************************************************************************
***             Table 4 Loans from Non-Financial Sources                  ***
*****************************************************************************

logit use7 literate money_limitation riskdummy age age2 female education_years living_together less1 farm_size highaltitude if
type_loans !=1, cluster(village)
est store mod2
estat ic

esttab  mod2  ///
using "$path1\excel_doc\Financial_Literacy_Table4_Non_Financial.rtf", replace ///
cells(b(star fmt(3) label(Coef.)) se(par fmt(2) label(std.errors))) ///
label ///
star(* 0.10 ** 0.05 *** 0.01) ///
legend starlevels( * 0.10 ** 0.05 *** 0.010) stats(N r2_p, fmt(0 3 3 3)) ///
title("Table 4 Multinomial Logit Estimates: Source of the Loans")

* Hosmer-Lemeshow Test
qui logit use7 literate money_limitation riskdummy age age2 female education_years living_together less1 farm_size highaltitude
if type_loans !=1, cluster(village)
lfit, group(10) table

* Pregibon Link Test
qui logit use7 literate money_limitation riskdummy age age2 female education_years living_together less1 farm_size highaltitude
if type_loans !=1, cluster(village)
```

```
linktest

* Wald test
qui logit use7 literate money_limitation riskdummy age age2 female education_years living_together less1 farm_size highaltitude
if type_loans !=1, cluster(village)
test literate money_limitation riskdummy

qui logit use7 literate money_limitation riskdummy age age2 female education_years living_together less1 farm_size highaltitude
if type_loans !=1, cluster(village)
test literate

qui logit use7 literate money_limitation riskdummy age age2 female education_years living_together less1 farm_size highaltitude
if type_loans !=1, cluster(village)
test money_limitation

qui logit use7 literate money_limitation riskdummy age age2 female education_years living_together less1 farm_size highaltitude
if type_loans !=1, cluster(village)
test riskdummy

******************************************************************************
***                Table 5 Extended Logit Estimates: Interaction Term                ***
******************************************************************************

logit use7 literate c.age#literate money_limitation riskdummy age age2 female education_years living_together less1 farm_size
highaltitude if type_loans !=1, cluster(village)
est store mod3
estat ic

esttab  mod3  ///
using "$path1\excel_doc\Financial_Literacy_Table5_Interaction_Term.rtf", replace ///
cells(b(star fmt(3) label(Coef.)) se(par fmt(2) label(std.errors))) ///
label ///
star(* 0.10 ** 0.05 *** 0.01) ///
legend starlevels( * 0.10 ** 0.05 *** 0.010) stats(N r2_p, fmt(0 3 3 3)) ///
title("Table 5 Extended Logit Estimates: Interaction Term")

* Hosmer-Lemeshow Test
qui logit use7 literate c.age#literate money_limitation riskdummy age age2 female education_years living_together less1
farm_size highaltitude if type_loans !=1, cluster(village)
lfit, group(10) table

* Pregibon Link Test
qui logit use7 literate c.age#literate money_limitation riskdummy age age2 female education_years living_together less1
farm_size highaltitude if type_loans !=1, cluster(village)
linktest

* Wald test
qui logit use7 literate c.age#literate money_limitation riskdummy age age2 female education_years living_together less1
farm_size highaltitude if type_loans !=1, cluster(village)
test literate money_limitation riskdummy c.age#1.literate

qui logit use7 literate c.age#literate money_limitation riskdummy age age2 female education_years living_together less1
farm_size highaltitude if type_loans !=1, cluster(village)
test literate

qui logit use7 literate c.age#literate money_limitation riskdummy age age2 female education_years living_together less1
farm_size highaltitude if type_loans !=1, cluster(village)
test money_limitation

qui logit use7 literate c.age#literate money_limitation riskdummy age age2 female education_years living_together less1
farm_size highaltitude if type_loans !=1, cluster(village)
test riskdummy
```

```
qui logit use7 literate c.age#literate money_limitation riskdummy age age2 female education_years living_together less1
farm_size highaltitude if type_loans !=1, cluster(village)
test c.age#1.literate

********************************************************************************
***                    Table 6 Marginal Effects for All Models                 ***
********************************************************************************

* Both loans *
qui logit loans literate money_limitation riskdummy age age2 female education_years living_together less1 farm_size
highaltitude, cluster(village)
margins, dydx(*) post
est store mod1_margins

* Loans from non-financial sources *
qui logit use7 literate money_limitation riskdummy age age2 female education_years living_together less1 farm_size highaltitude
if type_loans !=1, cluster(village)
margins, dydx(*) post
est store mod2_margins

* Loans from non-financial sources with interaction term *
qui logit use7  c.age##literate money_limitation riskdummy  age2 female education_years living_together less1 farm_size
highaltitude if type_loans !=1, cluster(village)
margins, dydx(*) post
est store mod3_margins

qui logit use7  c.age##literate money_limitation riskdummy  age2 female education_years living_together less1 farm_size
highaltitude if type_loans !=1, cluster(village)
margins, dydx(age) at(literate=(0,1))

esttab  mod1_margins mod2_margins mod3_margins ///
using "$path1\excel_doc\Financial_Literacy_Table6_Margins.rtf", replace ///
cells(b(star fmt(3) label(Coef.)) se(par fmt(2) label(std.errors))) ///
label ///
star(* 0.10 ** 0.05 *** 0.01) ///
legend starlevels( * 0.10 ** 0.05 *** 0.010) stats(N r2_p, fmt(0 3 3 3)) ///
title("Table 6 Margins")


********************************************************************************
***              Figure 6: Average Marginal Effects - Interaction Term         ***
********************************************************************************

qui logit use7 money_limitation riskdummy  age2 female education_years living_together less1 farm_size highaltitude
literate##c.age if type_loans !=1, cluster(village)
qui margins, dydx(literate) at(age=(20 30 40 50 60 70)) noesample
marginsplot

********************************************************************************
***    Table 7: Robustness Check: Logit Estimates and Extended Model by Gender  ***
********************************************************************************

* Both loans (female) *
qui logit loans literate money_limitation riskdummy age age2 education_years living_together less1 farm_size highaltitude if
female==1, cluster(village)
est store mod1_f
estat ic

* Both loans (male) *
```

```
qui logit loans literate money_limitation riskdummy age age2 education_years living_together less1 farm_size highaltitude if
female==0, cluster(village)
est store mod1_m
estat ic

* Loans from non-financial sources (female) *
qui logit use7 literate money_limitation riskdummy age age2 education_years living_together less1 farm_size highaltitude if
type_loans !=1 & female==1, cluster(village)
est store mod2_f
estat ic

* Loans from non-financial sources (male) *
qui logit use7 literate money_limitation riskdummy age age2 education_years living_together less1 farm_size highaltitude if
type_loans !=1 & female==0, cluster(village)
est store mod2_m
estat ic

* Loans from non-financial sources/interaction term (female) *
logit use7 literate c.age#literate money_limitation riskdummy age age2 education_years living_together less1 farm_size
highaltitude if type_loans !=1 & female==1, cluster(village)
est store mod3_f
estat ic

* Loans from non-financial sources/interaction term (male) *
logit use7 literate c.age#literate money_limitation riskdummy age age2 education_years living_together less1 farm_size
highaltitude if type_loans !=1 & female==0, cluster(village)
est store mod3_m
estat ic

esttab  mod1_f mod1_m mod2_f mod2_m mod3_f mod3_m ///
using "$path1\excel_doc\Table7_Robustness_Check_Loan.rtf", replace ///
cells(b(star fmt(3) label(Coef.)) se(par fmt(2) label(std.errors))) ///
label ///
star(* 0.10 ** 0.05 *** 0.01) ///
legend starlevels( * 0.10 ** 0.05 *** 0.010) stats(N r2_p, fmt(0 3 3 3)) ///
title("Table 7 Robustness Check - Loan")
```

A.2: Stata Coding for Chapter 4

```
version 18
clear
set more off
set matsize 11000

use "$path2/data.dta", clear

**************************************************************************************
***                                    Variables                                  ***
**************************************************************************************

global severity sev1 sev2 sev3 /// Perceived severity
global vulnerability vul1 vul2 vul3 /// Perceived vulnerability
global psy_distance spa1 temp1 soc1 hyp1 spa2 temp2 soc2  hyp2 hyp3 hyp4 /// Psychological Distance

global ewes landslide drought /// Treatments
global farmer less60 female single primary less1 years_municipality /// Socio-demographics of the farmer
global farm workers less_5ha /// Farm characteristics
global nat_resources water_have forest_have /// Natural resources endowment of the farm

**************************************************************************************
***            Table 1: Description and Summary Statistics of Variables            ***
**************************************************************************************

* All Sample *
estpost summarize $ewes $severity $vulnerability $psy_distance $farmer $farm $nat_resources
est store mod1

* None Event *
estpost summarize $severity $psy_distance $vulnerability $farmer $farm       $nat_resources if emergency == 0
est store mod2

* Landslide *
estpost summarize $severity $psy_distance $vulnerability $farmer $farm       $nat_resources if emergency == 1
est store mod3

* Drought *
estpost summarize $severity $psy_distance $vulnerability $farmer $farm       $nat_resources if emergency == 2
est store mod4

esttab mod1 mod2 mod3 mod4 ///
using "$path1\excel_doc\EWE_Perceptions_Table1_Statistics.rtf", replace ///
cells ("mean(fmt(3)) sd(fmt(3))") ///
label ///
title("Table 1 - Descriptive Statistics")

**************************************************************************************
***                                      Tests                                    ***
**************************************************************************************

** Power estimation **

power twomeans 0, n1(120) n2(240) diff(0.4) sd(1) alpha(0.05)

** Cronbach's Alpha Perceived Severity **

alpha sev1 sev2 sev3
```

```
display "Perceived Severity's Alpha: " r(alpha)
* alpha = 0.815

** Cronbach's Alpha Perceived Vulnerability **
alpha vul1 vul2 vul3
display "Perceived Vulnerability's Alpha: " r(alpha)
* alpha = 0.882

** Cronbach's Alpha Psychological Distance **
* Reverting the responses for variables: spa2, temp2, soc2, hyp2
gen spa2_rev = 6 - spa2
gen temp2_rev = 6 - temp2
gen soc2_rev = 6 - soc2
gen hyp2_rev = 6 - hyp2

alpha spa1 temp1 soc1 hyp1 hyp3 hyp4 spa2_rev temp2_rev soc2_rev hyp2_rev
display "Psychological Distance's Alpha: " r(alpha)
* alpha = 0.843

*************************************************************************************
***                              Propensity Score                                 ***
*************************************************************************************

* Landslide *
xi: pscore landslide $farmer $farm $nat_resources, pscore(score_landslide) blockid(block_landslide)

* Drought *
xi: pscore drought $farmer $farm $nat_resources, pscore(score_drought) blockid(block_drought)

*************************************************************************************
***                       Balance of the Propensity Score                         ***
*************************************************************************************

* Figure 2 Propensity Score Balance – Landslides *
psgraph, treated (landslide) pscore (score_landslide)
graph export "C:\Users\cano-a\iCloudDrive\Desktop\Thesis\Stata\PMT_EWE\pic\Figure_2_PSM_Landslide.png", as(png)
replace

* Figure 3 Propensity Score Balance – Droughts *
psgraph, treated (drought) pscore (score_drought)
graph export "C:\Users\cano-a\iCloudDrive\Desktop\Thesis\Stata\PMT_EWE\pic\Figure_3_PSM_Drought.png", as(png) replace

// Calipers Estimation //
// Caliper = S.D.*0.2 (Austin, 2011; Garrido et al., 2014; Harder et al., 2010) //

summarize score_landslide
** S.D. = 0.056374
** Caliper = 0.056374*0.2 = 0.0112748 ~ 0.010

summarize score_drought
** S.D. = 0.1081623
** Caliper = 0.1081623*0.2 = 0.02163246 ~ 0.020

* Table 2 Balance of Covariates for Landslide PSM *
qui psmatch2 landslide, outcome(spa1) pscore(score_landslide)  neighbor(1) caliper(0.010)  noreplacement
pstest $farmer $farm $nat_resources, treated (landslide) both

* Table 3 Balance of Covariates for Drought PSM *
qui psmatch2 drought, outcome(soc1) pscore(score_drought)  neighbor(1) caliper(0.020)  noreplacement
pstest $farmer $farm $nat_resources, treated (drought) both
```

```
*********************************************************************************
***                  Figure 4: ATE & ATET Perceived Severity                  ***
*********************************************************************************

*** ATE Sev1: Farm ***

* NN
teffects nnmatch (sev1 less60 female single primary less1 workers less_5ha water_have forest_have) (landslide)
scalar ate_sev1_ls_nn = e(b)[1,1]
scalar se_sev1_ls_nn  = sqrt(e(V)[1,1])
scalar low_sev1_ls_nn = ate_sev1_ls_nn - 1.96 * se_sev1_ls_nn
scalar high_sev1_ls_nn = ate_sev1_ls_nn + 1.96 * se_sev1_ls_nn

teffects nnmatch (sev1 less60 female single primary less1 workers less_5ha water_have forest_have) (drought)
scalar ate_sev1_dr_nn = e(b)[1,1]
scalar se_sev1_dr_nn  = sqrt(e(V)[1,1])
scalar low_sev1_dr_nn = ate_sev1_dr_nn - 1.96 * se_sev1_dr_nn
scalar high_sev1_dr_nn = ate_sev1_dr_nn + 1.96 * se_sev1_dr_nn

* Caliper
teffects psmatch (sev1) (landslide less60 female single primary less1 workers less_5ha water_have forest_have), caliper(0.010)
osample(out_support) ate
teffects psmatch (sev1) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support==0, caliper(0.010) osample(out_support2) ate
teffects psmatch (sev1) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0, caliper(0.010) osample(out_support3) ate
teffects psmatch (sev1) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0, caliper(0.010) osample(out_support4) ate
teffects psmatch (sev1) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0, caliper(0.010) osample(out_support5) ate
teffects psmatch (sev1) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0, caliper(0.010) ate
scalar ate_sev1_ls_c = e(b)[1,1]
scalar se_sev1_ls_c  = sqrt(e(V)[1,1])
scalar low_sev1_ls_c = ate_sev1_ls_c - 1.96 * se_sev1_ls_c
scalar high_sev1_ls_c = ate_sev1_ls_c + 1.96 * se_sev1_ls_c

drop out_support out_support2  out_support3 out_support4 out_support5
teffects psmatch (sev1) (drought less60 female single primary less1 workers less_5ha water_have forest_have), caliper(0.020)
osample(out_support) ate
teffects psmatch (sev1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support==0, caliper(0.020) osample(out_support2) ate
teffects psmatch (sev1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0, caliper(0.020) osample(out_support3) ate
teffects psmatch (sev1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0, caliper(0.020) osample(out_support4) ate
teffects psmatch (sev1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0, caliper(0.020) osample(out_support5) ate
teffects psmatch (sev1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0, caliper(0.020)
osample(out_support6) ate
teffects psmatch (sev1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0,
caliper(0.020) osample(out_support7) ate
teffects psmatch (sev1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0, caliper(0.020) osample(out_support8) ate
teffects psmatch (sev1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0 & out_support8==0, caliper(0.020) osample(out_support9) ate
```

```
teffects psmatch (sev1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0 & out_support8==0 & out_support9==0, caliper(0.020) osample(out_support10) ate
teffects psmatch (sev1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0 & out_support8==0 & out_support9==0 & out_support10==0, caliper(0.020) osample(out_support11) ate
teffects psmatch (sev1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0 & out_support8==0 & out_support9==0 & out_support10==0 & out_support11==0, caliper(0.020) ate
scalar ate_sev1_dr_c = e(b)[1,1]
scalar se_sev1_dr_c  = sqrt(e(V)[1,1])
scalar low_sev1_dr_c = ate_sev1_dr_c - 1.96 * se_sev1_dr_c
scalar high_sev1_dr_c = ate_sev1_dr_c + 1.96 * se_sev1_dr_c

*  P-values
scalar pval_sev1_ls_nn = 2 * (1 - normal(abs(ate_sev1_ls_nn / se_sev1_ls_nn)))
scalar pval_sev1_dr_nn = 2 * (1 - normal(abs(ate_sev1_dr_nn / se_sev1_dr_nn)))
scalar pval_sev1_ls_c  = 2 * (1 - normal(abs(ate_sev1_ls_c / se_sev1_ls_c)))
scalar pval_sev1_dr_c  = 2 * (1 - normal(abs(ate_sev1_dr_c / se_sev1_dr_c)))

* Dataset for the graph:
preserve
clear
set obs 6

gen outcome = ""
replace outcome = "sev1" in 1
replace outcome = "sev1" in 2
replace outcome = "sev1" in 3
replace outcome = "sev1" in 4

gen shock = ""
replace shock = "landslide" in 1
replace shock = "drought" in 2
replace shock = "landslide" in 3
replace shock = "drought" in 4

gen x = _n
gen ate = .
gen ci_low = .
gen ci_high = .

replace ate = ate_sev1_ls_nn in 1
replace ci_low = low_sev1_ls_nn in 1
replace ci_high = high_sev1_ls_nn in 1

replace ate = ate_sev1_dr_nn in 2
replace ci_low = low_sev1_dr_nn in 2
replace ci_high = high_sev1_dr_nn in 2

replace ate = ate_sev1_ls_c in 3
replace ci_low = low_sev1_ls_c in 3
replace ci_high = high_sev1_ls_c in 3

replace ate = ate_sev1_dr_c in 4
replace ci_low = low_sev1_dr_c in 4
replace ci_high = high_sev1_dr_c in 4

* Graph ATE Sev1:
gen str15 ate_label = ""

replace ate_label = string(ate, "%9.3f") + ///
```

```
    cond(pval_sev1_ls_nn < 0.01, "***", cond(pval_sev1_ls_nn < 0.05, "**", cond(pval_sev1_ls_nn < 0.1, "*", ""))) in 1
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_sev1_dr_nn < 0.01, "***", cond(pval_sev1_dr_nn < 0.05, "**", cond(pval_sev1_dr_nn < 0.1, "*", ""))) in 2
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_sev1_ls_c < 0.01, "***", cond(pval_sev1_ls_c < 0.05, "**", cond(pval_sev1_ls_c < 0.1, "*", ""))) in 3
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_sev1_dr_c < 0.01, "***", cond(pval_sev1_dr_c < 0.05, "**", cond(pval_sev1_dr_c < 0.1, "*", ""))) in 4

* Adjust the values on the x-axis
replace x = 1 in 1   // NN - Landslide
replace x = 2 in 2   // NN - Drought
replace x = 4 in 3   // Caliper - Landslide
replace x = 5 in 4   // Caliper - Drought

twoway ///
    (scatter ate x if shock == "landslide", msymbol(circle) mcolor(blue) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
    (scatter ate x if shock == "drought", msymbol(diamond) mcolor(green) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
    (rcap ci_low ci_high x if shock == "landslide", lcolor(blue)) ///
    (rcap ci_low ci_high x if shock == "drought", lcolor(green)) ///
    ,   title("Farm") ///
    xlabel(none) ///
    ylabel(-0.8(0.2)0.8, angle(0) labsize(small) labcolor(black)) ///
    yscale(range(-0.8 0.8)) ///
    ytitle("Average Treatment Effect") ///
    yline(0, lcolor(red)) ///
    legend(order(1 "Landslide" 2 "Drought") rows(1)) ///
    xscale(range(1 5.5)) ///
    xsize(6) ysize(4)

restore

*** ATE Sev2: Natural Resources ***

* NN
teffects nnmatch (sev2 less60 female single primary less1 workers less_5ha water_have forest_have) (landslide)
scalar ate_sev2_ls_nn = e(b)[1,1]
scalar se_sev2_ls_nn  = sqrt(e(V)[1,1])
scalar low_sev2_ls_nn = ate_sev2_ls_nn - 1.96 * se_sev2_ls_nn
scalar high_sev2_ls_nn = ate_sev2_ls_nn + 1.96 * se_sev2_ls_nn

teffects nnmatch (sev2 less60 female single primary less1 workers less_5ha water_have forest_have) (drought)
scalar ate_sev2_dr_nn = e(b)[1,1]
scalar se_sev2_dr_nn  = sqrt(e(V)[1,1])
scalar low_sev2_dr_nn = ate_sev2_dr_nn - 1.96 * se_sev2_dr_nn
scalar high_sev2_dr_nn = ate_sev2_dr_nn + 1.96 * se_sev2_dr_nn

* Caliper
drop out_support out_support2  out_support3 out_support4 out_support5 out_support6 out_support7 out_support8 out_support9
out_support10 out_support11
teffects psmatch (sev2) (landslide less60 female single primary less1 workers less_5ha water_have forest_have), caliper(0.010)
osample(out_support) ate
teffects psmatch (sev2) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support==0, caliper(0.010) osample(out_support2) ate
teffects psmatch (sev2) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0, caliper(0.010) osample(out_support3) ate
teffects psmatch (sev2) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0, caliper(0.010) osample(out_support4) ate
teffects psmatch (sev2) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0, caliper(0.010) osample(out_support5) ate
teffects psmatch (sev2) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0, caliper(0.010) ate
scalar ate_sev2_ls_c = e(b)[1,1]
```

```
scalar se_sev2_ls_c  = sqrt(e(V)[1,1])
scalar low_sev2_ls_c = ate_sev2_ls_c - 1.96 * se_sev2_ls_c
scalar high_sev2_ls_c = ate_sev2_ls_c + 1.96 * se_sev2_ls_c

drop out_support out_support2  out_support3 out_support4 out_support5
teffects psmatch (sev2) (drought less60 female single primary less1 workers less_5ha water_have forest_have), caliper(0.020)
osample(out_support) ate
teffects psmatch (sev2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support==0, caliper(0.020) osample(out_support2) ate
teffects psmatch (sev2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0, caliper(0.020) osample(out_support3) ate
teffects psmatch (sev2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0, caliper(0.020) osample(out_support4) ate
teffects psmatch (sev2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0, caliper(0.020) osample(out_support5) ate
teffects psmatch (sev2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0, caliper(0.020)
osample(out_support6) ate
teffects psmatch (sev2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0,
caliper(0.020) osample(out_support7) ate
teffects psmatch (sev2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0, caliper(0.020) osample(out_support8) ate
teffects psmatch (sev2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0 & out_support8==0, caliper(0.020) osample(out_support9) ate
teffects psmatch (sev2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0 & out_support8==0 & out_support9==0, caliper(0.020) osample(out_support10) ate
teffects psmatch (sev2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0 & out_support8==0 & out_support9==0 & out_support10==0, caliper(0.020) osample(out_support11) ate
teffects psmatch (sev2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0 & out_support8==0 & out_support9==0 & out_support10==0 & out_support11==0, caliper(0.020) ate
scalar ate_sev2_dr_c = e(b)[1,1]
scalar se_sev2_dr_c  = sqrt(e(V)[1,1])
scalar low_sev2_dr_c = ate_sev2_dr_c - 1.96 * se_sev2_dr_c
scalar high_sev2_dr_c = ate_sev2_dr_c + 1.96 * se_sev2_dr_c

*  P-values
scalar pval_sev2_ls_nn = 2 * (1 - normal(abs(ate_sev2_ls_nn / se_sev2_ls_nn)))
scalar pval_sev2_dr_nn = 2 * (1 - normal(abs(ate_sev2_dr_nn / se_sev2_dr_nn)))
scalar pval_sev2_ls_c  = 2 * (1 - normal(abs(ate_sev2_ls_c / se_sev2_ls_c)))
scalar pval_sev2_dr_c  = 2 * (1 - normal(abs(ate_sev2_dr_c / se_sev2_dr_c)))

* Dataset for the graph:
preserve
clear
set obs 6

gen outcome = ""
replace outcome = "sev2" in 1
replace outcome = "sev2" in 2
replace outcome = "sev2" in 3
replace outcome = "sev2" in 4

gen shock = ""
replace shock = "landslide" in 1
replace shock = "drought" in 2
replace shock = "landslide" in 3
```

```
replace shock = "drought" in 4

gen x = _n
gen ate = .
gen ci_low = .
gen ci_high = .

replace ate = ate_sev2_ls_nn in 1
replace ci_low = low_sev2_ls_nn in 1
replace ci_high = high_sev2_ls_nn in 1

replace ate = ate_sev2_dr_nn in 2
replace ci_low = low_sev2_dr_nn in 2
replace ci_high = high_sev2_dr_nn in 2

replace ate = ate_sev2_ls_c in 3
replace ci_low = low_sev2_ls_c in 3
replace ci_high = high_sev2_ls_c in 3

replace ate = ate_sev2_dr_c in 4
replace ci_low = low_sev2_dr_c in 4
replace ci_high = high_sev2_dr_c in 4

* Graph ATE Sev2:
gen str15 ate_label = ""

replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_sev2_ls_nn < 0.01, "***", cond(pval_sev2_ls_nn < 0.05, "**", cond(pval_sev2_ls_nn < 0.1, "*", ""))) in 1
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_sev2_dr_nn < 0.01, "***", cond(pval_sev2_dr_nn < 0.05, "**", cond(pval_sev2_dr_nn < 0.1, "*", ""))) in 2
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_sev2_ls_c < 0.01, "***", cond(pval_sev2_ls_c < 0.05, "**", cond(pval_sev2_ls_c < 0.1, "*", ""))) in 3
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_sev2_dr_c < 0.01, "***", cond(pval_sev2_dr_c < 0.05, "**", cond(pval_sev2_dr_c < 0.1, "*", ""))) in 4

* Adjust the values on the x-axis
replace x = 1 in 1   // NN - Landslide
replace x = 2 in 2   // NN - Drought
replace x = 4 in 3   // Caliper - Landslide
replace x = 5 in 4   // Caliper - Drought

twoway ///
    (scatter ate x if shock == "landslide", msymbol(circle) mcolor(blue) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
    (scatter ate x if shock == "drought", msymbol(diamond) mcolor(green) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
    (rcap ci_low ci_high x if shock == "landslide", lcolor(blue)) ///
    (rcap ci_low ci_high x if shock == "drought", lcolor(green)) ///
    , title("Natural Resources") ///
    xlabel(none) ///
    ylabel(-0.8(0.2)0.8, angle(0) labsize(small) labcolor(black)) ///
    yscale(range(-0.8 0.8)) ///
    ytitle("Average Treatment Effect") ///
    yline(0, lcolor(red)) ///
    legend(order(1 "Landslide" 2 "Drought") rows(1)) ///
    xscale(range(1 5.5)) ///
    xsize(6) ysize(4)

*** ATE Sev3: Farmers ***

* NN
teffects nnmatch (sev3 less60 female single primary less1 workers less_5ha water_have forest_have) (landslide)
scalar ate_sev3_ls_nn = e(b)[1,1]
scalar se_sev3_ls_nn  = sqrt(e(V)[1,1])
```

```
scalar low_sev3_ls_nn = ate_sev3_ls_nn - 1.96 * se_sev3_ls_nn
scalar high_sev3_ls_nn = ate_sev3_ls_nn + 1.96 * se_sev3_ls_nn

teffects nnmatch (sev3 less60 female single primary less1 workers less_5ha water_have forest_have) (drought)
scalar ate_sev3_dr_nn = e(b)[1,1]
scalar se_sev3_dr_nn  = sqrt(e(V)[1,1])
scalar low_sev3_dr_nn = ate_sev3_dr_nn - 1.96 * se_sev3_dr_nn
scalar high_sev3_dr_nn = ate_sev3_dr_nn + 1.96 * se_sev3_dr_nn

* Caliper
drop out_support out_support2  out_support3 out_support4 out_support5 out_support6 out_support7 out_support8 out_support9
out_support10 out_support11
teffects psmatch (sev3) (landslide less60 female single primary less1 workers less_5ha water_have forest_have), caliper(0.010)
osample(out_support) ate
teffects psmatch (sev3) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support==0, caliper(0.010) osample(out_support2) ate
teffects psmatch (sev3) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0, caliper(0.010) osample(out_support3) ate
teffects psmatch (sev3) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0, caliper(0.010) osample(out_support4) ate
teffects psmatch (sev3) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0, caliper(0.010) osample(out_support5) ate
teffects psmatch (sev3) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0, caliper(0.010) ate
scalar ate_sev3_ls_c = e(b)[1,1]
scalar se_sev3_ls_c  = sqrt(e(V)[1,1])
scalar low_sev3_ls_c = ate_sev3_ls_c - 1.96 * se_sev3_ls_c
scalar high_sev3_ls_c = ate_sev3_ls_c + 1.96 * se_sev3_ls_c

drop out_support out_support2  out_support3 out_support4 out_support5
teffects psmatch (sev3) (drought less60 female single primary less1 workers less_5ha water_have forest_have), caliper(0.020)
osample(out_support) ate
teffects psmatch (sev3) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support==0, caliper(0.020) osample(out_support2) ate
teffects psmatch (sev3) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0, caliper(0.020) osample(out_support3) ate
teffects psmatch (sev3) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0, caliper(0.020) osample(out_support4) ate
teffects psmatch (sev3) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0, caliper(0.020) osample(out_support5) ate
teffects psmatch (sev3) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0, caliper(0.020)
osample(out_support6) ate
teffects psmatch (sev3) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0,
caliper(0.020) osample(out_support7) ate
teffects psmatch (sev3) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0, caliper(0.020) osample(out_support8) ate
teffects psmatch (sev3) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0 & out_support8==0, caliper(0.020) osample(out_support9) ate
teffects psmatch (sev3) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0 & out_support8==0 & out_support9==0, caliper(0.020) osample(out_support10) ate
teffects psmatch (sev3) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0 & out_support8==0 & out_support9==0 & out_support10==0, caliper(0.020) osample(out_support11) ate
teffects psmatch (sev3) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0 & out_support8==0 & out_support9==0 & out_support10==0 & out_support11==0, caliper(0.020) ate
scalar ate_sev3_dr_c = e(b)[1,1]
```

```
scalar se_sev3_dr_c  = sqrt(e(V)[1,1])
scalar low_sev3_dr_c = ate_sev3_dr_c - 1.96 * se_sev3_dr_c
scalar high_sev3_dr_c = ate_sev3_dr_c + 1.96 * se_sev3_dr_c

*  P-values
scalar pval_sev3_ls_nn = 2 * (1 - normal(abs(ate_sev3_ls_nn / se_sev3_ls_nn)))
scalar pval_sev3_dr_nn = 2 * (1 - normal(abs(ate_sev3_dr_nn / se_sev3_dr_nn)))
scalar pval_sev3_ls_c  = 2 * (1 - normal(abs(ate_sev3_ls_c / se_sev3_ls_c)))
scalar pval_sev3_dr_c  = 2 * (1 - normal(abs(ate_sev3_dr_c / se_sev3_dr_c)))

* Dataset for the graph:
preserve
clear
set obs 6

gen outcome = ""
replace outcome = "sev3" in 1
replace outcome = "sev3" in 2
replace outcome = "sev3" in 3
replace outcome = "sev3" in 4

gen shock = ""
replace shock = "landslide" in 1
replace shock = "drought" in 2
replace shock = "landslide" in 3
replace shock = "drought" in 4

gen x = _n
gen ate = .
gen ci_low = .
gen ci_high = .

replace ate = ate_sev3_ls_nn in 1
replace ci_low = low_sev3_ls_nn in 1
replace ci_high = high_sev3_ls_nn in 1

replace ate = ate_sev3_dr_nn in 2
replace ci_low = low_sev3_dr_nn in 2
replace ci_high = high_sev3_dr_nn in 2

replace ate = ate_sev3_ls_c in 3
replace ci_low = low_sev3_ls_c in 3
replace ci_high = high_sev3_ls_c in 3

replace ate = ate_sev3_dr_c in 4
replace ci_low = low_sev3_dr_c in 4
replace ci_high = high_sev3_dr_c in 4

* Graph ATE Sev3:
gen str15 ate_label = ""

replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_sev3_ls_nn < 0.01, "***", cond(pval_sev3_ls_nn < 0.05, "**", cond(pval_sev3_ls_nn < 0.1, "*", ""))) in 1
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_sev3_dr_nn < 0.01, "***", cond(pval_sev3_dr_nn < 0.05, "**", cond(pval_sev3_dr_nn < 0.1, "*", ""))) in 2
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_sev3_ls_c < 0.01, "***", cond(pval_sev3_ls_c < 0.05, "**", cond(pval_sev3_ls_c < 0.1, "*", ""))) in 3
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_sev3_dr_c < 0.01, "***", cond(pval_sev3_dr_c < 0.05, "**", cond(pval_sev3_dr_c < 0.1, "*", ""))) in 4

* Adjust the values on the x-axis
replace x = 1 in 1   // NN - Landslide
```

```
replace x = 2 in 2   // NN - Drought
replace x = 4 in 3   // Caliper - Landslide
replace x = 5 in 4   // Caliper - Drought

twoway ///
   (scatter ate x if shock == "landslide", msymbol(circle) mcolor(blue) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
   (scatter ate x if shock == "drought", msymbol(diamond) mcolor(green) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
   (rcap ci_low ci_high x if shock == "landslide", lcolor(blue)) ///
   (rcap ci_low ci_high x if shock == "drought", lcolor(green)) ///
   , title("Farmers") ///
   xlabel(none) ///
   ylabel(-0.8(0.2)0.8, angle(0) labsize(small) labcolor(black)) ///
   yscale(range(-0.8 0.8)) ///
   ytitle("Average Treatment Effect") ///
   yline(0, lcolor(red)) ///
   legend(order(1 "Landslide" 2 "Drought") rows(1)) ///
   xscale(range(1 5.5)) ///
   xsize(6) ysize(4)

* Merge ATE graphs Sev1 Sev2 Sev3
graph combine ///
   /Users/alexcano86/Desktop/Thesis/Stata/Dissertation/pic/sev1.gph ///
   /Users/alexcano86/Desktop/Thesis/Stata/Dissertation/pic/sev2.gph ///
   /Users/alexcano86/Desktop/Thesis/Stata/Dissertation/pic/sev3.gph, ///
   cols(3) ///
         note("* p<0.10, ** p<0.05, *** p<0.010" ///
      "Balancing property satisfied:  YES" ///
      "Common support imposed:    YES" ///
      "Number of Neighbors: 1" ///
      "Caliper for landslides: 0.010" ///
      "Caliper for drought: 0.020" ///
      "Source: Authors.") ///
   title("Average Treatment Effect")

*** ATET Sev1: Farm ***

* NN Matching
psmatch2 landslide, outcome(sev1) pscore(score_landslide) noreplacement neighbor(1) common
scalar ate_sev1_ls_nn = r(att)
scalar se_sev1_ls_nn = r(seatt)
scalar low_sev1_ls_nn = ate_sev1_ls_nn - 1.96 * se_sev1_ls_nn
scalar high_sev1_ls_nn = ate_sev1_ls_nn + 1.96 * se_sev1_ls_nn
scalar pval_sev1_ls_nn = 2 * (1 - normal(abs(ate_sev1_ls_nn / se_sev1_ls_nn)))

psmatch2 drought, outcome(sev1) pscore(score_drought) noreplacement neighbor(1) common
scalar ate_sev1_dr_nn = r(att)
scalar se_sev1_dr_nn = r(seatt)
scalar low_sev1_dr_nn = ate_sev1_dr_nn - 1.96 * se_sev1_dr_nn
scalar high_sev1_dr_nn = ate_sev1_dr_nn + 1.96 * se_sev1_dr_nn
scalar pval_sev1_dr_nn = 2 * (1 - normal(abs(ate_sev1_dr_nn / se_sev1_dr_nn)))

* Caliper Matching
psmatch2 landslide, outcome(sev1) pscore(score_landslide) noreplacement caliper(0.010)
scalar ate_sev1_ls_c = r(att)
scalar se_sev1_ls_c = r(seatt)
scalar low_sev1_ls_c = ate_sev1_ls_c - 1.96 * se_sev1_ls_c
scalar high_sev1_ls_c = ate_sev1_ls_c + 1.96 * se_sev1_ls_c
scalar pval_sev1_ls_c = 2 * (1 - normal(abs(ate_sev1_ls_c / se_sev1_ls_c)))

psmatch2 drought, outcome(sev1) pscore(score_drought) noreplacement caliper(0.020)
scalar ate_sev1_dr_c = r(att)
scalar se_sev1_dr_c = r(seatt)
```

```
scalar low_sev1_dr_c = ate_sev1_dr_c - 1.96 * se_sev1_dr_c
scalar high_sev1_dr_c = ate_sev1_dr_c + 1.96 * se_sev1_dr_c
scalar pval_sev1_dr_c = 2 * (1 - normal(abs(ate_sev1_dr_c / se_sev1_dr_c)))

* Dataset for the graph
preserve
clear
set obs 4

gen outcome = "sev1"

gen shock = ""
replace shock = "landslide" in 1
replace shock = "drought" in 2
replace shock = "landslide" in 3
replace shock = "drought" in 4

gen method = ""
replace method = "NN" in 1/2
replace method = "Caliper" in 3/4

gen x = .
replace x = 1 in 1
replace x = 2 in 2
replace x = 4 in 3
replace x = 5 in 4

gen ate = .
replace ate = ate_sev1_ls_nn in 1
replace ate = ate_sev1_dr_nn in 2
replace ate = ate_sev1_ls_c in 3
replace ate = ate_sev1_dr_c in 4

gen ci_low = .
replace ci_low = low_sev1_ls_nn in 1
replace ci_low = low_sev1_dr_nn in 2
replace ci_low = low_sev1_ls_c in 3
replace ci_low = low_sev1_dr_c in 4

gen ci_high = .
replace ci_high = high_sev1_ls_nn in 1
replace ci_high = high_sev1_dr_nn in 2
replace ci_high = high_sev1_ls_c in 3
replace ci_high = high_sev1_dr_c in 4

* Graph ATET Sev1
gen str15 ate_label = ""
replace ate_label = string(ate, "%9.3f") + ///
   cond(pval_sev1_ls_nn < 0.01, "***", cond(pval_sev1_ls_nn < 0.05, "**", cond(pval_sev1_ls_nn < 0.1, "*", ""))) in 1
replace ate_label = string(ate, "%9.3f") + ///
   cond(pval_sev1_dr_nn < 0.01, "***", cond(pval_sev1_dr_nn < 0.05, "**", cond(pval_sev1_dr_nn < 0.1, "*", ""))) in 2
replace ate_label = string(ate, "%9.3f") + ///
   cond(pval_sev1_ls_c < 0.01, "***", cond(pval_sev1_ls_c < 0.05, "**", cond(pval_sev1_ls_c < 0.1, "*", ""))) in 3
replace ate_label = string(ate, "%9.3f") + ///
   cond(pval_sev1_dr_c < 0.01, "***", cond(pval_sev1_dr_c < 0.05, "**", cond(pval_sev1_dr_c < 0.1, "*", ""))) in 4

twoway ///
   (scatter ate x if shock == "landslide", msymbol(circle) mcolor(blue) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
   (scatter ate x if shock == "drought", msymbol(diamond) mcolor(green) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
   (rcap ci_low ci_high x if shock == "landslide", lcolor(blue)) ///
   (rcap ci_low ci_high x if shock == "drought", lcolor(green)) ///
   ,   title("Farm") ///
```

```
    xlabel(none) ///
    ylabel(-0.8(0.2)0.8, angle(0) labsize(small) labcolor(black)) ///
    yscale(range(-0.8 0.8)) ///
    ytitle("Average Treatment Effect on the Treated") ///
    yline(0, lcolor(red)) ///
    legend(order(1 "Landslide" 2 "Drought") rows(1)) ///
    xscale(range(1 5.5)) ///
    xsize(6) ysize(4)

*** ATET Sev2: Natural Resources ***

* NN Matching
psmatch2 landslide, outcome(sev2) pscore(score_landslide) noreplacement neighbor(1) common
scalar ate_sev2_ls_nn = r(att)
scalar se_sev2_ls_nn = r(seatt)
scalar low_sev2_ls_nn = ate_sev2_ls_nn - 1.96 * se_sev2_ls_nn
scalar high_sev2_ls_nn = ate_sev2_ls_nn + 1.96 * se_sev2_ls_nn
scalar pval_sev2_ls_nn = 2 * (1 - normal(abs(ate_sev2_ls_nn / se_sev2_ls_nn)))

psmatch2 drought, outcome(sev2) pscore(score_drought) noreplacement neighbor(1) common
scalar ate_sev2_dr_nn = r(att)
scalar se_sev2_dr_nn = r(seatt)
scalar low_sev2_dr_nn = ate_sev2_dr_nn - 1.96 * se_sev2_dr_nn
scalar high_sev2_dr_nn = ate_sev2_dr_nn + 1.96 * se_sev2_dr_nn
scalar pval_sev2_dr_nn = 2 * (1 - normal(abs(ate_sev2_dr_nn / se_sev2_dr_nn)))

* Caliper Matching
psmatch2 landslide, outcome(sev2) pscore(score_landslide) noreplacement caliper(0.010)
scalar ate_sev2_ls_c = r(att)
scalar se_sev2_ls_c = r(seatt)
scalar low_sev2_ls_c = ate_sev2_ls_c - 1.96 * se_sev2_ls_c
scalar high_sev2_ls_c = ate_sev2_ls_c + 1.96 * se_sev2_ls_c
scalar pval_sev2_ls_c = 2 * (1 - normal(abs(ate_sev2_ls_c / se_sev2_ls_c)))

psmatch2 drought, outcome(sev2) pscore(score_drought) noreplacement caliper(0.020)
scalar ate_sev2_dr_c = r(att)
scalar se_sev2_dr_c = r(seatt)
scalar low_sev2_dr_c = ate_sev2_dr_c - 1.96 * se_sev2_dr_c
scalar high_sev2_dr_c = ate_sev2_dr_c + 1.96 * se_sev2_dr_c
scalar pval_sev2_dr_c = 2 * (1 - normal(abs(ate_sev2_dr_c / se_sev2_dr_c)))

* Dataset for the graph
preserve
clear
set obs 4

gen outcome = "sev2"

gen shock = ""
replace shock = "landslide" in 1
replace shock = "drought" in 2
replace shock = "landslide" in 3
replace shock = "drought" in 4

gen method = ""
replace method = "NN" in 1/2
replace method = "Caliper" in 3/4

gen x = .
replace x = 1 in 1
replace x = 2 in 2
replace x = 4 in 3
```

```
replace x = 5 in 4

gen ate = .
replace ate = ate_sev2_ls_nn in 1
replace ate = ate_sev2_dr_nn in 2
replace ate = ate_sev2_ls_c in 3
replace ate = ate_sev2_dr_c in 4

gen ci_low = .
replace ci_low = low_sev2_ls_nn in 1
replace ci_low = low_sev2_dr_nn in 2
replace ci_low = low_sev2_ls_c in 3
replace ci_low = low_sev2_dr_c in 4

gen ci_high = .
replace ci_high = high_sev2_ls_nn in 1
replace ci_high = high_sev2_dr_nn in 2
replace ci_high = high_sev2_ls_c in 3
replace ci_high = high_sev2_dr_c in 4

* Graph ATET Sev2
gen str15 ate_label = ""
replace ate_label = string(ate, "%9.3f") + ///
   cond(pval_sev2_ls_nn < 0.01, "***", cond(pval_sev2_ls_nn < 0.05, "**", cond(pval_sev2_ls_nn < 0.1, "*", ""))) in 1
replace ate_label = string(ate, "%9.3f") + ///
   cond(pval_sev2_dr_nn < 0.01, "***", cond(pval_sev2_dr_nn < 0.05, "**", cond(pval_sev2_dr_nn < 0.1, "*", ""))) in 2
replace ate_label = string(ate, "%9.3f") + ///
   cond(pval_sev2_ls_c < 0.01, "***", cond(pval_sev2_ls_c < 0.05, "**", cond(pval_sev2_ls_c < 0.1, "*", ""))) in 3
replace ate_label = string(ate, "%9.3f") + ///
   cond(pval_sev2_dr_c < 0.01, "***", cond(pval_sev2_dr_c < 0.05, "**", cond(pval_sev2_dr_c < 0.1, "*", ""))) in 4

twoway ///
   (scatter ate x if shock == "landslide", msymbol(circle) mcolor(blue) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
   (scatter ate x if shock == "drought", msymbol(diamond) mcolor(green) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
   (rcap ci_low ci_high x if shock == "landslide", lcolor(blue)) ///
   (rcap ci_low ci_high x if shock == "drought", lcolor(green)) ///
   ,   title("Natural Resources") ///
   xlabel(none) ///
   ylabel(-0.8(0.2)0.8, angle(0) labsize(small) labcolor(black)) ///
   yscale(range(-0.8 0.8)) ///
   ytitle("Average Treatment Effect on the Treated") ///
   yline(0, lcolor(red)) ///
   legend(order(1 "Landslide" 2 "Drought") rows(1)) ///
   xscale(range(1 5.5)) ///
   xsize(6) ysize(4)

*** ATET Sev3: Farmers ***

* NN Matching
psmatch2 landslide, outcome(sev3) pscore(score_landslide) noreplacement neighbor(1) common
scalar ate_sev3_ls_nn = r(att)
scalar se_sev3_ls_nn = r(seatt)
scalar low_sev3_ls_nn = ate_sev3_ls_nn - 1.96 * se_sev3_ls_nn
scalar high_sev3_ls_nn = ate_sev3_ls_nn + 1.96 * se_sev3_ls_nn
scalar pval_sev3_ls_nn = 2 * (1 - normal(abs(ate_sev3_ls_nn / se_sev3_ls_nn)))

psmatch2 drought, outcome(sev3) pscore(score_drought) noreplacement neighbor(1) common
scalar ate_sev3_dr_nn = r(att)
scalar se_sev3_dr_nn = r(seatt)
scalar low_sev3_dr_nn = ate_sev3_dr_nn - 1.96 * se_sev3_dr_nn
scalar high_sev3_dr_nn = ate_sev3_dr_nn + 1.96 * se_sev3_dr_nn
scalar pval_sev3_dr_nn = 2 * (1 - normal(abs(ate_sev3_dr_nn / se_sev3_dr_nn)))
```

```
* Caliper Matching
psmatch2 landslide, outcome(sev3) pscore(score_landslide) noreplacement caliper(0.010)
scalar ate_sev3_ls_c = r(att)
scalar se_sev3_ls_c = r(seatt)
scalar low_sev3_ls_c = ate_sev3_ls_c - 1.96 * se_sev3_ls_c
scalar high_sev3_ls_c = ate_sev3_ls_c + 1.96 * se_sev3_ls_c
scalar pval_sev3_ls_c = 2 * (1 - normal(abs(ate_sev3_ls_c / se_sev3_ls_c)))

psmatch2 drought, outcome(sev3) pscore(score_drought) noreplacement caliper(0.020)
scalar ate_sev3_dr_c = r(att)
scalar se_sev3_dr_c = r(seatt)
scalar low_sev3_dr_c = ate_sev3_dr_c - 1.96 * se_sev3_dr_c
scalar high_sev3_dr_c = ate_sev3_dr_c + 1.96 * se_sev3_dr_c
scalar pval_sev3_dr_c = 2 * (1 - normal(abs(ate_sev3_dr_c / se_sev3_dr_c)))

* Dataset for the graph
preserve
clear
set obs 4

gen outcome = "sev3"

gen shock = ""
replace shock = "landslide" in 1
replace shock = "drought" in 2
replace shock = "landslide" in 3
replace shock = "drought" in 4

gen method = ""
replace method = "NN" in 1/2
replace method = "Caliper" in 3/4

gen x = .
replace x = 1 in 1
replace x = 2 in 2
replace x = 4 in 3
replace x = 5 in 4

gen ate = .
replace ate = ate_sev3_ls_nn in 1
replace ate = ate_sev3_dr_nn in 2
replace ate = ate_sev3_ls_c in 3
replace ate = ate_sev3_dr_c in 4

gen ci_low = .
replace ci_low = low_sev3_ls_nn in 1
replace ci_low = low_sev3_dr_nn in 2
replace ci_low = low_sev3_ls_c in 3
replace ci_low = low_sev3_dr_c in 4

gen ci_high = .
replace ci_high = high_sev3_ls_nn in 1
replace ci_high = high_sev3_dr_nn in 2
replace ci_high = high_sev3_ls_c in 3
replace ci_high = high_sev3_dr_c in 4

* Graph ATET Sev3
gen str15 ate_label = ""
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_sev3_ls_nn < 0.01, "***", cond(pval_sev3_ls_nn < 0.05, "**", cond(pval_sev3_ls_nn < 0.1, "*", ""))) in 1
replace ate_label = string(ate, "%9.3f") + ///
```

```
   cond(pval_sev3_dr_nn < 0.01, "***", cond(pval_sev3_dr_nn < 0.05, "**", cond(pval_sev3_dr_nn < 0.1, "*", ""))) in 2
replace ate_label = string(ate, "%9.3f") + ///
   cond(pval_sev3_ls_c < 0.01, "***", cond(pval_sev3_ls_c < 0.05, "**", cond(pval_sev3_ls_c < 0.1, "*", ""))) in 3
replace ate_label = string(ate, "%9.3f") + ///
   cond(pval_sev3_dr_c < 0.01, "***", cond(pval_sev3_dr_c < 0.05, "**", cond(pval_sev3_dr_c < 0.1, "*", ""))) in 4

twoway ///
   (scatter ate x if shock == "landslide", msymbol(circle) mcolor(blue) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
   (scatter ate x if shock == "drought", msymbol(diamond) mcolor(green) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
   (rcap ci_low ci_high x if shock == "landslide", lcolor(blue)) ///
   (rcap ci_low ci_high x if shock == "drought", lcolor(green)) ///
   ,   title("Farmers") ///
   xlabel(none) ///
   ylabel(-0.8(0.2)0.8, angle(0) labsize(small) labcolor(black)) ///
   yscale(range(-0.8 0.8)) ///
   ytitle("Average Treatment Effect on the Treated") ///
   yline(0, lcolor(red)) ///
   legend(order(1 "Landslide" 2 "Drought") rows(1)) ///
   xscale(range(1 5.5)) ///
   xsize(6) ysize(4)

* * Merge ATET graphs Sev1 Sev2 Sev3
graph combine ///
   /Users/alexcano86/Desktop/Thesis/Stata/Dissertation/pic/sev1_atet.gph ///
   /Users/alexcano86/Desktop/Thesis/Stata/Dissertation/pic/sev2_atet.gph ///
   /Users/alexcano86/Desktop/Thesis/Stata/Dissertation/pic/sev3_atet.gph, ///
   cols(3) ///
         note("* p<0.10, ** p<0.05, *** p<0.010" ///
      "Balancing property satisfied:  YES" ///
      "Common support imposed:    YES" ///
      "Number of Neighbors: 1" ///
      "Caliper for landslides: 0.010" ///
      "Caliper for drought: 0.020" ///
      "Source: Authors.") ///
   title("Average Treatment Effect on the Treated")

* Merge Graphs ATE & ATET (Figure 4)
graph combine ///
   /Users/alexcano86/Desktop/Thesis/Stata/Dissertation/pic/sev_ate.gph ///
   /Users/alexcano86/Desktop/Thesis/Stata/Dissertation/pic/sev_atet.gph, ///
   cols(1) ysize(8) xsize(10)  ///
         note("* p<0.10, ** p<0.05, *** p<0.010" ///
      "Balancing property satisfied:  YES" ///
      "Common support imposed:    YES" ///
      "Number of Neighbors: 1" ///
      "Caliper for landslides: 0.010" ///
      "Caliper for drought: 0.020" ///
      "Source: Authors.") ///
   title("")

*************************************************************************************
***                     Figure 5: ATE & ATET Perceived Vulnerability                    ***
*************************************************************************************

*** ATE Vul1: Farm ***

* NN
teffects nnmatch (vul1 less60 female single primary less1 workers less_5ha water_have forest_have) (landslide)
scalar ate_vul1_ls_nn = e(b)[1,1]
scalar se_vul1_ls_nn  = sqrt(e(V)[1,1])
scalar low_vul1_ls_nn = ate_vul1_ls_nn - 1.96 * se_vul1_ls_nn
scalar high_vul1_ls_nn = ate_vul1_ls_nn + 1.96 * se_vul1_ls_nn
```

```
teffects nnmatch (vul1 less60 female single primary less1 workers less_5ha water_have forest_have) (drought)
scalar ate_vul1_dr_nn = e(b)[1,1]
scalar se_vul1_dr_nn  = sqrt(e(V)[1,1])
scalar low_vul1_dr_nn = ate_vul1_dr_nn - 1.96 * se_vul1_dr_nn
scalar high_vul1_dr_nn = ate_vul1_dr_nn + 1.96 * se_vul1_dr_nn

* Caliper
drop out_support out_support2  out_support3 out_support4 out_support5 out_support6 out_support7 out_support8 out_support9
out_support10 out_support11
teffects psmatch (vul1) (landslide less60 female single primary less1 workers less_5ha water_have forest_have), caliper(0.010)
osample(out_support) ate
teffects psmatch (vul1) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support==0, caliper(0.010) osample(out_support2) ate
teffects psmatch (vul1) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0, caliper(0.010) osample(out_support3) ate
teffects psmatch (vul1) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0, caliper(0.010) osample(out_support4) ate
teffects psmatch (vul1) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0, caliper(0.010) osample(out_support5) ate
teffects psmatch (vul1) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0, caliper(0.010) ate
scalar ate_vul1_ls_c = e(b)[1,1]
scalar se_vul1_ls_c  = sqrt(e(V)[1,1])
scalar low_vul1_ls_c = ate_vul1_ls_c - 1.96 * se_vul1_ls_c
scalar high_vul1_ls_c = ate_vul1_ls_c + 1.96 * se_vul1_ls_c

drop out_support out_support2  out_support3 out_support4 out_support5
teffects psmatch (vul1) (drought less60 female single primary less1 workers less_5ha water_have forest_have), caliper(0.020)
osample(out_support) ate
teffects psmatch (vul1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0,
caliper(0.020) osample(out_support2) ate
teffects psmatch (vul1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0, caliper(0.020) osample(out_support3) ate
teffects psmatch (vul1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0, caliper(0.020) osample(out_support4) ate
teffects psmatch (vul1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0, caliper(0.020) osample(out_support5) ate
teffects psmatch (vul1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0, caliper(0.020)
osample(out_support6) ate
teffects psmatch (vul1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0,
caliper(0.020) osample(out_support7) ate
teffects psmatch (vul1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0, caliper(0.020) osample(out_support8) ate
teffects psmatch (vul1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0 & out_support8==0, caliper(0.020) osample(out_support9) ate
teffects psmatch (vul1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0 & out_support8==0 & out_support9==0, caliper(0.020) osample(out_support10) ate
teffects psmatch (vul1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0 & out_support8==0 & out_support9==0 & out_support10==0, caliper(0.020) osample(out_support11) ate
teffects psmatch (vul1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0 & out_support8==0 & out_support9==0 & out_support10==0 & out_support11==0, caliper(0.020) ate
scalar ate_vul1_dr_c = e(b)[1,1]
scalar se_vul1_dr_c  = sqrt(e(V)[1,1])
scalar low_vul1_dr_c = ate_vul1_dr_c - 1.96 * se_vul1_dr_c
```

```
scalar high_vul1_dr_c = ate_vul1_dr_c + 1.96 * se_vul1_dr_c

*  P-values
scalar pval_vul1_ls_nn = 2 * (1 - normal(abs(ate_vul1_ls_nn / se_vul1_ls_nn)))
scalar pval_vul1_dr_nn = 2 * (1 - normal(abs(ate_vul1_dr_nn / se_vul1_dr_nn)))
scalar pval_vul1_ls_c  = 2 * (1 - normal(abs(ate_vul1_ls_c / se_vul1_ls_c)))
scalar pval_vul1_dr_c  = 2 * (1 - normal(abs(ate_vul1_dr_c / se_vul1_dr_c)))

* Dataset for the graph:
preserve
clear
set obs 6

gen outcome = ""
replace outcome = "vul1" in 1
replace outcome = "vul1" in 2
replace outcome = "vul1" in 3
replace outcome = "vul1" in 4

gen shock = ""
replace shock = "landslide" in 1
replace shock = "drought" in 2
replace shock = "landslide" in 3
replace shock = "drought" in 4

gen x = _n
gen ate = .
gen ci_low = .
gen ci_high = .

replace ate = ate_vul1_ls_nn in 1
replace ci_low = low_vul1_ls_nn in 1
replace ci_high = high_vul1_ls_nn in 1

replace ate = ate_vul1_dr_nn in 2
replace ci_low = low_vul1_dr_nn in 2
replace ci_high = high_vul1_dr_nn in 2

replace ate = ate_vul1_ls_c in 3
replace ci_low = low_vul1_ls_c in 3
replace ci_high = high_vul1_ls_c in 3

replace ate = ate_vul1_dr_c in 4
replace ci_low = low_vul1_dr_c in 4
replace ci_high = high_vul1_dr_c in 4

* Graph ATE Vul1
gen str15 ate_label = ""

replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_vul1_ls_nn < 0.01, "***", cond(pval_vul1_ls_nn < 0.05, "**", cond(pval_vul1_ls_nn < 0.1, "*", ""))) in 1
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_vul1_dr_nn < 0.01, "***", cond(pval_vul1_dr_nn < 0.05, "**", cond(pval_vul1_dr_nn < 0.1, "*", ""))) in 2
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_vul1_ls_c < 0.01, "***", cond(pval_vul1_ls_c < 0.05, "**", cond(pval_vul1_ls_c < 0.1, "*", ""))) in 3
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_vul1_dr_c < 0.01, "***", cond(pval_vul1_dr_c < 0.05, "**", cond(pval_vul1_dr_c < 0.1, "*", ""))) in 4

* Adjust the values on the x-axis
replace x = 1 in 1   // NN - Landslide
replace x = 2 in 2   // NN - Drought
replace x = 4 in 3   // Caliper - Landslide
```

```
replace x = 5 in 4   // Caliper - Drought

twoway ///
    (scatter ate x if shock == "landslide", msymbol(circle) mcolor(blue) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
    (scatter ate x if shock == "drought", msymbol(diamond) mcolor(green) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
    (rcap ci_low ci_high x if shock == "landslide", lcolor(blue)) ///
    (rcap ci_low ci_high x if shock == "drought", lcolor(green)) ///
    ,   title("Climate Change") ///
    xlabel(none) ///
    ylabel(-0.8(0.2)0.8, angle(0) labsize(small) labcolor(black)) ///
    yscale(range(-0.8 0.8)) ///
    ytitle("Average Treatment Effect") ///
    yline(0, lcolor(red)) ///
    legend(order(1 "Landslide" 2 "Drought") rows(1)) ///
    xscale(range(1 5.5)) ///
    xsize(6) ysize(4)

restore

*** ATE Vul2: Impacts of Climate Change ***

* NN
teffects nnmatch (vul2 less60 female single primary less1 workers less_5ha water_have forest_have) (landslide)
scalar ate_vul2_ls_nn = e(b)[1,1]
scalar se_vul2_ls_nn  = sqrt(e(V)[1,1])
scalar low_vul2_ls_nn = ate_vul2_ls_nn - 1.96 * se_vul2_ls_nn
scalar high_vul2_ls_nn = ate_vul2_ls_nn + 1.96 * se_vul2_ls_nn

teffects nnmatch (vul2 less60 female single primary less1 workers less_5ha water_have forest_have) (drought)
scalar ate_vul2_dr_nn = e(b)[1,1]
scalar se_vul2_dr_nn  = sqrt(e(V)[1,1])
scalar low_vul2_dr_nn = ate_vul2_dr_nn - 1.96 * se_vul2_dr_nn
scalar high_vul2_dr_nn = ate_vul2_dr_nn + 1.96 * se_vul2_dr_nn

* Caliper
drop out_support out_support2  out_support3 out_support4 out_support5 out_support6 out_support7 out_support8 out_support9
out_support10 out_support11
teffects psmatch (vul2) (landslide less60 female single primary less1 workers less_5ha water_have forest_have), caliper(0.010)
osample(out_support) ate
teffects psmatch (vul2) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support==0, caliper(0.010) osample(out_support2) ate
teffects psmatch (vul2) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0, caliper(0.010) osample(out_support3) ate
teffects psmatch (vul2) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0, caliper(0.010) osample(out_support4) ate
teffects psmatch (vul2) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0, caliper(0.010) osample(out_support5) ate
teffects psmatch (vul2) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0, caliper(0.010) ate
scalar ate_vul2_ls_c = e(b)[1,1]
scalar se_vul2_ls_c  = sqrt(e(V)[1,1])
scalar low_vul2_ls_c = ate_vul2_ls_c - 1.96 * se_vul2_ls_c
scalar high_vul2_ls_c = ate_vul2_ls_c + 1.96 * se_vul2_ls_c

drop out_support out_support2  out_support3 out_support4 out_support5
teffects psmatch (vul2) (drought less60 female single primary less1 workers less_5ha water_have forest_have), caliper(0.020)
osample(out_support) ate
teffects psmatch (vul2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0,
caliper(0.020) osample(out_support2) ate
teffects psmatch (vul2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0, caliper(0.020) osample(out_support3) ate
```

```
teffects psmatch (vul2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0, caliper(0.020) osample(out_support4) ate
teffects psmatch (vul2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0, caliper(0.020) osample(out_support5) ate
teffects psmatch (vul2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0, caliper(0.020)
osample(out_support6) ate
teffects psmatch (vul2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0,
caliper(0.020) osample(out_support7) ate
teffects psmatch (vul2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0, caliper(0.020) osample(out_support8) ate
teffects psmatch (vul2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0 & out_support8==0, caliper(0.020) osample(out_support9) ate
teffects psmatch (vul2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0 & out_support8==0 & out_support9==0, caliper(0.020) osample(out_support10) ate
teffects psmatch (vul2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0 & out_support8==0 & out_support9==0 & out_support10==0, caliper(0.020) osample(out_support11) ate
teffects psmatch (vul2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0 & out_support8==0 & out_support9==0 & out_support10==0 & out_support11==0, caliper(0.020) ate
scalar ate_vul2_dr_c = e(b)[1,1]
scalar se_vul2_dr_c  = sqrt(e(V)[1,1])
scalar low_vul2_dr_c = ate_vul2_dr_c - 1.96 * se_vul2_dr_c
scalar high_vul2_dr_c = ate_vul2_dr_c + 1.96 * se_vul2_dr_c

*  P-values
scalar pval_vul2_ls_nn = 2 * (1 - normal(abs(ate_vul2_ls_nn / se_vul2_ls_nn)))
scalar pval_vul2_dr_nn = 2 * (1 - normal(abs(ate_vul2_dr_nn / se_vul2_dr_nn)))
scalar pval_vul2_ls_c  = 2 * (1 - normal(abs(ate_vul2_ls_c / se_vul2_ls_c)))
scalar pval_vul2_dr_c  = 2 * (1 - normal(abs(ate_vul2_dr_c / se_vul2_dr_c)))

* Dataset for the graph:
preserve
clear
set obs 6

gen outcome = ""
replace outcome = "vul2" in 1
replace outcome = "vul2" in 2
replace outcome = "vul2" in 3
replace outcome = "vul2" in 4

gen shock = ""
replace shock = "landslide" in 1
replace shock = "drought" in 2
replace shock = "landslide" in 3
replace shock = "drought" in 4

gen x = _n
gen ate = .
gen ci_low = .
gen ci_high = .

replace ate = ate_vul2_ls_nn in 1
replace ci_low = low_vul2_ls_nn in 1
replace ci_high = high_vul2_ls_nn in 1
```

```
replace ate = ate_vul2_dr_nn in 2
replace ci_low = low_vul2_dr_nn in 2
replace ci_high = high_vul2_dr_nn in 2

replace ate = ate_vul2_ls_c in 3
replace ci_low = low_vul2_ls_c in 3
replace ci_high = high_vul2_ls_c in 3

replace ate = ate_vul2_dr_c in 4
replace ci_low = low_vul2_dr_c in 4
replace ci_high = high_vul2_dr_c in 4

* Graph ATE Vul2
gen str15 ate_label = ""

replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_vul2_ls_nn < 0.01, "***", cond(pval_vul2_ls_nn < 0.05, "**", cond(pval_vul2_ls_nn < 0.1, "*", ""))) in 1
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_vul2_dr_nn < 0.01, "***", cond(pval_vul2_dr_nn < 0.05, "**", cond(pval_vul2_dr_nn < 0.1, "*", ""))) in 2
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_vul2_ls_c < 0.01, "***", cond(pval_vul2_ls_c < 0.05, "**", cond(pval_vul2_ls_c < 0.1, "*", ""))) in 3
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_vul2_dr_c < 0.01, "***", cond(pval_vul2_dr_c < 0.05, "**", cond(pval_vul2_dr_c < 0.1, "*", ""))) in 4

* Adjust the values on the x-axis
replace x = 1 in 1   // NN - Landslide
replace x = 2 in 2   // NN - Drought
replace x = 4 in 3   // Caliper - Landslide
replace x = 5 in 4   // Caliper - Drought

twoway ///
    (scatter ate x if shock == "landslide", msymbol(circle) mcolor(blue) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
    (scatter ate x if shock == "drought", msymbol(diamond) mcolor(green) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
    (rcap ci_low ci_high x if shock == "landslide", lcolor(blue)) ///
    (rcap ci_low ci_high x if shock == "drought", lcolor(green)) ///
    , title("Impacts of Climate Change") ///
    xlabel(none) ///
    ylabel(-0.8(0.2)0.8, angle(0) labsize(small) labcolor(black)) ///
    yscale(range(-0.8 0.8)) ///
    ytitle("Average Treatment Effect") ///
    yline(0, lcolor(red)) ///
    legend(order(1 "Landslide" 2 "Drought") rows(1)) ///
    xscale(range(1 5.5)) ///
    xsize(6) ysize(4)

*** ATe Sev3: Operation of the Farm ***

* NN
teffects nnmatch (vul3 less60 female single primary less1 workers less_5ha water_have forest_have) (landslide)
scalar ate_vul3_ls_nn = e(b)[1,1]
scalar se_vul3_ls_nn  = sqrt(e(V)[1,1])
scalar low_vul3_ls_nn = ate_vul3_ls_nn - 1.96 * se_vul3_ls_nn
scalar high_vul3_ls_nn = ate_vul3_ls_nn + 1.96 * se_vul3_ls_nn

teffects nnmatch (vul3 less60 female single primary less1 workers less_5ha water_have forest_have) (drought)
scalar ate_vul3_dr_nn = e(b)[1,1]
scalar se_vul3_dr_nn  = sqrt(e(V)[1,1])
scalar low_vul3_dr_nn = ate_vul3_dr_nn - 1.96 * se_vul3_dr_nn
scalar high_vul3_dr_nn = ate_vul3_dr_nn + 1.96 * se_vul3_dr_nn

* Caliper
```

```
drop out_support out_support2  out_support3 out_support4 out_support5 out_support6 out_support7 out_support8 out_support9
out_support10 out_support11
teffects psmatch (vul3) (landslide less60 female single primary less1 workers less_5ha water_have forest_have), caliper(0.010)
osample(out_support) ate
teffects psmatch (vul3) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support==0, caliper(0.010) osample(out_support2) ate
teffects psmatch (vul3) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0, caliper(0.010) osample(out_support3) ate
teffects psmatch (vul3) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0, caliper(0.010) osample(out_support4) ate
teffects psmatch (vul3) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0, caliper(0.010) osample(out_support5) ate
teffects psmatch (vul3) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0, caliper(0.010) ate
scalar ate_vul3_ls_c = e(b)[1,1]
scalar se_vul3_ls_c  = sqrt(e(V)[1,1])
scalar low_vul3_ls_c = ate_sev3_ls_c - 1.96 * se_sev3_ls_c
scalar high_vul3_ls_c = ate_sev3_ls_c + 1.96 * se_sev3_ls_c

drop out_support out_support2  out_support3 out_support4 out_support5
teffects psmatch (vul3) (drought less60 female single primary less1 workers less_5ha water_have forest_have), caliper(0.020)
osample(out_support) ate
teffects psmatch (vul3) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0,
caliper(0.020) osample(out_support2) ate
teffects psmatch (vul3) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0, caliper(0.020) osample(out_support3) ate
teffects psmatch (vul3) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0, caliper(0.020) osample(out_support4) ate
teffects psmatch (vul3) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0, caliper(0.020) osample(out_support5) ate
teffects psmatch (vul3) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0, caliper(0.020)
osample(out_support6) ate
teffects psmatch (vul3) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0,
caliper(0.020) osample(out_support7) ate
teffects psmatch (vul3) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0, caliper(0.020) osample(out_support8) ate
teffects psmatch (vul3) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0 & out_support8==0, caliper(0.020) osample(out_support9) ate
teffects psmatch (vul3) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0 & out_support8==0 & out_support9==0, caliper(0.020) osample(out_support10) ate
teffects psmatch (vul3) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0 & out_support8==0 & out_support9==0 & out_support10==0, caliper(0.020) osample(out_support11) ate
teffects psmatch (vul3) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0 & out_support8==0 & out_support9==0 & out_support10==0 & out_support11==0, caliper(0.020) ate
scalar ate_vul3_dr_c = e(b)[1,1]
scalar se_vul3_dr_c  = sqrt(e(V)[1,1])
scalar low_vul3_dr_c = ate_vul3_dr_c - 1.96 * se_vul3_dr_c
scalar high_vul3_dr_c = ate_vul3_dr_c + 1.96 * se_vul3_dr_c

*  P-values
scalar pval_vul3_ls_nn = 2 * (1 - normal(abs(ate_vul3_ls_nn / se_vul3_ls_nn)))
scalar pval_vul3_dr_nn = 2 * (1 - normal(abs(ate_vul3_dr_nn / se_vul3_dr_nn)))
scalar pval_vul3_ls_c  = 2 * (1 - normal(abs(ate_vul3_ls_c / se_vul3_ls_c)))
scalar pval_vul3_dr_c  = 2 * (1 - normal(abs(ate_vul3_dr_c / se_vul3_dr_c)))
```

```
* Dataset for the graph:
preserve
clear
set obs 6

gen outcome = ""
replace outcome = "vul3" in 1
replace outcome = "vul3" in 2
replace outcome = "vul3" in 3
replace outcome = "vul3" in 4

gen shock = ""
replace shock = "landslide" in 1
replace shock = "drought" in 2
replace shock = "landslide" in 3
replace shock = "drought" in 4

gen x = _n
gen ate = .
gen ci_low = .
gen ci_high = .

replace ate = ate_vul3_ls_nn in 1
replace ci_low = low_vul3_ls_nn in 1
replace ci_high = high_vul3_ls_nn in 1

replace ate = ate_vul3_dr_nn in 2
replace ci_low = low_vul3_dr_nn in 2
replace ci_high = high_vul3_dr_nn in 2

replace ate = ate_vul3_ls_c in 3
replace ci_low = low_vul3_ls_c in 3
replace ci_high = high_vul3_ls_c in 3

replace ate = ate_vul3_dr_c in 4
replace ci_low = low_vul3_dr_c in 4
replace ci_high = high_vul3_dr_c in 4

* Graph ATE Vul3
gen str15 ate_label = ""

replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_vul3_ls_nn < 0.01, "***", cond(pval_vul3_ls_nn < 0.05, "**", cond(pval_vul3_ls_nn < 0.1, "*", ""))) in 1
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_vul3_dr_nn < 0.01, "***", cond(pval_vul3_dr_nn < 0.05, "**", cond(pval_vul3_dr_nn < 0.1, "*", ""))) in 2
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_vul3_ls_c < 0.01, "***", cond(pval_vul3_ls_c < 0.05, "**", cond(pval_vul3_ls_c < 0.1, "*", ""))) in 3
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_vul3_dr_c < 0.01, "***", cond(pval_vul3_dr_c < 0.05, "**", cond(pval_vul3_dr_c < 0.1, "*", ""))) in 4

* Adjust the values on the x-axis
replace x = 1 in 1   // NN - Landslide
replace x = 2 in 2   // NN - Drought
replace x = 4 in 3   // Caliper - Landslide
replace x = 5 in 4   // Caliper - Drought

twoway ///
    (scatter ate x if shock == "landslide", msymbol(circle) mcolor(blue) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
    (scatter ate x if shock == "drought", msymbol(diamond) mcolor(green) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
    (rcap ci_low ci_high x if shock == "landslide", lcolor(blue)) ///
    (rcap ci_low ci_high x if shock == "drought", lcolor(green)) ///
    , title("Operation of the Farm") ///
```

```
    xlabel(none) ///
    ylabel(-0.8(0.2)0.8, angle(0) labsize(small) labcolor(black)) ///
    yscale(range(-0.8 0.8)) ///
    ytitle("Average Treatment Effect") ///
    yline(0, lcolor(red)) ///
    legend(order(1 "Landslide" 2 "Drought") rows(1)) ///
    xscale(range(1 5.5)) ///
    xsize(6) ysize(4)

* Merge ATE graphs Vul1 Vul2 Vul3
graph combine ///
    /Users/alexcano86/Desktop/Thesis/Stata/Dissertation/pic/Vul1.gph ///
    /Users/alexcano86/Desktop/Thesis/Stata/Dissertation/pic/Vul2.gph ///
    /Users/alexcano86/Desktop/Thesis/Stata/Dissertation/pic/Vul3.gph, ///
    cols(3) ///
            note("* p<0.10, ** p<0.05, *** p<0.010" ///
        "Balancing property satisfied:  YES" ///
        "Common support imposed:    YES" ///
        "Number of Neighbors: 1" ///
        "Caliper for landslides: 0.010" ///
        "Caliper for drought: 0.020" ///
        "Source: Authors.") ///
    title("Average Treatment Effect")

*** ATET Vul1: Climate Change ***

* NN Matching
psmatch2 landslide, outcome(vul1) pscore(score_landslide) noreplacement neighbor(1) common
scalar ate_vul1_ls_nn = r(att)
scalar se_vul1_ls_nn = r(seatt)
scalar low_vul1_ls_nn = ate_vul1_ls_nn - 1.96 * se_vul1_ls_nn
scalar high_vul1_ls_nn = ate_vul1_ls_nn + 1.96 * se_vul1_ls_nn
scalar pval_vul1_ls_nn = 2 * (1 - normal(abs(ate_vul1_ls_nn / se_vul1_ls_nn)))

psmatch2 drought, outcome(vul1) pscore(score_drought) noreplacement neighbor(1) common
scalar ate_vul1_dr_nn = r(att)
scalar se_vul1_dr_nn = r(seatt)
scalar low_vul1_dr_nn = ate_vul1_dr_nn - 1.96 * se_vul1_dr_nn
scalar high_vul1_dr_nn = ate_vul1_dr_nn + 1.96 * se_vul1_dr_nn
scalar pval_vul1_dr_nn = 2 * (1 - normal(abs(ate_vul1_dr_nn / se_vul1_dr_nn)))

* Caliper Matching
psmatch2 landslide, outcome(vul1) pscore(score_landslide) noreplacement caliper(0.010)
scalar ate_vul1_ls_c = r(att)
scalar se_vul1_ls_c = r(seatt)
scalar low_vul1_ls_c = ate_vul1_ls_c - 1.96 * se_vul1_ls_c
scalar high_vul1_ls_c = ate_vul1_ls_c + 1.96 * se_vul1_ls_c
scalar pval_vul1_ls_c = 2 * (1 - normal(abs(ate_vul1_ls_c / se_vul1_ls_c)))

psmatch2 drought, outcome(vul1) pscore(score_drought) noreplacement caliper(0.020)
scalar ate_vul1_dr_c = r(att)
scalar se_vul1_dr_c = r(seatt)
scalar low_vul1_dr_c = ate_vul1_dr_c - 1.96 * se_vul1_dr_c
scalar high_vul1_dr_c = ate_vul1_dr_c + 1.96 * se_vul1_dr_c
scalar pval_vul1_dr_c = 2 * (1 - normal(abs(ate_vul1_dr_c / se_vul1_dr_c)))

* Dataset for the graph
preserve
clear
set obs 4

gen outcome = "vul1"
```

```
gen shock = ""
replace shock = "landslide" in 1
replace shock = "drought" in 2
replace shock = "landslide" in 3
replace shock = "drought" in 4

gen method = ""
replace method = "NN" in 1/2
replace method = "Caliper" in 3/4

gen x = .
replace x = 1 in 1
replace x = 2 in 2
replace x = 4 in 3
replace x = 5 in 4

gen ate = .
replace ate = ate_vul1_ls_nn in 1
replace ate = ate_vul1_dr_nn in 2
replace ate = ate_vul1_ls_c in 3
replace ate = ate_vul1_dr_c in 4

gen ci_low = .
replace ci_low = low_vul1_ls_nn in 1
replace ci_low = low_vul1_dr_nn in 2
replace ci_low = low_vul1_ls_c in 3
replace ci_low = low_vul1_dr_c in 4

gen ci_high = .
replace ci_high = high_vul1_ls_nn in 1
replace ci_high = high_vul1_dr_nn in 2
replace ci_high = high_vul1_ls_c in 3
replace ci_high = high_vul1_dr_c in 4

* Graph ATET Vul1
gen str15 ate_label = ""
replace ate_label = string(ate, "%9.3f") + ///
   cond(pval_vul1_ls_nn < 0.01, "***", cond(pval_vul1_ls_nn < 0.05, "**", cond(pval_vul1_ls_nn < 0.1, "*", ""))) in 1
replace ate_label = string(ate, "%9.3f") + ///
   cond(pval_vul1_dr_nn < 0.01, "***", cond(pval_vul1_dr_nn < 0.05, "**", cond(pval_vul1_dr_nn < 0.1, "*", ""))) in 2
replace ate_label = string(ate, "%9.3f") + ///
   cond(pval_vul1_ls_c < 0.01, "***", cond(pval_vul1_ls_c < 0.05, "**", cond(pval_vul1_ls_c < 0.1, "*", ""))) in 3
replace ate_label = string(ate, "%9.3f") + ///
   cond(pval_vul1_dr_c < 0.01, "***", cond(pval_vul1_dr_c < 0.05, "**", cond(pval_vul1_dr_c < 0.1, "*", ""))) in 4

twoway ///
   (scatter ate x if shock == "landslide", msymbol(circle) mcolor(blue) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
   (scatter ate x if shock == "drought", msymbol(diamond) mcolor(green) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
   (rcap ci_low ci_high x if shock == "landslide", lcolor(blue)) ///
   (rcap ci_low ci_high x if shock == "drought", lcolor(green)) ///
   ,   title("Climate Change") ///
   xlabel(none) ///
   ylabel(-0.8(0.2)0.8, angle(0) labsize(small) labcolor(black)) ///
   yscale(range(-0.8 0.8)) ///
   ytitle("Average Treatment Effect on the Treated") ///
   yline(0, lcolor(red)) ///
   legend(order(1 "Landslide" 2 "Drought") rows(1)) ///
   xscale(range(1 5.5)) ///
   xsize(6) ysize(4)

*** ATET Vul2: Impacts of Climate Change ***
```

```
* NN Matching
psmatch2 landslide, outcome(vul2) pscore(score_landslide) noreplacement neighbor(1) common
scalar ate_vul2_ls_nn = r(att)
scalar se_vul2_ls_nn = r(seatt)
scalar low_vul2_ls_nn = ate_vul2_ls_nn - 1.96 * se_vul2_ls_nn
scalar high_vul2_ls_nn = ate_vul2_ls_nn + 1.96 * se_vul2_ls_nn
scalar pval_vul2_ls_nn = 2 * (1 - normal(abs(ate_vul2_ls_nn / se_vul2_ls_nn)))

psmatch2 drought, outcome(vul2) pscore(score_drought) noreplacement neighbor(1) common
scalar ate_vul2_dr_nn = r(att)
scalar se_vul2_dr_nn = r(seatt)
scalar low_vul2_dr_nn = ate_vul2_dr_nn - 1.96 * se_vul2_dr_nn
scalar high_vul2_dr_nn = ate_vul2_dr_nn + 1.96 * se_vul2_dr_nn
scalar pval_vul2_dr_nn = 2 * (1 - normal(abs(ate_vul2_dr_nn / se_vul2_dr_nn)))

* Caliper Matching
psmatch2 landslide, outcome(vul2) pscore(score_landslide) noreplacement caliper(0.010)
scalar ate_vul2_ls_c = r(att)
scalar se_vul2_ls_c = r(seatt)
scalar low_vul2_ls_c = ate_vul2_ls_c - 1.96 * se_vul2_ls_c
scalar high_vul2_ls_c = ate_vul2_ls_c + 1.96 * se_vul2_ls_c
scalar pval_vul2_ls_c = 2 * (1 - normal(abs(ate_vul2_ls_c / se_vul2_ls_c)))

psmatch2 drought, outcome(vul2) pscore(score_drought) noreplacement caliper(0.020)
scalar ate_vul2_dr_c = r(att)
scalar se_vul2_dr_c = r(seatt)
scalar low_vul2_dr_c = ate_vul2_dr_c - 1.96 * se_vul2_dr_c
scalar high_vul2_dr_c = ate_vul2_dr_c + 1.96 * se_vul2_dr_c
scalar pval_vul2_dr_c = 2 * (1 - normal(abs(ate_vul2_dr_c / se_vul2_dr_c)))

* Dataset for the graph
preserve
clear
set obs 4

gen outcome = "vul2"

gen shock = ""
replace shock = "landslide" in 1
replace shock = "drought" in 2
replace shock = "landslide" in 3
replace shock = "drought" in 4

gen method = ""
replace method = "NN" in 1/2
replace method = "Caliper" in 3/4

gen x = .
replace x = 1 in 1
replace x = 2 in 2
replace x = 4 in 3
replace x = 5 in 4

gen ate = .
replace ate = ate_vul2_ls_nn in 1
replace ate = ate_vul2_dr_nn in 2
replace ate = ate_vul2_ls_c in 3
replace ate = ate_vul2_dr_c in 4

gen ci_low = .
replace ci_low = low_vul2_ls_nn in 1
```

```
replace ci_low = low_vul2_dr_nn in 2
replace ci_low = low_vul2_ls_c in 3
replace ci_low = low_vul2_dr_c in 4

gen ci_high = .
replace ci_high = high_vul2_ls_nn in 1
replace ci_high = high_vul2_dr_nn in 2
replace ci_high = high_vul2_ls_c in 3
replace ci_high = high_vul2_dr_c in 4

* Graph ATET Vul2
gen str15 ate_label = ""
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_vul2_ls_nn < 0.01, "***", cond(pval_vul2_ls_nn < 0.05, "**", cond(pval_vul2_ls_nn < 0.1, "*", ""))) in 1
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_vul2_dr_nn < 0.01, "***", cond(pval_vul2_dr_nn < 0.05, "**", cond(pval_vul2_dr_nn < 0.1, "*", ""))) in 2
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_vul2_ls_c < 0.01, "***", cond(pval_vul2_ls_c < 0.05, "**", cond(pval_vul2_ls_c < 0.1, "*", ""))) in 3
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_vul2_dr_c < 0.01, "***", cond(pval_vul2_dr_c < 0.05, "**", cond(pval_vul2_dr_c < 0.1, "*", ""))) in 4

twoway ///
    (scatter ate x if shock == "landslide", msymbol(circle) mcolor(blue) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
    (scatter ate x if shock == "drought", msymbol(diamond) mcolor(green) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
    (rcap ci_low ci_high x if shock == "landslide", lcolor(blue)) ///
    (rcap ci_low ci_high x if shock == "drought", lcolor(green)) ///
    ,   title("Impacts of Climate Change") ///
    xlabel(none) ///
    ylabel(-0.8(0.2)0.8, angle(0) labsize(small) labcolor(black)) ///
    yscale(range(-0.8 0.8)) ///
    ytitle("Average Treatment Effect on the Treated") ///
    yline(0, lcolor(red)) ///
    legend(order(1 "Landslide" 2 "Drought") rows(1)) ///
    xscale(range(1 5.5)) ///
    xsize(6) ysize(4)

*** ATET Vul3: Operation of the Farm ***

* NN Matching
psmatch2 landslide, outcome(vul3) pscore(score_landslide) noreplacement neighbor(1) common
scalar ate_vul3_ls_nn = r(att)
scalar se_vul3_ls_nn = r(seatt)
scalar low_vul3_ls_nn = ate_vul3_ls_nn - 1.96 * se_vul3_ls_nn
scalar high_vul3_ls_nn = ate_vul3_ls_nn + 1.96 * se_vul3_ls_nn
scalar pval_vul3_ls_nn = 2 * (1 - normal(abs(ate_vul3_ls_nn / se_vul3_ls_nn)))

psmatch2 drought, outcome(vul3) pscore(score_drought) noreplacement neighbor(1) common
scalar ate_vul3_dr_nn = r(att)
scalar se_vul3_dr_nn = r(seatt)
scalar low_vul3_dr_nn = ate_vul3_dr_nn - 1.96 * se_vul3_dr_nn
scalar high_vul3_dr_nn = ate_vul3_dr_nn + 1.96 * se_vul3_dr_nn
scalar pval_vul3_dr_nn = 2 * (1 - normal(abs(ate_vul3_dr_nn / se_vul3_dr_nn)))

* Caliper Matching
psmatch2 landslide, outcome(vul3) pscore(score_landslide) noreplacement caliper(0.010)
scalar ate_vul3_ls_c = r(att)
scalar se_vul3_ls_c = r(seatt)
scalar low_vul3_ls_c = ate_vul3_ls_c - 1.96 * se_vul3_ls_c
scalar high_vul3_ls_c = ate_vul3_ls_c + 1.96 * se_vul3_ls_c
scalar pval_vul3_ls_c = 2 * (1 - normal(abs(ate_vul3_ls_c / se_vul3_ls_c)))

psmatch2 drought, outcome(vul3) pscore(score_drought) noreplacement caliper(0.020)
```

```
scalar ate_vul3_dr_c = r(att)
scalar se_vul3_dr_c = r(seatt)
scalar low_vul3_dr_c = ate_vul3_dr_c - 1.96 * se_vul3_dr_c
scalar high_vul3_dr_c = ate_vul3_dr_c + 1.96 * se_vul3_dr_c
scalar pval_vul3_dr_c = 2 * (1 - normal(abs(ate_vul3_dr_c / se_vul3_dr_c)))

* Dataset for the graph
preserve
clear
set obs 4

gen outcome = "vul3"

gen shock = ""
replace shock = "landslide" in 1
replace shock = "drought" in 2
replace shock = "landslide" in 3
replace shock = "drought" in 4

gen method = ""
replace method = "NN" in 1/2
replace method = "Caliper" in 3/4

gen x = .
replace x = 1 in 1
replace x = 2 in 2
replace x = 4 in 3
replace x = 5 in 4

gen ate = .
replace ate = ate_vul3_ls_nn in 1
replace ate = ate_vul3_dr_nn in 2
replace ate = ate_vul3_ls_c in 3
replace ate = ate_vul3_dr_c in 4

gen ci_low = .
replace ci_low = low_vul3_ls_nn in 1
replace ci_low = low_vul3_dr_nn in 2
replace ci_low = low_vul3_ls_c in 3
replace ci_low = low_vul3_dr_c in 4

gen ci_high = .
replace ci_high = high_vul3_ls_nn in 1
replace ci_high = high_vul3_dr_nn in 2
replace ci_high = high_vul3_ls_c in 3
replace ci_high = high_vul3_dr_c in 4

* Graph ATET Vul3
gen str15 ate_label = ""
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_vul3_ls_nn < 0.01, "***", cond(pval_vul3_ls_nn < 0.05, "**", cond(pval_vul3_ls_nn < 0.1, "*", ""))) in 1
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_vul3_dr_nn < 0.01, "***", cond(pval_vul3_dr_nn < 0.05, "**", cond(pval_vul3_dr_nn < 0.1, "*", ""))) in 2
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_vul3_ls_c < 0.01, "***", cond(pval_vul3_ls_c < 0.05, "**", cond(pval_vul3_ls_c < 0.1, "*", ""))) in 3
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_vul3_dr_c < 0.01, "***", cond(pval_vul3_dr_c < 0.05, "**", cond(pval_vul3_dr_c < 0.1, "*", ""))) in 4

twoway ///
    (scatter ate x if shock == "landslide", msymbol(circle) mcolor(blue) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
    (scatter ate x if shock == "drought", msymbol(diamond) mcolor(green) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
    (rcap ci_low ci_high x if shock == "landslide", lcolor(blue)) ///
```

```
   (rcap ci_low ci_high x if shock == "drought", lcolor(green)) ///
   ,   title("Operation of the Farm") ///
   xlabel(none) ///
   ylabel(-0.8(0.2)0.8, angle(0) labsize(small) labcolor(black)) ///
   yscale(range(-0.8 0.8)) ///
   ytitle("Average Treatment Effect on the Treated") ///
   yline(0, lcolor(red)) ///
   legend(order(1 "Landslide" 2 "Drought") rows(1)) ///
   xscale(range(1 5.5)) ///
   xsize(6) ysize(4)

* Merge ATET graphs Vul1 Vul2 Vul3
graph combine ///
   /Users/alexcano86/Desktop/Thesis/Stata/Dissertation/pic/vul1_atet.gph ///
   /Users/alexcano86/Desktop/Thesis/Stata/Dissertation/pic/vul2_atet.gph ///
   /Users/alexcano86/Desktop/Thesis/Stata/Dissertation/pic/vul3_atet.gph, ///
   cols(3) ///
         note("* p<0.10, ** p<0.05, *** p<0.010" ///
      "Balancing property satisfied:  YES" ///
      "Common support imposed:    YES" ///
      "Number of Neighbors: 1" ///
      "Caliper for landslides: 0.010" ///
      "Caliper for drought: 0.020" ///
      "Source: Authors.") ///
   title("Average Treatment Effect on the Treated")

* Merge Graphs ATE & ATET (Figure 5)
graph combine ///
   /Users/alexcano86/Desktop/Thesis/Stata/Dissertation/pic/vul_ate.gph ///
   /Users/alexcano86/Desktop/Thesis/Stata/Dissertation/pic/vul_atet.gph, ///
   cols(1) ysize(8) xsize(10)  ///
         note("* p<0.10, ** p<0.05, *** p<0.010" ///
      "Balancing property satisfied:  YES" ///
      "Common support imposed:    YES" ///
      "Number of Neighbors: 1" ///
      "Caliper for landslides: 0.010" ///
      "Caliper for drought: 0.020" ///
      "Source: Authors.") ///
   title("")

***************************************************************************************
***                        Figure 6: ATE Psychological Distance                     ***
***************************************************************************************

*** ATE Spatial 1 ***

* NN
teffects nnmatch (spa1 less60 female single primary less1 workers less_5ha water_have forest_have) (landslide)
scalar ate_spa1_ls_nn = e(b)[1,1]
scalar se_spa1_ls_nn  = sqrt(e(V)[1,1])
scalar low_spa1_ls_nn = ate_spa1_ls_nn - 1.96 * se_spa1_ls_nn
scalar high_spa1_ls_nn = ate_spa1_ls_nn + 1.96 * se_spa1_ls_nn

teffects nnmatch (spa1 less60 female single primary less1 workers less_5ha water_have forest_have) (drought)
scalar ate_spa1_dr_nn = e(b)[1,1]
scalar se_spa1_dr_nn  = sqrt(e(V)[1,1])
scalar low_spa1_dr_nn = ate_spa1_dr_nn - 1.96 * se_spa1_dr_nn
scalar high_spa1_dr_nn = ate_spa1_dr_nn + 1.96 * se_spa1_dr_nn

* Caliper
drop out_support out_support2  out_support3 out_support4 out_support5 out_support6 out_support7 out_support8 out_support9
out_support10 out_support11
```

```
teffects psmatch (spa1) (landslide less60 female single primary less1 workers less_5ha water_have forest_have), caliper(0.010)
osample(out_support) ate
teffects psmatch (spa1) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support==0, caliper(0.010) osample(out_support2) ate
teffects psmatch (spa1) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0, caliper(0.010) osample(out_support3) ate
teffects psmatch (spa1) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0, caliper(0.010) osample(out_support4) ate
teffects psmatch (spa1) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0, caliper(0.010) osample(out_support5) ate
teffects psmatch (spa1) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0, caliper(0.010) ate
scalar ate_spa1_ls_c = e(b)[1,1]
scalar se_spa1_ls_c  = sqrt(e(V)[1,1])
scalar low_spa1_ls_c = ate_spa1_ls_c - 1.96 * se_spa1_ls_c
scalar high_spa1_ls_c = ate_spa1_ls_c + 1.96 * se_spa1_ls_c

drop out_support out_support2  out_support3 out_support4 out_support5
teffects psmatch (spa1) (drought less60 female single primary less1 workers less_5ha water_have forest_have), caliper(0.020)
osample(out_support) ate
teffects psmatch (spa1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support==0, caliper(0.020) osample(out_support2) ate
teffects psmatch (spa1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0, caliper(0.020) osample(out_support3) ate
teffects psmatch (spa1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0, caliper(0.020) osample(out_support4) ate
teffects psmatch (spa1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0, caliper(0.020) osample(out_support5) ate
teffects psmatch (spa1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0, caliper(0.020)
osample(out_support6) ate
teffects psmatch (spa1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0,
caliper(0.020) osample(out_support7) ate
teffects psmatch (spa1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0, caliper(0.020) osample(out_support8) ate
teffects psmatch (spa1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0 & out_support8==0, caliper(0.020) osample(out_support9) ate
teffects psmatch (spa1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0 & out_support8==0 & out_support9==0, caliper(0.020) osample(out_support10) ate
teffects psmatch (spa1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0 & out_support8==0 & out_support9==0 & out_support10==0, caliper(0.020) osample(out_support11) ate
teffects psmatch (spa1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0 & out_support8==0 & out_support9==0 & out_support10==0 & out_support11==0, caliper(0.020) ate
scalar ate_spa1_dr_c = e(b)[1,1]
scalar se_spa1_dr_c  = sqrt(e(V)[1,1])
scalar low_spa1_dr_c = ate_spa1_dr_c - 1.96 * se_spa1_dr_c
scalar high_spa1_dr_c = ate_spa1_dr_c + 1.96 * se_spa1_dr_c

*  P-values
scalar pval_spa1_ls_nn = 2 * (1 - normal(abs(ate_spa1_ls_nn / se_spa1_ls_nn)))
scalar pval_spa1_dr_nn = 2 * (1 - normal(abs(ate_spa1_dr_nn / se_spa1_dr_nn)))
scalar pval_spa1_ls_c  = 2 * (1 - normal(abs(ate_spa1_ls_c / se_spa1_ls_c)))
scalar pval_spa1_dr_c  = 2 * (1 - normal(abs(ate_spa1_dr_c / se_spa1_dr_c)))

* Dataset for the graph:
preserve
```

```
clear
set obs 6

gen outcome = ""
replace outcome = "spa1" in 1
replace outcome = "spa1" in 2
replace outcome = "spa1" in 3
replace outcome = "spa1" in 4

gen shock = ""
replace shock = "landslide" in 1
replace shock = "drought" in 2
replace shock = "landslide" in 3
replace shock = "drought" in 4

gen x = _n
gen ate = .
gen ci_low = .
gen ci_high = .

replace ate = ate_spa1_ls_nn in 1
replace ci_low = low_spa1_ls_nn in 1
replace ci_high = high_spa1_ls_nn in 1

replace ate = ate_spa1_dr_nn in 2
replace ci_low = low_spa1_dr_nn in 2
replace ci_high = high_spa1_dr_nn in 2

replace ate = ate_spa1_ls_c in 3
replace ci_low = low_spa1_ls_c in 3
replace ci_high = high_spa1_ls_c in 3

replace ate = ate_spa1_dr_c in 4
replace ci_low = low_spa1_dr_c in 4
replace ci_high = high_spa1_dr_c in 4

* Graph ATE Spatial1
gen str15 ate_label = ""

replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_spa1_ls_nn < 0.01, "***", cond(pval_spa1_ls_nn < 0.05, "**", cond(pval_spa1_ls_nn < 0.1, "*", ""))) in 1
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_spa1_dr_nn < 0.01, "***", cond(pval_spa1_dr_nn < 0.05, "**", cond(pval_spa1_dr_nn < 0.1, "*", ""))) in 2
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_spa1_ls_c < 0.01, "***", cond(pval_spa1_ls_c < 0.05, "**", cond(pval_spa1_ls_c < 0.1, "*", ""))) in 3
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_spa1_dr_c < 0.01, "***", cond(pval_spa1_dr_c < 0.05, "**", cond(pval_spa1_dr_c < 0.1, "*", ""))) in 4

* Adjust the values on the x-axis
replace x = 1 in 1   // NN - Landslide
replace x = 2 in 2   // NN - Drought
replace x = 4 in 3   // Caliper - Landslide
replace x = 5 in 4   // Caliper - Drought

twoway ///
    (scatter ate x if shock == "landslide", msymbol(circle) mcolor(blue) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
    (scatter ate x if shock == "drought", msymbol(diamond) mcolor(green) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
    (rcap ci_low ci_high x if shock == "landslide", lcolor(blue)) ///
    (rcap ci_low ci_high x if shock == "drought", lcolor(green)) ///
    ,   title("Spatial 1") ///
    xlabel(none) ///
    ylabel(-0.8(0.2)0.8, angle(0) labsize(small) labcolor(black)) ///
```

```
    yscale(range(-0.8 0.8)) ///
    ytitle("Average Treatment Effect") ///
    yline(0, lcolor(red)) ///
    legend(order(1 "Landslide" 2 "Drought") rows(1)) ///
    xscale(range(1 5.5)) ///
    xsize(6) ysize(4)

restore

*** ATE Spatial 2 ***

* NN
teffects nnmatch (spa2 less60 female single primary less1 workers less_5ha water_have forest_have) (landslide)
scalar ate_spa2_ls_nn = e(b)[1,1]
scalar se_spa2_ls_nn  = sqrt(e(V)[1,1])
scalar low_spa2_ls_nn = ate_spa2_ls_nn - 1.96 * se_spa2_ls_nn
scalar high_spa2_ls_nn = ate_spa2_ls_nn + 1.96 * se_spa2_ls_nn

teffects nnmatch (spa2 less60 female single primary less1 workers less_5ha water_have forest_have) (drought)
scalar ate_spa2_dr_nn = e(b)[1,1]
scalar se_spa2_dr_nn  = sqrt(e(V)[1,1])
scalar low_spa2_dr_nn = ate_spa2_dr_nn - 1.96 * se_spa2_dr_nn
scalar high_spa2_dr_nn = ate_spa2_dr_nn + 1.96 * se_spa2_dr_nn

* Caliper
drop out_support out_support2  out_support3 out_support4 out_support5 out_support6 out_support7 out_support8 out_support9
out_support10 out_support11
teffects psmatch (spa2) (landslide less60 female single primary less1 workers less_5ha water_have forest_have), caliper(0.010)
osample(out_support) ate
teffects psmatch (spa2) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support==0, caliper(0.010) osample(out_support2) ate
teffects psmatch (spa2) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0, caliper(0.010) osample(out_support3) ate
teffects psmatch (spa2) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0, caliper(0.010) osample(out_support4) ate
teffects psmatch (spa2) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0, caliper(0.010) osample(out_support5) ate
teffects psmatch (spa2) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0, caliper(0.010) ate
scalar ate_spa2_ls_c = e(b)[1,1]
scalar se_spa2_ls_c  = sqrt(e(V)[1,1])
scalar low_spa2_ls_c = ate_spa2_ls_c - 1.96 * se_spa2_ls_c
scalar high_spa2_ls_c = ate_spa2_ls_c + 1.96 * se_spa2_ls_c

drop out_support out_support2  out_support3 out_support4 out_support5
teffects psmatch (spa2) (drought less60 female single primary less1 workers less_5ha water_have forest_have), caliper(0.020)
osample(out_support) ate
teffects psmatch (spa2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support==0, caliper(0.020) osample(out_support2) ate
teffects psmatch (spa2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0, caliper(0.020) osample(out_support3) ate
teffects psmatch (spa2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0, caliper(0.020) osample(out_support4) ate
teffects psmatch (spa2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0, caliper(0.020) osample(out_support5) ate
teffects psmatch (spa2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0, caliper(0.020)
osample(out_support6) ate
teffects psmatch (spa2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0,
caliper(0.020) osample(out_support7) ate
```

```
teffects psmatch (spa2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0, caliper(0.020) osample(out_support8) ate
teffects psmatch (spa2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0 & out_support8==0, caliper(0.020) osample(out_support9) ate
teffects psmatch (spa2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0 & out_support8==0 & out_support9==0, caliper(0.020) osample(out_support10) ate
teffects psmatch (spa2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0 & out_support8==0 & out_support9==0 & out_support10==0, caliper(0.020) osample(out_support11) ate
teffects psmatch (spa2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0 & out_support8==0 & out_support9==0 & out_support10==0 & out_support11==0, caliper(0.020) ate
scalar ate_spa2_dr_c = e(b)[1,1]
scalar se_spa2_dr_c  = sqrt(e(V)[1,1])
scalar low_spa2_dr_c = ate_spa2_dr_c - 1.96 * se_spa2_dr_c
scalar high_spa2_dr_c = ate_spa2_dr_c + 1.96 * se_spa2_dr_c

*  P-values
scalar pval_spa2_ls_nn = 2 * (1 - normal(abs(ate_spa2_ls_nn / se_spa2_ls_nn)))
scalar pval_spa2_dr_nn = 2 * (1 - normal(abs(ate_spa2_dr_nn / se_spa2_dr_nn)))
scalar pval_spa2_ls_c  = 2 * (1 - normal(abs(ate_spa2_ls_c / se_spa2_ls_c)))
scalar pval_spa2_dr_c  = 2 * (1 - normal(abs(ate_spa2_dr_c / se_spa2_dr_c)))

* Dataset for the graph:
preserve
clear
set obs 6

gen outcome = ""
replace outcome = "spa2" in 1
replace outcome = "spa2" in 2
replace outcome = "spa2" in 3
replace outcome = "spa2" in 4

gen shock = ""
replace shock = "landslide" in 1
replace shock = "drought" in 2
replace shock = "landslide" in 3
replace shock = "drought" in 4

gen x = _n
gen ate = .
gen ci_low = .
gen ci_high = .

replace ate = ate_spa2_ls_nn in 1
replace ci_low = low_spa2_ls_nn in 1
replace ci_high = high_spa2_ls_nn in 1

replace ate = ate_spa2_dr_nn in 2
replace ci_low = low_spa2_dr_nn in 2
replace ci_high = high_spa2_dr_nn in 2

replace ate = ate_spa2_ls_c in 3
replace ci_low = low_spa2_ls_c in 3
replace ci_high = high_spa2_ls_c in 3

replace ate = ate_spa2_dr_c in 4
replace ci_low = low_spa2_dr_c in 4
```

```
replace ci_high = high_spa2_dr_c in 4

* Graph ATE Spatial2:

gen str15 ate_label = ""

replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_spa2_ls_nn < 0.01, "***", cond(pval_spa2_ls_nn < 0.05, "**", cond(pval_spa2_ls_nn < 0.1, "*", ""))) in 1
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_spa2_dr_nn < 0.01, "***", cond(pval_spa2_dr_nn < 0.05, "**", cond(pval_spa2_dr_nn < 0.1, "*", ""))) in 2
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_spa2_ls_c < 0.01, "***", cond(pval_spa2_ls_c < 0.05, "**", cond(pval_spa2_ls_c < 0.1, "*", ""))) in 3
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_spa2_dr_c < 0.01, "***", cond(pval_spa2_dr_c < 0.05, "**", cond(pval_spa2_dr_c < 0.1, "*", ""))) in 4

* Adjust the values on the x-axis
replace x = 1 in 1   // NN - Landslide
replace x = 2 in 2   // NN - Drought
replace x = 4 in 3   // Caliper - Landslide
replace x = 5 in 4   // Caliper - Drought

twoway ///
    (scatter ate x if shock == "landslide", msymbol(circle) mcolor(blue) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
    (scatter ate x if shock == "drought", msymbol(diamond) mcolor(green) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
    (rcap ci_low ci_high x if shock == "landslide", lcolor(blue)) ///
    (rcap ci_low ci_high x if shock == "drought", lcolor(green)) ///
    , title("Spatial 2") ///
    xlabel(none) ///
    ylabel(-0.8(0.2)0.8, angle(0) labsize(small) labcolor(black)) ///
    yscale(range(-0.8 0.8)) ///
    ytitle("Average Treatment Effect") ///
    yline(0, lcolor(red)) ///
    legend(order(1 "Landslide" 2 "Drought") rows(1)) ///
    xscale(range(1 5.5)) ///
    xsize(6) ysize(4)

*** ATE Temporal 1 ***

* NN
teffects nnmatch (temp1 less60 female single primary less1 workers less_5ha water_have forest_have) (landslide)
scalar ate_temp1_ls_nn = e(b)[1,1]
scalar se_temp1_ls_nn  = sqrt(e(V)[1,1])
scalar low_temp1_ls_nn = ate_temp1_ls_nn - 1.96 * se_temp1_ls_nn
scalar high_temp1_ls_nn = ate_temp1_ls_nn + 1.96 * se_temp1_ls_nn

teffects nnmatch (temp1 less60 female single primary less1 workers less_5ha water_have forest_have) (drought)
scalar ate_temp1_dr_nn = e(b)[1,1]
scalar se_temp1_dr_nn  = sqrt(e(V)[1,1])
scalar low_temp1_dr_nn = ate_temp1_dr_nn - 1.96 * se_temp1_dr_nn
scalar high_temp1_dr_nn = ate_temp1_dr_nn + 1.96 * se_temp1_dr_nn

* Caliper
drop out_support out_support2  out_support3 out_support4 out_support5 out_support6 out_support7 out_support8 out_support9
out_support10 out_support11
teffects psmatch (temp1) (landslide less60 female single primary less1 workers less_5ha water_have forest_have), caliper(0.010)
osample(out_support) ate
teffects psmatch (temp1) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support==0, caliper(0.010) osample(out_support2) ate
teffects psmatch (temp1) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0, caliper(0.010) osample(out_support3) ate
teffects psmatch (temp1) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0, caliper(0.010) osample(out_support4) ate
```

```
teffects psmatch (temp1) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0, caliper(0.010) osample(out_support5) ate
teffects psmatch (temp1) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0, caliper(0.010) ate
scalar ate_temp1_ls_c = e(b)[1,1]
scalar se_temp1_ls_c  = sqrt(e(V)[1,1])
scalar low_temp1_ls_c = ate_temp1_ls_c - 1.96 * se_temp1_ls_c
scalar high_temp1_ls_c = ate_temp1_ls_c + 1.96 * se_temp1_ls_c

drop out_support out_support2  out_support3 out_support4 out_support5
teffects psmatch (temp1) (drought less60 female single primary less1 workers less_5ha water_have forest_have), caliper(0.020)
osample(out_support) ate
teffects psmatch (temp1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support==0, caliper(0.020) osample(out_support2) ate
teffects psmatch (temp1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0, caliper(0.020) osample(out_support3) ate
teffects psmatch (temp1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0, caliper(0.020) osample(out_support4) ate
teffects psmatch (temp1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0, caliper(0.020) osample(out_support5) ate
teffects psmatch (temp1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0, caliper(0.020)
osample(out_support6) ate
teffects psmatch (temp1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0,
caliper(0.020) osample(out_support7) ate
teffects psmatch (temp1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0, caliper(0.020) osample(out_support8) ate
teffects psmatch (temp1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0 & out_support8==0, caliper(0.020) osample(out_support9) ate
teffects psmatch (temp1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0 & out_support8==0 & out_support9==0, caliper(0.020) osample(out_support10) ate
teffects psmatch (temp1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0 & out_support8==0 & out_support9==0 & out_support10==0, caliper(0.020) osample(out_support11) ate
teffects psmatch (temp1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0 & out_support8==0 & out_support9==0 & out_support10==0 & out_support11==0, caliper(0.020) ate
scalar ate_temp1_dr_c = e(b)[1,1]
scalar se_temp1_dr_c  = sqrt(e(V)[1,1])
scalar low_temp1_dr_c = ate_temp1_dr_c - 1.96 * se_temp1_dr_c
scalar high_temp1_dr_c = ate_temp1_dr_c + 1.96 * se_temp1_dr_c

*  P-values
scalar pval_temp1_ls_nn = 2 * (1 - normal(abs(ate_temp1_ls_nn / se_temp1_ls_nn)))
scalar pval_temp1_dr_nn = 2 * (1 - normal(abs(ate_temp1_dr_nn / se_temp1_dr_nn)))
scalar pval_temp1_ls_c  = 2 * (1 - normal(abs(ate_temp1_ls_c / se_temp1_ls_c)))
scalar pval_temp1_dr_c  = 2 * (1 - normal(abs(ate_temp1_dr_c / se_temp1_dr_c)))

* Dataset for the graph:
preserve
clear
set obs 6

gen outcome = ""
replace outcome = "temp1" in 1
replace outcome = "temp1" in 2
replace outcome = "temp1" in 3
replace outcome = "temp1" in 4
```

```
gen shock = ""
replace shock = "landslide" in 1
replace shock = "drought" in 2
replace shock = "landslide" in 3
replace shock = "drought" in 4

gen x = _n
gen ate = .
gen ci_low = .
gen ci_high = .

replace ate = ate_temp1_ls_nn in 1
replace ci_low = low_temp1_ls_nn in 1
replace ci_high = high_temp1_ls_nn in 1

replace ate = ate_temp1_dr_nn in 2
replace ci_low = low_temp1_dr_nn in 2
replace ci_high = high_temp1_dr_nn in 2

replace ate = ate_temp1_ls_c in 3
replace ci_low = low_temp1_ls_c in 3
replace ci_high = high_temp1_ls_c in 3

replace ate = ate_temp1_dr_c in 4
replace ci_low = low_temp1_dr_c in 4
replace ci_high = high_temp1_dr_c in 4

* Graph ATE Temporal1
gen str15 ate_label = ""

replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_temp1_ls_nn < 0.01, "***", cond(pval_temp1_ls_nn < 0.05, "**", cond(pval_temp1_ls_nn < 0.1, "*", ""))) in 1
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_temp1_dr_nn < 0.01, "***", cond(pval_temp1_dr_nn < 0.05, "**", cond(pval_temp1_dr_nn < 0.1, "*", ""))) in 2
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_temp1_ls_c < 0.01, "***", cond(pval_temp1_ls_c < 0.05, "**", cond(pval_temp1_ls_c < 0.1, "*", ""))) in 3
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_temp1_dr_c < 0.01, "***", cond(pval_temp1_dr_c < 0.05, "**", cond(pval_temp1_dr_c < 0.1, "*", ""))) in 4

* Adjust the values on the x-axis
replace x = 1 in 1   // NN - Landslide
replace x = 2 in 2   // NN - Drought
replace x = 4 in 3   // Caliper - Landslide
replace x = 5 in 4   // Caliper - Drought

twoway ///
    (scatter ate x if shock == "landslide", msymbol(circle) mcolor(blue) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
    (scatter ate x if shock == "drought", msymbol(diamond) mcolor(green) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
    (rcap ci_low ci_high x if shock == "landslide", lcolor(blue)) ///
    (rcap ci_low ci_high x if shock == "drought", lcolor(green)) ///
    , title("Temporal 1") ///
    xlabel(none) ///
    ylabel(-0.8(0.2)0.8, angle(0) labsize(small) labcolor(black)) ///
    yscale(range(-0.8 0.8)) ///
    ytitle("Average Treatment Effect") ///
    yline(0, lcolor(red)) ///
    legend(order(1 "Landslide" 2 "Drought") rows(1)) ///
    xscale(range(1 5.5)) ///
    xsize(6) ysize(4)

*** ATE Temporal 2 ***
```

```
* NN
teffects nnmatch (temp2 less60 female single primary less1 workers less_5ha water_have forest_have) (landslide)
scalar ate_temp2_ls_nn = e(b)[1,1]
scalar se_temp2_ls_nn  = sqrt(e(V)[1,1])
scalar low_temp2_ls_nn = ate_temp2_ls_nn - 1.96 * se_temp2_ls_nn
scalar high_temp2_ls_nn = ate_temp2_ls_nn + 1.96 * se_temp2_ls_nn

teffects nnmatch (temp2 less60 female single primary less1 workers less_5ha water_have forest_have) (drought)
scalar ate_temp2_dr_nn = e(b)[1,1]
scalar se_temp2_dr_nn  = sqrt(e(V)[1,1])
scalar low_temp2_dr_nn = ate_temp2_dr_nn - 1.96 * se_temp2_dr_nn
scalar high_temp2_dr_nn = ate_temp2_dr_nn + 1.96 * se_temp2_dr_nn

* Caliper
drop out_support out_support2  out_support3 out_support4 out_support5 out_support6 out_support7 out_support8 out_support9
out_support10 out_support11
teffects psmatch (temp2) (landslide less60 female single primary less1 workers less_5ha water_have forest_have), caliper(0.010)
osample(out_support) ate
teffects psmatch (temp2) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support==0, caliper(0.010) osample(out_support2) ate
teffects psmatch (temp2) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0, caliper(0.010) osample(out_support3) ate
teffects psmatch (temp2) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0, caliper(0.010) osample(out_support4) ate
teffects psmatch (temp2) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0, caliper(0.010) osample(out_support5) ate
teffects psmatch (temp2) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0, caliper(0.010) ate
scalar ate_temp2_ls_c = e(b)[1,1]
scalar se_temp2_ls_c  = sqrt(e(V)[1,1])
scalar low_temp2_ls_c = ate_temp2_ls_c - 1.96 * se_temp1_ls_c
scalar high_temp2_ls_c = ate_temp2_ls_c + 1.96 * se_temp1_ls_c

drop out_support out_support2  out_support3 out_support4 out_support5
teffects psmatch (temp2) (drought less60 female single primary less1 workers less_5ha water_have forest_have), caliper(0.020)
osample(out_support) ate
teffects psmatch (temp2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support==0, caliper(0.020) osample(out_support2) ate
teffects psmatch (temp2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0, caliper(0.020) osample(out_support3) ate
teffects psmatch (temp2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0, caliper(0.020) osample(out_support4) ate
teffects psmatch (temp2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0, caliper(0.020) osample(out_support5) ate
teffects psmatch (temp2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0, caliper(0.020)
osample(out_support6) ate
teffects psmatch (temp2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0,
caliper(0.020) osample(out_support7) ate
teffects psmatch (temp2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0, caliper(0.020) osample(out_support8) ate
teffects psmatch (temp2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0 & out_support8==0, caliper(0.020) osample(out_support9) ate
teffects psmatch (temp2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0 & out_support8==0 & out_support9==0, caliper(0.020) osample(out_support10) ate
```

```
teffects psmatch (temp2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0 & out_support8==0 & out_support9==0 & out_support10==0, caliper(0.020) osample(out_support11) ate
teffects psmatch (temp2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 &
out_support7==0 & out_support8==0 & out_support9==0 & out_support10==0 & out_support11==0, caliper(0.020) ate
scalar ate_temp2_dr_c = e(b)[1,1]
scalar se_temp2_dr_c  = sqrt(e(V)[1,1])
scalar low_temp2_dr_c = ate_temp2_dr_c - 1.96 * se_temp2_dr_c
scalar high_temp2_dr_c = ate_temp2_dr_c + 1.96 * se_temp2_dr_c

*  P-values
scalar pval_temp2_ls_nn = 2 * (1 - normal(abs(ate_temp2_ls_nn / se_temp2_ls_nn)))
scalar pval_temp2_dr_nn = 2 * (1 - normal(abs(ate_temp2_dr_nn / se_temp2_dr_nn)))
scalar pval_temp2_ls_c  = 2 * (1 - normal(abs(ate_temp2_ls_c / se_temp2_ls_c)))
scalar pval_temp2_dr_c  = 2 * (1 - normal(abs(ate_temp2_dr_c / se_temp2_dr_c)))

* Dataset for the graph:
preserve
clear
set obs 6

gen outcome = ""
replace outcome = "temp2" in 1
replace outcome = "temp2" in 2
replace outcome = "temp2" in 3
replace outcome = "temp2" in 4

gen shock = ""
replace shock = "landslide" in 1
replace shock = "drought" in 2
replace shock = "landslide" in 3
replace shock = "drought" in 4

gen x = _n
gen ate = .
gen ci_low = .
gen ci_high = .

replace ate = ate_temp2_ls_nn in 1
replace ci_low = low_temp2_ls_nn in 1
replace ci_high = high_temp2_ls_nn in 1

replace ate = ate_temp2_dr_nn in 2
replace ci_low = low_temp2_dr_nn in 2
replace ci_high = high_temp2_dr_nn in 2

replace ate = ate_temp2_ls_c in 3
replace ci_low = low_temp2_ls_c in 3
replace ci_high = high_temp2_ls_c in 3

replace ate = ate_temp2_dr_c in 4
replace ci_low = low_temp2_dr_c in 4
replace ci_high = high_temp2_dr_c in 4

* Graph ATE Temporal2
gen str15 ate_label = ""

replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_temp2_ls_nn < 0.01, "***", cond(pval_temp2_ls_nn < 0.05, "**", cond(pval_temp2_ls_nn < 0.1, "*", ""))) in 1
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_temp2_dr_nn < 0.01, "***", cond(pval_temp2_dr_nn < 0.05, "**", cond(pval_temp2_dr_nn < 0.1, "*", ""))) in 2
```

```
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_temp2_ls_c < 0.01, "***", cond(pval_temp2_ls_c < 0.05, "**", cond(pval_temp2_ls_c < 0.1, "*", ""))) in 3
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_temp2_dr_c < 0.01, "***", cond(pval_temp2_dr_c < 0.05, "**", cond(pval_temp2_dr_c < 0.1, "*", ""))) in 4

* Adjust the values on the x-axis
replace x = 1 in 1   // NN - Landslide
replace x = 2 in 2   // NN - Drought
replace x = 4 in 3   // Caliper - Landslide
replace x = 5 in 4   // Caliper - Drought

twoway ///
    (scatter ate x if shock == "landslide", msymbol(circle) mcolor(blue) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
    (scatter ate x if shock == "drought", msymbol(diamond) mcolor(green) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
    (rcap ci_low ci_high x if shock == "landslide", lcolor(blue)) ///
    (rcap ci_low ci_high x if shock == "drought", lcolor(green)) ///
    , title("Temporal 2") ///
    xlabel(none) ///
    ylabel(-0.8(0.2)0.8, angle(0) labsize(small) labcolor(black)) ///
    yscale(range(-0.8 0.8)) ///
    ytitle("Average Treatment Effect") ///
    yline(0, lcolor(red)) ///
    legend(order(1 "Landslide" 2 "Drought") rows(1)) ///
    xscale(range(1 5.5)) ///
    xsize(6) ysize(4)

*** ATE Social 1 ***

* NN matching
teffects nnmatch (soc1 less60 female single primary less1 workers less_5ha water_have forest_have) (landslide)
scalar ate_soc1_ls_nn = e(b)[1,1]
scalar se_soc1_ls_nn  = sqrt(e(V)[1,1])
scalar low_soc1_ls_nn = ate_soc1_ls_nn - 1.96 * se_soc1_ls_nn
scalar high_soc1_ls_nn = ate_soc1_ls_nn + 1.96 * se_soc1_ls_nn

teffects nnmatch (soc1 less60 female single primary less1 workers less_5ha water_have forest_have) (drought)
scalar ate_soc1_dr_nn = e(b)[1,1]
scalar se_soc1_dr_nn  = sqrt(e(V)[1,1])
scalar low_soc1_dr_nn = ate_soc1_dr_nn - 1.96 * se_soc1_dr_nn
scalar high_soc1_dr_nn = ate_soc1_dr_nn + 1.96 * se_soc1_dr_nn

* Caliper matching
drop out_support out_support2 out_support3 out_support4 out_support5
teffects psmatch (soc1) (landslide less60 female single primary less1 workers less_5ha water_have forest_have), caliper(0.010)
osample(out_support) ate
teffects psmatch (soc1) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support==0, caliper(0.010) osample(out_support2) ate
teffects psmatch (soc1) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support==0 & out_support2==0, caliper(0.010) osample(out_support3) ate
teffects psmatch (soc1) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support==0 & out_support2==0 & out_support3==0, caliper(0.010) osample(out_support4) ate
teffects psmatch (soc1) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0, caliper(0.010) osample(out_support5) ate
teffects psmatch (soc1) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0, caliper(0.010) ate
scalar ate_soc1_ls_c = e(b)[1,1]
scalar se_soc1_ls_c  = sqrt(e(V)[1,1])
scalar low_soc1_ls_c = ate_soc1_ls_c - 1.96 * se_soc1_ls_c
scalar high_soc1_ls_c = ate_soc1_ls_c + 1.96 * se_soc1_ls_c

drop out_support out_support2 out_support3 out_support4 out_support5 out_support6 out_support7 out_support8 out_support9
out_support10 out_support11
```

```
teffects psmatch (soc1) (drought less60 female single primary less1 workers less_5ha water_have forest_have), caliper(0.020)
osample(out_support) ate
teffects psmatch (soc1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support==0, caliper(0.020) osample(out_support2) ate
teffects psmatch (soc1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0, caliper(0.020) osample(out_support3) ate
teffects psmatch (soc1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0, caliper(0.020) osample(out_support4) ate
teffects psmatch (soc1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0 & out_support4==0, caliper(0.020) osample(out_support5) ate
teffects psmatch (soc1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0 & out_support4==0 & out_support5==0, caliper(0.020) osample(out_support6) ate
teffects psmatch (soc1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0, caliper(0.020)
osample(out_support7) ate
teffects psmatch (soc1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 & out_support7==0,
caliper(0.020) osample(out_support8) ate
teffects psmatch (soc1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 & out_support7==0 &
out_support8==0, caliper(0.020) osample(out_support9) ate
teffects psmatch (soc1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 & out_support7==0 &
out_support8==0 & out_support9==0, caliper(0.020) osample(out_support10) ate
teffects psmatch (soc1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 & out_support7==0 &
out_support8==0 & out_support9==0 & out_support10==0, caliper(0.020) osample(out_support11) ate
teffects psmatch (soc1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 & out_support7==0 &
out_support8==0 & out_support9==0 & out_support10==0 & out_support11==0, caliper(0.020) ate
scalar ate_soc1_dr_c = e(b)[1,1]
scalar se_soc1_dr_c  = sqrt(e(V)[1,1])
scalar low_soc1_dr_c = ate_soc1_dr_c - 1.96 * se_soc1_dr_c
scalar high_soc1_dr_c = ate_soc1_dr_c + 1.96 * se_soc1_dr_c

* P-values
scalar pval_soc1_ls_nn = 2 * (1 - normal(abs(ate_soc1_ls_nn / se_soc1_ls_nn)))
scalar pval_soc1_dr_nn = 2 * (1 - normal(abs(ate_soc1_dr_nn / se_soc1_dr_nn)))
scalar pval_soc1_ls_c  = 2 * (1 - normal(abs(ate_soc1_ls_c / se_soc1_ls_c)))
scalar pval_soc1_dr_c  = 2 * (1 - normal(abs(ate_soc1_dr_c / se_soc1_dr_c)))

* Dataset for the graph
preserve
clear
set obs 6

gen outcome = ""
replace outcome = "soc1" in 1
replace outcome = "soc1" in 2
replace outcome = "soc1" in 3
replace outcome = "soc1" in 4

gen shock = ""
replace shock = "landslide" in 1
replace shock = "drought" in 2
replace shock = "landslide" in 3
replace shock = "drought" in 4

gen x = _n
gen ate = .
gen ci_low = .
gen ci_high = .
```

```
replace ate = ate_soc1_ls_nn in 1
replace ci_low = low_soc1_ls_nn in 1
replace ci_high = high_soc1_ls_nn in 1

replace ate = ate_soc1_dr_nn in 2
replace ci_low = low_soc1_dr_nn in 2
replace ci_high = high_soc1_dr_nn in 2

replace ate = ate_soc1_ls_c in 3
replace ci_low = low_soc1_ls_c in 3
replace ci_high = high_soc1_ls_c in 3

replace ate = ate_soc1_dr_c in 4
replace ci_low = low_soc1_dr_c in 4
replace ci_high = high_soc1_dr_c in 4

* Graph ATE Social1
gen str15 ate_label = ""
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_soc1_ls_nn < 0.01, "***", cond(pval_soc1_ls_nn < 0.05, "**", cond(pval_soc1_ls_nn < 0.1, "*", ""))) in 1
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_soc1_dr_nn < 0.01, "***", cond(pval_soc1_dr_nn < 0.05, "**", cond(pval_soc1_dr_nn < 0.1, "*", ""))) in 2
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_soc1_ls_c < 0.01, "***", cond(pval_soc1_ls_c < 0.05, "**", cond(pval_soc1_ls_c < 0.1, "*", ""))) in 3
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_soc1_dr_c < 0.01, "***", cond(pval_soc1_dr_c < 0.05, "**", cond(pval_soc1_dr_c < 0.1, "*", ""))) in 4

replace x = 1 in 1   // NN - Landslide
replace x = 2 in 2   // NN - Drought
replace x = 4 in 3   // Caliper - Landslide
replace x = 5 in 4   // Caliper - Drought

twoway ///
   (scatter ate x if shock == "landslide", msymbol(circle) mcolor(blue) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
   (scatter ate x if shock == "drought", msymbol(diamond) mcolor(green) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
   (rcap ci_low ci_high x if shock == "landslide", lcolor(blue)) ///
   (rcap ci_low ci_high x if shock == "drought", lcolor(green)) ///
   , title("Social 1") ///
   xlabel(none) ///
   ylabel(-0.8(0.2)0.8, angle(0) labsize(small) labcolor(black)) ///
   yscale(range(-0.8 0.8)) ///
   ytitle("Average Treatment Effect") ///
   yline(0, lcolor(red)) ///
   legend(order(1 "Landslide" 2 "Drought") rows(1)) ///
   xscale(range(1 5.5)) ///
   xsize(6) ysize(4)

*** ATE Social 2 ***

* NN matching
teffects nnmatch (soc2 less60 female single primary less1 workers less_5ha water_have forest_have) (landslide)
scalar ate_soc2_ls_nn = e(b)[1,1]
scalar se_soc2_ls_nn  = sqrt(e(V)[1,1])
scalar low_soc2_ls_nn = ate_soc2_ls_nn - 1.96 * se_soc2_ls_nn
scalar high_soc2_ls_nn = ate_soc2_ls_nn + 1.96 * se_soc2_ls_nn

teffects nnmatch (soc2 less60 female single primary less1 workers less_5ha water_have forest_have) (drought)
scalar ate_soc2_dr_nn = e(b)[1,1]
scalar se_soc2_dr_nn  = sqrt(e(V)[1,1])
scalar low_soc2_dr_nn = ate_soc2_dr_nn - 1.96 * se_soc2_dr_nn
scalar high_soc2_dr_nn = ate_soc2_dr_nn + 1.96 * se_soc2_dr_nn
```

```
* Caliper matching
drop out_support out_support2 out_support3 out_support4 out_support5
teffects psmatch (soc2) (landslide less60 female single primary less1 workers less_5ha water_have forest_have), caliper(0.010)
osample(out_support) ate
teffects psmatch (soc2) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support==0, caliper(0.010) osample(out_support2) ate
teffects psmatch (soc2) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support==0 & out_support2==0, caliper(0.010) osample(out_support3) ate
teffects psmatch (soc2) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support==0 & out_support2==0 & out_support3==0, caliper(0.010) osample(out_support4) ate
teffects psmatch (soc2) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0, caliper(0.010) osample(out_support5) ate
teffects psmatch (soc2) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support2==0 & out_support==0 & out_support3==0 & out_support4==0 & out_support5==0, caliper(0.010) ate
scalar ate_soc2_ls_c = e(b)[1,1]
scalar se_soc2_ls_c  = sqrt(e(V)[1,1])
scalar low_soc2_ls_c = ate_soc2_ls_c - 1.96 * se_soc2_ls_c
scalar high_soc2_ls_c = ate_soc2_ls_c + 1.96 * se_soc2_ls_c

drop out_support out_support2 out_support3 out_support4 out_support5 out_support6 out_support7 out_support8 out_support9
out_support10 out_support11
teffects psmatch (soc2) (drought less60 female single primary less1 workers less_5ha water_have forest_have), caliper(0.020)
osample(out_support) ate
teffects psmatch (soc2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support==0, caliper(0.020) osample(out_support2) ate
teffects psmatch (soc2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0, caliper(0.020) osample(out_support3) ate
teffects psmatch (soc2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0, caliper(0.020) osample(out_support4) ate
teffects psmatch (soc2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0 & out_support4==0, caliper(0.020) osample(out_support5) ate
teffects psmatch (soc2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0 & out_support4==0 & out_support5==0, caliper(0.020) osample(out_support6) ate
teffects psmatch (soc2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0, caliper(0.020)
osample(out_support7) ate
teffects psmatch (soc2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 & out_support7==0,
caliper(0.020) osample(out_support8) ate
teffects psmatch (soc2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 & out_support7==0 &
out_support8==0, caliper(0.020) osample(out_support9) ate
teffects psmatch (soc2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 & out_support7==0 &
out_support8==0 & out_support9==0, caliper(0.020) osample(out_support10) ate
teffects psmatch (soc2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 & out_support7==0 &
out_support8==0 & out_support9==0 & out_support10==0, caliper(0.020) osample(out_support11) ate
teffects psmatch (soc2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 & out_support7==0 &
out_support8==0 & out_support9==0 & out_support10==0 & out_support11==0, caliper(0.020) ate
scalar ate_soc2_dr_c = e(b)[1,1]
scalar se_soc2_dr_c  = sqrt(e(V)[1,1])
scalar low_soc2_dr_c = ate_soc2_dr_c - 1.96 * se_soc2_dr_c
scalar high_soc2_dr_c = ate_soc2_dr_c + 1.96 * se_soc2_dr_c

* P-values
scalar pval_soc2_ls_nn = 2 * (1 - normal(abs(ate_soc2_ls_nn / se_soc2_ls_nn)))
scalar pval_soc2_dr_nn = 2 * (1 - normal(abs(ate_soc2_dr_nn / se_soc2_dr_nn)))
scalar pval_soc2_ls_c  = 2 * (1 - normal(abs(ate_soc2_ls_c / se_soc2_ls_c)))
scalar pval_soc2_dr_c  = 2 * (1 - normal(abs(ate_soc2_dr_c / se_soc2_dr_c)))
```

```
* Dataset for the graph
preserve
clear
set obs 6

gen outcome = ""
replace outcome = "soc2" in 1
replace outcome = "soc2" in 2
replace outcome = "soc2" in 3
replace outcome = "soc2" in 4

gen shock = ""
replace shock = "landslide" in 1
replace shock = "drought" in 2
replace shock = "landslide" in 3
replace shock = "drought" in 4

gen x = _n
gen ate = .
gen ci_low = .
gen ci_high = .

replace ate = ate_soc2_ls_nn in 1
replace ci_low = low_soc2_ls_nn in 1
replace ci_high = high_soc2_ls_nn in 1

replace ate = ate_soc2_dr_nn in 2
replace ci_low = low_soc2_dr_nn in 2
replace ci_high = high_soc2_dr_nn in 2

replace ate = ate_soc2_ls_c in 3
replace ci_low = low_soc2_ls_c in 3
replace ci_high = high_soc2_ls_c in 3

replace ate = ate_soc2_dr_c in 4
replace ci_low = low_soc2_dr_c in 4
replace ci_high = high_soc2_dr_c in 4

* Graph ATE Social2
gen str15 ate_label = ""
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_soc2_ls_nn < 0.01, "***", cond(pval_soc2_ls_nn < 0.05, "**", cond(pval_soc2_ls_nn < 0.1, "*", ""))) in 1
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_soc2_dr_nn < 0.01, "***", cond(pval_soc2_dr_nn < 0.05, "**", cond(pval_soc2_dr_nn < 0.1, "*", ""))) in 2
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_soc2_ls_c < 0.01, "***", cond(pval_soc2_ls_c < 0.05, "**", cond(pval_soc2_ls_c < 0.1, "*", ""))) in 3
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_soc2_dr_c < 0.01, "***", cond(pval_soc2_dr_c < 0.05, "**", cond(pval_soc2_dr_c < 0.1, "*", ""))) in 4

replace x = 1 in 1   // NN - Landslide
replace x = 2 in 2   // NN - Drought
replace x = 4 in 3   // Caliper - Landslide
replace x = 5 in 4   // Caliper - Drought

twoway ///
   (scatter ate x if shock == "landslide", msymbol(circle) mcolor(blue) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
   (scatter ate x if shock == "drought", msymbol(diamond) mcolor(green) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
   (rcap ci_low ci_high x if shock == "landslide", lcolor(blue)) ///
   (rcap ci_low ci_high x if shock == "drought", lcolor(green)) ///
   , title("Social 2") ///
   xlabel(none) ///
```

```
    ylabel(-0.8(0.2)0.8, angle(0) labsize(small) labcolor(black)) ///
    yscale(range(-0.8 0.8)) ///
    ytitle("Average Treatment Effect") ///
    yline(0, lcolor(red)) ///
    legend(order(1 "Landslide" 2 "Drought") rows(1)) ///
    xscale(range(1 5.5)) ///
    xsize(6) ysize(4)

*** ATE Hypothetical 1 ***

* NN matching
teffects nnmatch (hyp1 less60 female single primary less1 workers less_5ha water_have forest_have) (landslide)
scalar ate_hyp1_ls_nn = e(b)[1,1]
scalar se_hyp1_ls_nn  = sqrt(e(V)[1,1])
scalar low_hyp1_ls_nn = ate_hyp1_ls_nn - 1.96 * se_hyp1_ls_nn
scalar high_hyp1_ls_nn = ate_hyp1_ls_nn + 1.96 * se_hyp1_ls_nn

teffects nnmatch (hyp1 less60 female single primary less1 workers less_5ha water_have forest_have) (drought)
scalar ate_hyp1_dr_nn = e(b)[1,1]
scalar se_hyp1_dr_nn  = sqrt(e(V)[1,1])
scalar low_hyp1_dr_nn = ate_hyp1_dr_nn - 1.96 * se_hyp1_dr_nn
scalar high_hyp1_dr_nn = ate_hyp1_dr_nn + 1.96 * se_hyp1_dr_nn

* Caliper matching
drop out_support out_support2 out_support3 out_support4 out_support5
teffects psmatch (hyp1) (landslide less60 female single primary less1 workers less_5ha water_have forest_have), caliper(0.010)
osample(out_support) ate
teffects psmatch (hyp1) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support==0, caliper(0.010) osample(out_support2) ate
teffects psmatch (hyp1) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support==0 & out_support2==0, caliper(0.010) osample(out_support3) ate
teffects psmatch (hyp1) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support==0 & out_support2==0 & out_support3==0, caliper(0.010) osample(out_support4) ate
teffects psmatch (hyp1) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support==0 & out_support2==0 & out_support3==0 & out_support4==0, caliper(0.010) osample(out_support5) ate
teffects psmatch (hyp1) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support==0 & out_support2==0 & out_support3==0 & out_support4==0 & out_support5==0, caliper(0.010) ate
scalar ate_hyp1_ls_c = e(b)[1,1]
scalar se_hyp1_ls_c  = sqrt(e(V)[1,1])
scalar low_hyp1_ls_c = ate_hyp1_ls_c - 1.96 * se_hyp1_ls_c
scalar high_hyp1_ls_c = ate_hyp1_ls_c + 1.96 * se_hyp1_ls_c

drop out_support out_support2 out_support3 out_support4 out_support5 out_support6 out_support7 out_support8 out_support9
out_support10 out_support11
teffects psmatch (hyp1) (drought less60 female single primary less1 workers less_5ha water_have forest_have), caliper(0.020)
osample(out_support) ate
teffects psmatch (hyp1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support==0, caliper(0.020) osample(out_support2) ate
teffects psmatch (hyp1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0, caliper(0.020) osample(out_support3) ate
teffects psmatch (hyp1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0, caliper(0.020) osample(out_support4) ate
teffects psmatch (hyp1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0 & out_support4==0, caliper(0.020) osample(out_support5) ate
teffects psmatch (hyp1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0 & out_support4==0 & out_support5==0, caliper(0.020) osample(out_support6) ate
teffects psmatch (hyp1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0, caliper(0.020)
osample(out_support7) ate
teffects psmatch (hyp1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 & out_support7==0,
caliper(0.020) osample(out_support8) ate
```

```
teffects psmatch (hyp1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0 & out_support2==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 & out_support7==0 & out_support8==0, caliper(0.020) osample(out_support9) ate
teffects psmatch (hyp1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0 & out_support2==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 & out_support7==0 & out_support8==0 & out_support9==0, caliper(0.020) osample(out_support10) ate
teffects psmatch (hyp1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0 & out_support2==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 & out_support7==0 & out_support8==0 & out_support9==0 & out_support10==0, caliper(0.020) osample(out_support11) ate
teffects psmatch (hyp1) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0 & out_support2==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 & out_support7==0 & out_support8==0 & out_support9==0 & out_support10==0 & out_support11==0, caliper(0.020) ate
scalar ate_hyp1_dr_c = e(b)[1,1]
scalar se_hyp1_dr_c  = sqrt(e(V)[1,1])
scalar low_hyp1_dr_c = ate_hyp1_dr_c - 1.96 * se_hyp1_dr_c
scalar high_hyp1_dr_c = ate_hyp1_dr_c + 1.96 * se_hyp1_dr_c

* P-values
scalar pval_hyp1_ls_nn = 2 * (1 - normal(abs(ate_hyp1_ls_nn / se_hyp1_ls_nn)))
scalar pval_hyp1_dr_nn = 2 * (1 - normal(abs(ate_hyp1_dr_nn / se_hyp1_dr_nn)))
scalar pval_hyp1_ls_c  = 2 * (1 - normal(abs(ate_hyp1_ls_c / se_hyp1_ls_c)))
scalar pval_hyp1_dr_c  = 2 * (1 - normal(abs(ate_hyp1_dr_c / se_hyp1_dr_c)))

* Dataset for the graph
preserve
clear
set obs 6

gen outcome = ""
replace outcome = "hyp1" in 1
replace outcome = "hyp1" in 2
replace outcome = "hyp1" in 3
replace outcome = "hyp1" in 4

gen shock = ""
replace shock = "landslide" in 1
replace shock = "drought" in 2
replace shock = "landslide" in 3
replace shock = "drought" in 4

gen x = _n
gen ate = .
gen ci_low = .
gen ci_high = .

replace ate = ate_hyp1_ls_nn in 1
replace ci_low = low_hyp1_ls_nn in 1
replace ci_high = high_hyp1_ls_nn in 1

replace ate = ate_hyp1_dr_nn in 2
replace ci_low = low_hyp1_dr_nn in 2
replace ci_high = high_hyp1_dr_nn in 2

replace ate = ate_hyp1_ls_c in 3
replace ci_low = low_hyp1_ls_c in 3
replace ci_high = high_hyp1_ls_c in 3

replace ate = ate_hyp1_dr_c in 4
replace ci_low = low_hyp1_dr_c in 4
replace ci_high = high_hyp1_dr_c in 4

* Graph ATE Hypothetical1
```

```
gen str15 ate_label = ""
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_hyp1_ls_nn < 0.01, "***", cond(pval_hyp1_ls_nn < 0.05, "**", cond(pval_hyp1_ls_nn < 0.1, "*", ""))) in 1
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_hyp1_dr_nn < 0.01, "***", cond(pval_hyp1_dr_nn < 0.05, "**", cond(pval_hyp1_dr_nn < 0.1, "*", ""))) in 2
replace ate_label = string(ate, "%9.3f") + ///
     cond(pval_hyp1_ls_c < 0.01, "***", cond(pval_hyp1_ls_c < 0.05, "**", cond(pval_hyp1_ls_c < 0.1, "*", ""))) in 3
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_hyp1_dr_c < 0.01, "***", cond(pval_hyp1_dr_c < 0.05, "**", cond(pval_hyp1_dr_c < 0.1, "*", ""))) in 4

replace x = 1 in 1   // NN - Landslide
replace x = 2 in 2   // NN - Drought
replace x = 4 in 3   // Caliper - Landslide
replace x = 5 in 4   // Caliper - Drought

twoway ///
   (scatter ate x if shock == "landslide", msymbol(circle) mcolor(blue) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
   (scatter ate x if shock == "drought", msymbol(diamond) mcolor(green) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
   (rcap ci_low ci_high x if shock == "landslide", lcolor(blue)) ///
   (rcap ci_low ci_high x if shock == "drought", lcolor(green)) ///
   , title("Hypothetical 1") ///
   xlabel(none) ///
   ylabel(-0.8(0.2)0.8, angle(0) labsize(small) labcolor(black)) ///
   yscale(range(-0.8 0.8)) ///
   ytitle("Average Treatment Effect") ///
   yline(0, lcolor(red)) ///
   legend(order(1 "Landslide" 2 "Drought") rows(1)) ///
   xscale(range(1 5.5)) ///
   xsize(6) ysize(4)

*** ATE Hypothetical 2 ***

* NN matching
teffects nnmatch (hyp2 less60 female single primary less1 workers less_5ha water_have forest_have) (landslide)
scalar ate_hyp2_ls_nn = e(b)[1,1]
scalar se_hyp2_ls_nn  = sqrt(e(V)[1,1])
scalar low_hyp2_ls_nn = ate_hyp2_ls_nn - 1.96 * se_hyp2_ls_nn
scalar high_hyp2_ls_nn = ate_hyp2_ls_nn + 1.96 * se_hyp2_ls_nn

teffects nnmatch (hyp2 less60 female single primary less1 workers less_5ha water_have forest_have) (drought)
scalar ate_hyp2_dr_nn = e(b)[1,1]
scalar se_hyp2_dr_nn  = sqrt(e(V)[1,1])
scalar low_hyp2_dr_nn = ate_hyp2_dr_nn - 1.96 * se_hyp2_dr_nn
scalar high_hyp2_dr_nn = ate_hyp2_dr_nn + 1.96 * se_hyp2_dr_nn

* Caliper matching
drop out_support out_support2 out_support3 out_support4 out_support5
teffects psmatch (hyp2) (landslide less60 female single primary less1 workers less_5ha water_have forest_have), caliper(0.010)
osample(out_support) ate
teffects psmatch (hyp2) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support==0, caliper(0.010) osample(out_support2) ate
teffects psmatch (hyp2) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support==0 & out_support2==0, caliper(0.010) osample(out_support3) ate
teffects psmatch (hyp2) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support==0 & out_support2==0 & out_support3==0, caliper(0.010) osample(out_support4) ate
teffects psmatch (hyp2) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support==0 & out_support2==0 & out_support3==0 & out_support4==0, caliper(0.010) osample(out_support5) ate
teffects psmatch (hyp2) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support==0 & out_support2==0 & out_support3==0 & out_support4==0 & out_support5==0, caliper(0.010) ate
scalar ate_hyp2_ls_c = e(b)[1,1]
scalar se_hyp2_ls_c  = sqrt(e(V)[1,1])
scalar low_hyp2_ls_c = ate_hyp2_ls_c - 1.96 * se_hyp2_ls_c
```

```
scalar high_hyp2_ls_c = ate_hyp2_ls_c + 1.96 * se_hyp2_ls_c

drop out_support out_support2 out_support3 out_support4 out_support5 out_support6 out_support7 out_support8 out_support9
out_support10 out_support11
teffects psmatch (hyp2) (drought less60 female single primary less1 workers less_5ha water_have forest_have), caliper(0.020)
osample(out_support) ate
teffects psmatch (hyp2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support==0, caliper(0.020) osample(out_support2) ate
teffects psmatch (hyp2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0, caliper(0.020) osample(out_support3) ate
teffects psmatch (hyp2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0, caliper(0.020) osample(out_support4) ate
teffects psmatch (hyp2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0 & out_support4==0, caliper(0.020) osample(out_support5) ate
teffects psmatch (hyp2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0 & out_support4==0 & out_support5==0, caliper(0.020) osample(out_support6) ate
teffects psmatch (hyp2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0, caliper(0.020)
osample(out_support7) ate
teffects psmatch (hyp2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 & out_support7==0,
caliper(0.020) osample(out_support8) ate
teffects psmatch (hyp2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 & out_support7==0 &
out_support8==0, caliper(0.020) osample(out_support9) ate
teffects psmatch (hyp2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 & out_support7==0 &
out_support8==0 & out_support9==0, caliper(0.020) osample(out_support10) ate
teffects psmatch (hyp2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 & out_support7==0 &
out_support8==0 & out_support9==0 & out_support10==0, caliper(0.020) osample(out_support11) ate
teffects psmatch (hyp2) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 & out_support7==0 &
out_support8==0 & out_support9==0 & out_support10==0 & out_support11==0, caliper(0.020) ate
scalar ate_hyp2_dr_c = e(b)[1,1]
scalar se_hyp2_dr_c  = sqrt(e(V)[1,1])
scalar low_hyp2_dr_c = ate_hyp2_dr_c - 1.96 * se_hyp2_dr_c
scalar high_hyp2_dr_c = ate_hyp2_dr_c + 1.96 * se_hyp2_dr_c

* P-values
scalar pval_hyp2_ls_nn = 2 * (1 - normal(abs(ate_hyp2_ls_nn / se_hyp2_ls_nn)))
scalar pval_hyp2_dr_nn = 2 * (1 - normal(abs(ate_hyp2_dr_nn / se_hyp2_dr_nn)))
scalar pval_hyp2_ls_c  = 2 * (1 - normal(abs(ate_hyp2_ls_c / se_hyp2_ls_c)))
scalar pval_hyp2_dr_c  = 2 * (1 - normal(abs(ate_hyp2_dr_c / se_hyp2_dr_c)))

* Dataset for the graph
preserve
clear
set obs 6

gen outcome = ""
replace outcome = "hyp2" in 1
replace outcome = "hyp2" in 2
replace outcome = "hyp2" in 3
replace outcome = "hyp2" in 4

gen shock = ""
replace shock = "landslide" in 1
replace shock = "drought" in 2
replace shock = "landslide" in 3
replace shock = "drought" in 4
```

```
gen x = _n
gen ate = .
gen ci_low = .
gen ci_high = .

replace ate = ate_hyp2_ls_nn in 1
replace ci_low = low_hyp2_ls_nn in 1
replace ci_high = high_hyp2_ls_nn in 1

replace ate = ate_hyp2_dr_nn in 2
replace ci_low = low_hyp2_dr_nn in 2
replace ci_high = high_hyp2_dr_nn in 2

replace ate = ate_hyp2_ls_c in 3
replace ci_low = low_hyp2_ls_c in 3
replace ci_high = high_hyp2_ls_c in 3

replace ate = ate_hyp2_dr_c in 4
replace ci_low = low_hyp2_dr_c in 4
replace ci_high = high_hyp2_dr_c in 4

* Graph ATE Hypothetical2
gen str15 ate_label = ""
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_hyp2_ls_nn < 0.01, "***", cond(pval_hyp2_ls_nn < 0.05, "**", cond(pval_hyp2_ls_nn < 0.1, "*", ""))) in 1
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_hyp2_dr_nn < 0.01, "***", cond(pval_hyp2_dr_nn < 0.05, "**", cond(pval_hyp2_dr_nn < 0.1, "*", ""))) in 2
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_hyp2_ls_c < 0.01, "***", cond(pval_hyp2_ls_c < 0.05, "**", cond(pval_hyp2_ls_c < 0.1, "*", ""))) in 3
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_hyp2_dr_c < 0.01, "***", cond(pval_hyp2_dr_c < 0.05, "**", cond(pval_hyp2_dr_c < 0.1, "*", ""))) in 4

replace x = 1 in 1   // NN - Landslide
replace x = 2 in 2   // NN - Drought
replace x = 4 in 3   // Caliper - Landslide
replace x = 5 in 4   // Caliper - Drought

twoway ///
    (scatter ate x if shock == "landslide", msymbol(circle) mcolor(blue) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
    (scatter ate x if shock == "drought", msymbol(diamond) mcolor(green) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
    (rcap ci_low ci_high x if shock == "landslide", lcolor(blue)) ///
    (rcap ci_low ci_high x if shock == "drought", lcolor(green)) ///
    , title("Hypothetical 2") ///
    xlabel(none) ///
    ylabel(-0.8(0.2)0.8, angle(0) labsize(small) labcolor(black)) ///
    yscale(range(-0.8 0.8)) ///
    ytitle("Average Treatment Effect") ///
    yline(0, lcolor(red)) ///
    legend(order(1 "Landslide" 2 "Drought") rows(1)) ///
    xscale(range(1 5.5)) ///
    xsize(6) ysize(4)

*** ATE Hypothetical 3 ***

* NN matching
teffects nnmatch (hyp3 less60 female single primary less1 workers less_5ha water_have forest_have) (landslide)
scalar ate_hyp3_ls_nn = e(b)[1,1]
scalar se_hyp3_ls_nn  = sqrt(e(V)[1,1])
scalar low_hyp3_ls_nn = ate_hyp3_ls_nn - 1.96 * se_hyp3_ls_nn
scalar high_hyp3_ls_nn = ate_hyp3_ls_nn + 1.96 * se_hyp3_ls_nn

teffects nnmatch (hyp3 less60 female single primary less1 workers less_5ha water_have forest_have) (drought)
```

```
scalar ate_hyp3_dr_nn = e(b)[1,1]
scalar se_hyp3_dr_nn  = sqrt(e(V)[1,1])
scalar low_hyp3_dr_nn = ate_hyp3_dr_nn - 1.96 * se_hyp3_dr_nn
scalar high_hyp3_dr_nn = ate_hyp3_dr_nn + 1.96 * se_hyp3_dr_nn

* Caliper matching
drop out_support out_support2 out_support3 out_support4 out_support5
teffects psmatch (hyp3) (landslide less60 female single primary less1 workers less_5ha water_have forest_have), caliper(0.010)
osample(out_support) ate
teffects psmatch (hyp3) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support==0, caliper(0.010) osample(out_support2) ate
teffects psmatch (hyp3) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support==0 & out_support2==0, caliper(0.010) osample(out_support3) ate
teffects psmatch (hyp3) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support==0 & out_support2==0 & out_support3==0, caliper(0.010) osample(out_support4) ate
teffects psmatch (hyp3) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support==0 & out_support2==0 & out_support3==0 & out_support4==0, caliper(0.010) osample(out_support5) ate
teffects psmatch (hyp3) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support==0 & out_support2==0 & out_support3==0 & out_support4==0 & out_support5==0, caliper(0.010) ate
scalar ate_hyp3_ls_c = e(b)[1,1]
scalar se_hyp3_ls_c  = sqrt(e(V)[1,1])
scalar low_hyp3_ls_c = ate_hyp3_ls_c - 1.96 * se_hyp3_ls_c
scalar high_hyp3_ls_c = ate_hyp3_ls_c + 1.96 * se_hyp3_ls_c

drop out_support out_support2 out_support3 out_support4 out_support5 out_support6 out_support7 out_support8 out_support9
out_support10 out_support11
teffects psmatch (hyp3) (drought less60 female single primary less1 workers less_5ha water_have forest_have), caliper(0.020)
osample(out_support) ate
teffects psmatch (hyp3) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support==0, caliper(0.020) osample(out_support2) ate
teffects psmatch (hyp3) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0, caliper(0.020) osample(out_support3) ate
teffects psmatch (hyp3) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0, caliper(0.020) osample(out_support4) ate
teffects psmatch (hyp3) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0 & out_support4==0, caliper(0.020) osample(out_support5) ate
teffects psmatch (hyp3) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0 & out_support4==0 & out_support5==0, caliper(0.020) osample(out_support6) ate
teffects psmatch (hyp3) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0, caliper(0.020)
osample(out_support7) ate
teffects psmatch (hyp3) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 & out_support7==0,
caliper(0.020) osample(out_support8) ate
teffects psmatch (hyp3) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 & out_support7==0 &
out_support8==0, caliper(0.020) osample(out_support9) ate
teffects psmatch (hyp3) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 & out_support7==0 &
out_support8==0 & out_support9==0, caliper(0.020) osample(out_support10) ate
teffects psmatch (hyp3) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 & out_support7==0 &
out_support8==0 & out_support9==0 & out_support10==0, caliper(0.020) osample(out_support11) ate
teffects psmatch (hyp3) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 & out_support7==0 &
out_support8==0 & out_support9==0 & out_support10==0 & out_support11==0, caliper(0.020) ate
scalar ate_hyp3_dr_c = e(b)[1,1]
scalar se_hyp3_dr_c  = sqrt(e(V)[1,1])
scalar low_hyp3_dr_c = ate_hyp3_dr_c - 1.96 * se_hyp3_dr_c
scalar high_hyp3_dr_c = ate_hyp3_dr_c + 1.96 * se_hyp3_dr_c

* P-values
```

```
scalar pval_hyp3_ls_nn = 2 * (1 - normal(abs(ate_hyp3_ls_nn / se_hyp3_ls_nn)))
scalar pval_hyp3_dr_nn = 2 * (1 - normal(abs(ate_hyp3_dr_nn / se_hyp3_dr_nn)))
scalar pval_hyp3_ls_c  = 2 * (1 - normal(abs(ate_hyp3_ls_c / se_hyp3_ls_c)))
scalar pval_hyp3_dr_c  = 2 * (1 - normal(abs(ate_hyp3_dr_c / se_hyp3_dr_c)))

* Dataset for the graph
preserve
clear
set obs 6

gen outcome = ""
replace outcome = "hyp3" in 1
replace outcome = "hyp3" in 2
replace outcome = "hyp3" in 3
replace outcome = "hyp3" in 4

gen shock = ""
replace shock = "landslide" in 1
replace shock = "drought" in 2
replace shock = "landslide" in 3
replace shock = "drought" in 4

gen x = _n
gen ate = .
gen ci_low = .
gen ci_high = .

replace ate = ate_hyp3_ls_nn in 1
replace ci_low = low_hyp3_ls_nn in 1
replace ci_high = high_hyp3_ls_nn in 1

replace ate = ate_hyp3_dr_nn in 2
replace ci_low = low_hyp3_dr_nn in 2
replace ci_high = high_hyp3_dr_nn in 2

replace ate = ate_hyp3_ls_c in 3
replace ci_low = low_hyp3_ls_c in 3
replace ci_high = high_hyp3_ls_c in 3

replace ate = ate_hyp3_dr_c in 4
replace ci_low = low_hyp3_dr_c in 4
replace ci_high = high_hyp3_dr_c in 4

* Graph ATE Hypothetical3
gen str15 ate_label = ""
replace ate_label = string(ate, "%9.3f") + ///
   cond(pval_hyp3_ls_nn < 0.01, "***", cond(pval_hyp3_ls_nn < 0.05, "**", cond(pval_hyp3_ls_nn < 0.1, "*", ""))) in 1
replace ate_label = string(ate, "%9.3f") + ///
   cond(pval_hyp3_dr_nn < 0.01, "***", cond(pval_hyp3_dr_nn < 0.05, "**", cond(pval_hyp3_dr_nn < 0.1, "*", ""))) in 2
replace ate_label = string(ate, "%9.3f") + ///
   cond(pval_hyp3_ls_c < 0.01, "***", cond(pval_hyp3_ls_c < 0.05, "**", cond(pval_hyp3_ls_c < 0.1, "*", ""))) in 3
replace ate_label = string(ate, "%9.3f") + ///
   cond(pval_hyp3_dr_c < 0.01, "***", cond(pval_hyp3_dr_c < 0.05, "**", cond(pval_hyp3_dr_c < 0.1, "*", ""))) in 4

replace x = 1 in 1   // NN - Landslide
replace x = 2 in 2   // NN - Drought
replace x = 4 in 3   // Caliper - Landslide
replace x = 5 in 4   // Caliper - Drought

twoway ///
   (scatter ate x if shock == "landslide", msymbol(circle) mcolor(blue) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
   (scatter ate x if shock == "drought", msymbol(diamond) mcolor(green) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
```

```
   (rcap ci_low ci_high x if shock == "landslide", lcolor(blue)) ///
   (rcap ci_low ci_high x if shock == "drought", lcolor(green)) ///
   , title("Hypothetical 3") ///
   xlabel(none) ///
   ylabel(-0.8(0.2)0.8, angle(0) labsize(small) labcolor(black)) ///
   yscale(range(-0.8 0.8)) ///
   ytitle("Average Treatment Effect") ///
   yline(0, lcolor(red)) ///
   legend(order(1 "Landslide" 2 "Drought") rows(1)) ///
   xscale(range(1 5.5)) ///
   xsize(6) ysize(4)

*** ATE Hypothetical 4 ***

* NN matching
teffects nnmatch (hyp4 less60 female single primary less1 workers less_5ha water_have forest_have) (landslide)
scalar ate_hyp4_ls_nn = e(b)[1,1]
scalar se_hyp4_ls_nn  = sqrt(e(V)[1,1])
scalar low_hyp4_ls_nn = ate_hyp4_ls_nn - 1.96 * se_hyp4_ls_nn
scalar high_hyp4_ls_nn = ate_hyp4_ls_nn + 1.96 * se_hyp4_ls_nn

teffects nnmatch (hyp4 less60 female single primary less1 workers less_5ha water_have forest_have) (drought)
scalar ate_hyp4_dr_nn = e(b)[1,1]
scalar se_hyp4_dr_nn  = sqrt(e(V)[1,1])
scalar low_hyp4_dr_nn = ate_hyp4_dr_nn - 1.96 * se_hyp4_dr_nn
scalar high_hyp4_dr_nn = ate_hyp4_dr_nn + 1.96 * se_hyp4_dr_nn

* Caliper matching
drop out_support out_support2 out_support3 out_support4 out_support5
teffects psmatch (hyp4) (landslide less60 female single primary less1 workers less_5ha water_have forest_have), caliper(0.010)
osample(out_support) ate
teffects psmatch (hyp4) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support==0, caliper(0.010) osample(out_support2) ate
teffects psmatch (hyp4) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support==0 & out_support2==0, caliper(0.010) osample(out_support3) ate
teffects psmatch (hyp4) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support==0 & out_support2==0 & out_support3==0, caliper(0.010) osample(out_support4) ate
teffects psmatch (hyp4) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support==0 & out_support2==0 & out_support3==0 & out_support4==0, caliper(0.010) osample(out_support5) ate
teffects psmatch (hyp4) (landslide less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support==0 & out_support2==0 & out_support3==0 & out_support4==0 & out_support5==0, caliper(0.010) ate
scalar ate_hyp4_ls_c = e(b)[1,1]
scalar se_hyp4_ls_c  = sqrt(e(V)[1,1])
scalar low_hyp4_ls_c = ate_hyp4_ls_c - 1.96 * se_hyp4_ls_c
scalar high_hyp4_ls_c = ate_hyp4_ls_c + 1.96 * se_hyp4_ls_c

drop out_support out_support2 out_support3 out_support4 out_support5 out_support6 out_support7 out_support8 out_support9
out_support10 out_support11
teffects psmatch (hyp4) (drought less60 female single primary less1 workers less_5ha water_have forest_have), caliper(0.020)
osample(out_support) ate
teffects psmatch (hyp4) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if
out_support==0, caliper(0.020) osample(out_support2) ate
teffects psmatch (hyp4) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0, caliper(0.020) osample(out_support3) ate
teffects psmatch (hyp4) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0, caliper(0.020) osample(out_support4) ate
teffects psmatch (hyp4) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0 & out_support4==0, caliper(0.020) osample(out_support5) ate
teffects psmatch (hyp4) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0 & out_support4==0 & out_support5==0, caliper(0.020) osample(out_support6) ate
```

```
teffects psmatch (hyp4) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0, caliper(0.020)
osample(out_support7) ate
teffects psmatch (hyp4) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 & out_support7==0,
caliper(0.020) osample(out_support8) ate
teffects psmatch (hyp4) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 & out_support7==0 &
out_support8==0, caliper(0.020) osample(out_support9) ate
teffects psmatch (hyp4) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 & out_support7==0 &
out_support8==0 & out_support9==0, caliper(0.020) osample(out_support10) ate
teffects psmatch (hyp4) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 & out_support7==0 &
out_support8==0 & out_support9==0 & out_support10==0, caliper(0.020) osample(out_support11) ate
teffects psmatch (hyp4) (drought less60 female single primary less1 workers less_5ha water_have forest_have) if out_support==0
& out_support2==0 & out_support3==0 & out_support4==0 & out_support5==0 & out_support6==0 & out_support7==0 &
out_support8==0 & out_support9==0 & out_support10==0 & out_support11==0, caliper(0.020) ate
scalar ate_hyp4_dr_c = e(b)[1,1]
scalar se_hyp4_dr_c  = sqrt(e(V)[1,1])
scalar low_hyp4_dr_c = ate_hyp4_dr_c - 1.96 * se_hyp4_dr_c
scalar high_hyp4_dr_c = ate_hyp4_dr_c + 1.96 * se_hyp4_dr_c

* P-values
scalar pval_hyp4_ls_nn = 2 * (1 - normal(abs(ate_hyp4_ls_nn / se_hyp4_ls_nn)))
scalar pval_hyp4_dr_nn = 2 * (1 - normal(abs(ate_hyp4_dr_nn / se_hyp4_dr_nn)))
scalar pval_hyp4_ls_c  = 2 * (1 - normal(abs(ate_hyp4_ls_c / se_hyp4_ls_c)))
scalar pval_hyp4_dr_c  = 2 * (1 - normal(abs(ate_hyp4_dr_c / se_hyp4_dr_c)))

* Dataset for the graph
preserve
clear
set obs 6

gen outcome = ""
replace outcome = "hyp4" in 1
replace outcome = "hyp4" in 2
replace outcome = "hyp4" in 3
replace outcome = "hyp4" in 4

gen shock = ""
replace shock = "landslide" in 1
replace shock = "drought" in 2
replace shock = "landslide" in 3
replace shock = "drought" in 4

gen x = _n
gen ate = .
gen ci_low = .
gen ci_high = .

replace ate = ate_hyp4_ls_nn in 1
replace ci_low = low_hyp4_ls_nn in 1
replace ci_high = high_hyp4_ls_nn in 1

replace ate = ate_hyp4_dr_nn in 2
replace ci_low = low_hyp4_dr_nn in 2
replace ci_high = high_hyp4_dr_nn in 2

replace ate = ate_hyp4_ls_c in 3
replace ci_low = low_hyp4_ls_c in 3
replace ci_high = high_hyp4_ls_c in 3
```

```
replace ate = ate_hyp4_dr_c in 4
replace ci_low = low_hyp4_dr_c in 4
replace ci_high = high_hyp4_dr_c in 4

* Graph ATE Hypothetical4
gen str15 ate_label = ""
replace ate_label = string(ate, "%9.3f") + ///
   cond(pval_hyp4_ls_nn < 0.01, "***", cond(pval_hyp4_ls_nn < 0.05, "**", cond(pval_hyp4_ls_nn < 0.1, "*", ""))) in 1
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_hyp4_dr_nn < 0.01, "***", cond(pval_hyp4_dr_nn < 0.05, "**", cond(pval_hyp4_dr_nn < 0.1, "*", ""))) in 2
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_hyp4_ls_c < 0.01, "***", cond(pval_hyp4_ls_c < 0.05, "**", cond(pval_hyp4_ls_c < 0.1, "*", ""))) in 3
replace ate_label = string(ate, "%9.3f") + ///
     cond(pval_hyp4_dr_c < 0.01, "***", cond(pval_hyp4_dr_c < 0.05, "**", cond(pval_hyp4_dr_c < 0.1, "*", ""))) in 4

replace x = 1 in 1   // NN - Landslide
replace x = 2 in 2   // NN - Drought
replace x = 4 in 3   // Caliper - Landslide
replace x = 5 in 4   // Caliper - Drought

twoway ///
   (scatter ate x if shock == "landslide", msymbol(circle) mcolor(blue) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
   (scatter ate x if shock == "drought", msymbol(diamond) mcolor(green) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
   (rcap ci_low ci_high x if shock == "landslide", lcolor(blue)) ///
   (rcap ci_low ci_high x if shock == "drought", lcolor(green)) ///
   , title("Hypothetical 4") ///
   xlabel(none) ///
   ylabel(-0.8(0.2)0.8, angle(0) labsize(small) labcolor(black)) ///
   yscale(range(-0.8 0.8)) ///
   ytitle("Average Treatment Effect") ///
   yline(0, lcolor(red)) ///
   legend(order(1 "Landslide" 2 "Drought") rows(1)) ///
   xscale(range(1 5.5)) ///
   xsize(6) ysize(4)

* Merge ATE graphs Spatial1 Spatial2 Temporal1 Temporal2 Social1 Social2 Hypothetical1 Hypothetical2 Hypothetical13
Hypothetical4 (Figure 6)
graph combine ///
   /Users/alexcano86/Desktop/Thesis/Stata/Dissertation/pic/spa1.gph ///
   /Users/alexcano86/Desktop/Thesis/Stata/Dissertation/pic/spa2.gph ///
   /Users/alexcano86/Desktop/Thesis/Stata/Dissertation/pic/temp1.gph ///
   /Users/alexcano86/Desktop/Thesis/Stata/Dissertation/pic/temp2.gph ///
   /Users/alexcano86/Desktop/Thesis/Stata/Dissertation/pic/soc1.gph ///
   /Users/alexcano86/Desktop/Thesis/Stata/Dissertation/pic/soc2.gph ///
   /Users/alexcano86/Desktop/Thesis/Stata/Dissertation/pic/hyp1.gph ///
   /Users/alexcano86/Desktop/Thesis/Stata/Dissertation/pic/hyp2.gph ///
   /Users/alexcano86/Desktop/Thesis/Stata/Dissertation/pic/hyp3.gph ///
   /Users/alexcano86/Desktop/Thesis/Stata/Dissertation/pic/hyp4.gph, ///
   cols(5) ysize(10) xsize(17) ///
         note("* p<0.10, ** p<0.05, *** p<0.010" ///
      "Balancing property satisfied:  YES" ///
      "Common support imposed:    YES" ///
      "Number of Neighbors: 1" ///
      "Caliper for landslides: 0.010" ///
      "Caliper for drought: 0.020" ///
      "Source: Authors.") ///
   title("Average Treatment Effect")

*********************************************************************************
***                        Figure 7: ATET Psychological Distance                   ***
*********************************************************************************
```

```
*** ATET Spatial 1 ***

* NN Matching
psmatch2 landslide, outcome(spa1) pscore(score_landslide) noreplacement neighbor(1) common
scalar ate_spa1_ls_nn = r(att)
scalar se_spa1_ls_nn = r(seatt)
scalar low_spa1_ls_nn = ate_spa1_ls_nn - 1.96 * se_spa1_ls_nn
scalar high_spa1_ls_nn = ate_spa1_ls_nn + 1.96 * se_spa1_ls_nn
scalar pval_spa1_ls_nn = 2 * (1 - normal(abs(ate_spa1_ls_nn / se_spa1_ls_nn)))

psmatch2 drought, outcome(spa1) pscore(score_drought) noreplacement neighbor(1) common
scalar ate_spa1_dr_nn = r(att)
scalar se_spa1_dr_nn = r(seatt)
scalar low_spa1_dr_nn = ate_spa1_dr_nn - 1.96 * se_spa1_dr_nn
scalar high_spa1_dr_nn = ate_spa1_dr_nn + 1.96 * se_spa1_dr_nn
scalar pval_spa1_dr_nn = 2 * (1 - normal(abs(ate_spa1_dr_nn / se_spa1_dr_nn)))

* Caliper Matching
psmatch2 landslide, outcome(spa1) pscore(score_landslide) noreplacement caliper(0.010)
scalar ate_spa1_ls_c = r(att)
scalar se_spa1_ls_c = r(seatt)
scalar low_spa1_ls_c = ate_spa1_ls_c - 1.96 * se_spa1_ls_c
scalar high_spa1_ls_c = ate_spa1_ls_c + 1.96 * se_spa1_ls_c
scalar pval_spa1_ls_c = 2 * (1 - normal(abs(ate_spa1_ls_c / se_spa1_ls_c)))

psmatch2 drought, outcome(spa1) pscore(score_drought) noreplacement caliper(0.020)
scalar ate_spa1_dr_c = r(att)
scalar se_spa1_dr_c = r(seatt)
scalar low_spa1_dr_c = ate_spa1_dr_c - 1.96 * se_spa1_dr_c
scalar high_spa1_dr_c = ate_spa1_dr_c + 1.96 * se_spa1_dr_c
scalar pval_spa1_dr_c = 2 * (1 - normal(abs(ate_spa1_dr_c / se_spa1_dr_c)))

* Dataset for the graph
preserve
clear
set obs 4

gen outcome = "spa1"

gen shock = ""
replace shock = "landslide" in 1
replace shock = "drought" in 2
replace shock = "landslide" in 3
replace shock = "drought" in 4

gen method = ""
replace method = "NN" in 1/2
replace method = "Caliper" in 3/4

gen x = .
replace x = 1 in 1
replace x = 2 in 2
replace x = 4 in 3
replace x = 5 in 4

gen ate = .
replace ate = ate_spa1_ls_nn in 1
replace ate = ate_spa1_dr_nn in 2
replace ate = ate_spa1_ls_c in 3
replace ate = ate_spa1_dr_c in 4
```

```
gen ci_low = .
replace ci_low = low_spa1_ls_nn in 1
replace ci_low = low_spa1_dr_nn in 2
replace ci_low = low_spa1_ls_c in 3
replace ci_low = low_spa1_dr_c in 4

gen ci_high = .
replace ci_high = high_spa1_ls_nn in 1
replace ci_high = high_spa1_dr_nn in 2
replace ci_high = high_spa1_ls_c in 3
replace ci_high = high_spa1_dr_c in 4

* Graph ATET Spatial1
gen str15 ate_label = ""
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_spa1_ls_nn < 0.01, "***", cond(pval_spa1_ls_nn < 0.05, "**", cond(pval_spa1_ls_nn < 0.1, "*", ""))) in 1
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_spa1_dr_nn < 0.01, "***", cond(pval_spa1_dr_nn < 0.05, "**", cond(pval_spa1_dr_nn < 0.1, "*", ""))) in 2
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_spa1_ls_c < 0.01, "***", cond(pval_spa1_ls_c < 0.05, "**", cond(pval_spa1_ls_c < 0.1, "*", ""))) in 3
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_spa1_dr_c < 0.01, "***", cond(pval_spa1_dr_c < 0.05, "**", cond(pval_spa1_dr_c < 0.1, "*", ""))) in 4

twoway ///
    (scatter ate x if shock == "landslide", msymbol(circle) mcolor(blue) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
    (scatter ate x if shock == "drought", msymbol(diamond) mcolor(green) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
    (rcap ci_low ci_high x if shock == "landslide", lcolor(blue)) ///
    (rcap ci_low ci_high x if shock == "drought", lcolor(green)) ///
    ,   title("Spatial 1") ///
    xlabel(none) ///
    ylabel(-0.8(0.2)0.8, angle(0) labsize(small) labcolor(black)) ///
    yscale(range(-0.8 0.8)) ///
    ytitle("Average Treatment Effect on the Treated") ///
    yline(0, lcolor(red)) ///
    legend(order(1 "Landslide" 2 "Drought") rows(1)) ///
    xscale(range(1 5.5)) ///
    xsize(6) ysize(4)

*** ATET Spatial 2 ***

* NN Matching
psmatch2 landslide, outcome(spa2) pscore(score_landslide) noreplacement neighbor(1) common
scalar ate_spa2_ls_nn = r(att)
scalar se_spa2_ls_nn = r(seatt)
scalar low_spa2_ls_nn = ate_spa2_ls_nn - 1.96 * se_spa2_ls_nn
scalar high_spa2_ls_nn = ate_spa2_ls_nn + 1.96 * se_spa2_ls_nn
scalar pval_spa2_ls_nn = 2 * (1 - normal(abs(ate_spa2_ls_nn / se_spa2_ls_nn)))

psmatch2 drought, outcome(spa2) pscore(score_drought) noreplacement neighbor(1) common
scalar ate_spa2_dr_nn = r(att)
scalar se_spa2_dr_nn = r(seatt)
scalar low_spa2_dr_nn = ate_spa2_dr_nn - 1.96 * se_spa2_dr_nn
scalar high_spa2_dr_nn = ate_spa2_dr_nn + 1.96 * se_spa2_dr_nn
scalar pval_spa2_dr_nn = 2 * (1 - normal(abs(ate_spa2_dr_nn / se_spa2_dr_nn)))

* Caliper Matching
psmatch2 landslide, outcome(spa2) pscore(score_landslide) noreplacement caliper(0.010)
scalar ate_spa2_ls_c = r(att)
scalar se_spa2_ls_c = r(seatt)
scalar low_spa2_ls_c = ate_spa2_ls_c - 1.96 * se_spa2_ls_c
scalar high_spa2_ls_c = ate_spa2_ls_c + 1.96 * se_spa2_ls_c
scalar pval_spa2_ls_c = 2 * (1 - normal(abs(ate_spa2_ls_c / se_spa2_ls_c)))
```

```
psmatch2 drought, outcome(spa2) pscore(score_drought) noreplacement caliper(0.020)
scalar ate_spa2_dr_c = r(att)
scalar se_spa2_dr_c = r(seatt)
scalar low_spa2_dr_c = ate_spa2_dr_c - 1.96 * se_spa2_dr_c
scalar high_spa2_dr_c = ate_spa2_dr_c + 1.96 * se_spa2_dr_c
scalar pval_spa2_dr_c = 2 * (1 - normal(abs(ate_spa2_dr_c / se_spa2_dr_c)))

* Dataset for the graph
preserve
clear
set obs 4

gen outcome = "spa2"

gen shock = ""
replace shock = "landslide" in 1
replace shock = "drought" in 2
replace shock = "landslide" in 3
replace shock = "drought" in 4

gen method = ""
replace method = "NN" in 1/2
replace method = "Caliper" in 3/4

gen x = .
replace x = 1 in 1
replace x = 2 in 2
replace x = 4 in 3
replace x = 5 in 4

gen ate = .
replace ate = ate_spa2_ls_nn in 1
replace ate = ate_spa2_dr_nn in 2
replace ate = ate_spa2_ls_c in 3
replace ate = ate_spa2_dr_c in 4

gen ci_low = .
replace ci_low = low_spa2_ls_nn in 1
replace ci_low = low_spa2_dr_nn in 2
replace ci_low = low_spa2_ls_c in 3
replace ci_low = low_spa2_dr_c in 4

gen ci_high = .
replace ci_high = high_spa2_ls_nn in 1
replace ci_high = high_spa2_dr_nn in 2
replace ci_high = high_spa2_ls_c in 3
replace ci_high = high_spa2_dr_c in 4

* Graph ATET Spatial2
gen str15 ate_label = ""
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_spa2_ls_nn < 0.01, "***", cond(pval_spa2_ls_nn < 0.05, "**", cond(pval_spa2_ls_nn < 0.1, "*", ""))) in 1
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_spa2_dr_nn < 0.01, "***", cond(pval_spa2_dr_nn < 0.05, "**", cond(pval_spa2_dr_nn < 0.1, "*", ""))) in 2
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_spa2_ls_c < 0.01, "***", cond(pval_spa2_ls_c < 0.05, "**", cond(pval_spa2_ls_c < 0.1, "*", ""))) in 3
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_spa2_dr_c < 0.01, "***", cond(pval_spa2_dr_c < 0.05, "**", cond(pval_spa2_dr_c < 0.1, "*", ""))) in 4

twoway ///
    (scatter ate x if shock == "landslide", msymbol(circle) mcolor(blue) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
```

```
    (scatter ate x if shock == "drought", msymbol(diamond) mcolor(green) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
    (rcap ci_low ci_high x if shock == "landslide", lcolor(blue)) ///
    (rcap ci_low ci_high x if shock == "drought", lcolor(green)) ///
    ,   title("Spatial 2") ///
    xlabel(none) ///
    ylabel(-0.8(0.2)0.8, angle(0) labsize(small) labcolor(black)) ///
    yscale(range(-0.8 0.8)) ///
    ytitle("Average Treatment Effect on the Treated") ///
    yline(0, lcolor(red)) ///
    legend(order(1 "Landslide" 2 "Drought") rows(1)) ///
    xscale(range(1 5.5)) ///
    xsize(6) ysize(4)

*** ATET Temporal 1 ***

* NN Matching
psmatch2 landslide, outcome(temp1) pscore(score_landslide) noreplacement neighbor(1) common
scalar ate_temp1_ls_nn = r(att)
scalar se_temp1_ls_nn = r(seatt)
scalar low_temp1_ls_nn = ate_temp1_ls_nn - 1.96 * se_temp1_ls_nn
scalar high_temp1_ls_nn = ate_temp1_ls_nn + 1.96 * se_temp1_ls_nn
scalar pval_temp1_ls_nn = 2 * (1 - normal(abs(ate_temp1_ls_nn / se_temp1_ls_nn)))

psmatch2 drought, outcome(temp1) pscore(score_drought) noreplacement neighbor(1) common
scalar ate_temp1_dr_nn = r(att)
scalar se_temp1_dr_nn = r(seatt)
scalar low_temp1_dr_nn = ate_temp1_dr_nn - 1.96 * se_temp1_dr_nn
scalar high_temp1_dr_nn = ate_temp1_dr_nn + 1.96 * se_temp1_dr_nn
scalar pval_temp1_dr_nn = 2 * (1 - normal(abs(ate_temp1_dr_nn / se_temp1_dr_nn)))

* Caliper Matching
psmatch2 landslide, outcome(temp1) pscore(score_landslide) noreplacement caliper(0.010)
scalar ate_temp1_ls_c = r(att)
scalar se_temp1_ls_c = r(seatt)
scalar low_temp1_ls_c = ate_temp1_ls_c - 1.96 * se_temp1_ls_c
scalar high_temp1_ls_c = ate_temp1_ls_c + 1.96 * se_temp1_ls_c
scalar pval_temp1_ls_c = 2 * (1 - normal(abs(ate_temp1_ls_c / se_temp1_ls_c)))

psmatch2 drought, outcome(temp1) pscore(score_drought) noreplacement caliper(0.020)
scalar ate_temp1_dr_c = r(att)
scalar se_temp1_dr_c = r(seatt)
scalar low_temp1_dr_c = ate_temp1_dr_c - 1.96 * se_temp1_dr_c
scalar high_temp1_dr_c = ate_temp1_dr_c + 1.96 * se_temp1_dr_c
scalar pval_temp1_dr_c = 2 * (1 - normal(abs(ate_temp1_dr_c / se_temp1_dr_c)))

* Dataset for the graph
preserve
clear
set obs 4

gen outcome = "temp1"

gen shock = ""
replace shock = "landslide" in 1
replace shock = "drought" in 2
replace shock = "landslide" in 3
replace shock = "drought" in 4

gen method = ""
replace method = "NN" in 1/2
replace method = "Caliper" in 3/4
```

```
gen x = .
replace x = 1 in 1
replace x = 2 in 2
replace x = 4 in 3
replace x = 5 in 4

gen ate = .
replace ate = ate_temp1_ls_nn in 1
replace ate = ate_temp1_dr_nn in 2
replace ate = ate_temp1_ls_c in 3
replace ate = ate_temp1_dr_c in 4

gen ci_low = .
replace ci_low = low_temp1_ls_nn in 1
replace ci_low = low_temp1_dr_nn in 2
replace ci_low = low_temp1_ls_c in 3
replace ci_low = low_temp1_dr_c in 4

gen ci_high = .
replace ci_high = high_temp1_ls_nn in 1
replace ci_high = high_temp1_dr_nn in 2
replace ci_high = high_temp1_ls_c in 3
replace ci_high = high_temp1_dr_c in 4

* Graph ATET Temporal1
gen str15 ate_label = ""
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_temp1_ls_nn < 0.01, "***", cond(pval_temp1_ls_nn < 0.05, "**", cond(pval_temp1_ls_nn < 0.1, "*", ""))) in 1
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_temp1_dr_nn < 0.01, "***", cond(pval_temp1_dr_nn < 0.05, "**", cond(pval_temp1_dr_nn < 0.1, "*", ""))) in 2
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_temp1_ls_c < 0.01, "***", cond(pval_temp1_ls_c < 0.05, "**", cond(pval_temp1_ls_c < 0.1, "*", ""))) in 3
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_temp1_dr_c < 0.01, "***", cond(pval_temp1_dr_c < 0.05, "**", cond(pval_temp1_dr_c < 0.1, "*", ""))) in 4

twoway ///
    (scatter ate x if shock == "landslide", msymbol(circle) mcolor(blue) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
    (scatter ate x if shock == "drought", msymbol(diamond) mcolor(green) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
    (rcap ci_low ci_high x if shock == "landslide", lcolor(blue)) ///
    (rcap ci_low ci_high x if shock == "drought", lcolor(green)) ///
    ,   title("Temporal 1") ///
    xlabel(none) ///
    ylabel(-0.8(0.2)0.8, angle(0) labsize(small) labcolor(black)) ///
    yscale(range(-0.8 0.8)) ///
    ytitle("Average Treatment Effect on the Treated") ///
    yline(0, lcolor(red)) ///
    legend(order(1 "Landslide" 2 "Drought") rows(1)) ///
    xscale(range(1 5.5)) ///
    xsize(6) ysize(4)

*** ATET Temporal 2 ***

* NN Matching
psmatch2 landslide, outcome(temp2) pscore(score_landslide) noreplacement neighbor(1) common
scalar ate_temp2_ls_nn = r(att)
scalar se_temp2_ls_nn = r(seatt)
scalar low_temp2_ls_nn = ate_temp2_ls_nn - 1.96 * se_temp2_ls_nn
scalar high_temp2_ls_nn = ate_temp2_ls_nn + 1.96 * se_temp2_ls_nn
scalar pval_temp2_ls_nn = 2 * (1 - normal(abs(ate_temp2_ls_nn / se_temp2_ls_nn)))

psmatch2 drought, outcome(temp2) pscore(score_drought) noreplacement neighbor(1) common
scalar ate_temp2_dr_nn = r(att)
```

```
scalar se_temp2_dr_nn = r(seatt)
scalar low_temp2_dr_nn = ate_temp2_dr_nn - 1.96 * se_temp2_dr_nn
scalar high_temp2_dr_nn = ate_temp2_dr_nn + 1.96 * se_temp2_dr_nn
scalar pval_temp2_dr_nn = 2 * (1 - normal(abs(ate_temp2_dr_nn / se_temp2_dr_nn)))

* Caliper Matching
psmatch2 landslide, outcome(temp2) pscore(score_landslide) noreplacement caliper(0.010)
scalar ate_temp2_ls_c = r(att)
scalar se_temp2_ls_c = r(seatt)
scalar low_temp2_ls_c = ate_temp2_ls_c - 1.96 * se_temp2_ls_c
scalar high_temp2_ls_c = ate_temp2_ls_c + 1.96 * se_temp2_ls_c
scalar pval_temp2_ls_c = 2 * (1 - normal(abs(ate_temp2_ls_c / se_temp2_ls_c)))

psmatch2 drought, outcome(temp2) pscore(score_drought) noreplacement caliper(0.020)
scalar ate_temp2_dr_c = r(att)
scalar se_temp2_dr_c = r(seatt)
scalar low_temp2_dr_c = ate_temp2_dr_c - 1.96 * se_temp2_dr_c
scalar high_temp2_dr_c = ate_temp2_dr_c + 1.96 * se_temp2_dr_c
scalar pval_temp2_dr_c = 2 * (1 - normal(abs(ate_temp2_dr_c / se_temp2_dr_c)))

* Dataset for the graph
preserve
clear
set obs 4

gen outcome = "temp2"

gen shock = ""
replace shock = "landslide" in 1
replace shock = "drought" in 2
replace shock = "landslide" in 3
replace shock = "drought" in 4

gen method = ""
replace method = "NN" in 1/2
replace method = "Caliper" in 3/4

gen x = .
replace x = 1 in 1
replace x = 2 in 2
replace x = 4 in 3
replace x = 5 in 4

gen ate = .
replace ate = ate_temp2_ls_nn in 1
replace ate = ate_temp2_dr_nn in 2
replace ate = ate_temp2_ls_c in 3
replace ate = ate_temp2_dr_c in 4

gen ci_low = .
replace ci_low = low_temp2_ls_nn in 1
replace ci_low = low_temp2_dr_nn in 2
replace ci_low = low_temp2_ls_c in 3
replace ci_low = low_temp2_dr_c in 4

gen ci_high = .
replace ci_high = high_temp2_ls_nn in 1
replace ci_high = high_temp2_dr_nn in 2
replace ci_high = high_temp2_ls_c in 3
replace ci_high = high_temp2_dr_c in 4

* Graph ATET Temporal2
```

```
gen str15 ate_label = ""
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_temp2_ls_nn < 0.01, "***", cond(pval_temp2_ls_nn < 0.05, "**", cond(pval_temp2_ls_nn < 0.1, "*", ""))) in 1
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_temp2_dr_nn < 0.01, "***", cond(pval_temp2_dr_nn < 0.05, "**", cond(pval_temp2_dr_nn < 0.1, "*", ""))) in 2
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_temp2_ls_c < 0.01, "***", cond(pval_temp2_ls_c < 0.05, "**", cond(pval_temp2_ls_c < 0.1, "*", ""))) in 3
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_temp2_dr_c < 0.01, "***", cond(pval_temp2_dr_c < 0.05, "**", cond(pval_temp2_dr_c < 0.1, "*", ""))) in 4

twoway ///
    (scatter ate x if shock == "landslide", msymbol(circle) mcolor(blue) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
    (scatter ate x if shock == "drought", msymbol(diamond) mcolor(green) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
    (rcap ci_low ci_high x if shock == "landslide", lcolor(blue)) ///
    (rcap ci_low ci_high x if shock == "drought", lcolor(green)) ///
    ,   title("Temporal 2") ///
    xlabel(none) ///
    ylabel(-0.8(0.2)0.8, angle(0) labsize(small) labcolor(black)) ///
    yscale(range(-0.8 0.8)) ///
    ytitle("Average Treatment Effect on the Treated") ///
    yline(0, lcolor(red)) ///
    legend(order(1 "Landslide" 2 "Drought") rows(1)) ///
    xscale(range(1 5.5)) ///
    xsize(6) ysize(4)

*** ATET Social 1 ***

* NN Matching
psmatch2 landslide, outcome(soc1) pscore(score_landslide) noreplacement neighbor(1) common
scalar ate_soc1_ls_nn = r(att)
scalar se_soc1_ls_nn = r(seatt)
scalar low_soc1_ls_nn = ate_soc1_ls_nn - 1.96 * se_soc1_ls_nn
scalar high_soc1_ls_nn = ate_soc1_ls_nn + 1.96 * se_soc1_ls_nn
scalar pval_soc1_ls_nn = 2 * (1 - normal(abs(ate_soc1_ls_nn / se_soc1_ls_nn)))

psmatch2 drought, outcome(soc1) pscore(score_drought) noreplacement neighbor(1) common
scalar ate_soc1_dr_nn = r(att)
scalar se_soc1_dr_nn = r(seatt)
scalar low_soc1_dr_nn = ate_soc1_dr_nn - 1.96 * se_soc1_dr_nn
scalar high_soc1_dr_nn = ate_soc1_dr_nn + 1.96 * se_soc1_dr_nn
scalar pval_soc1_dr_nn = 2 * (1 - normal(abs(ate_soc1_dr_nn / se_soc1_dr_nn)))

* Caliper Matching
psmatch2 landslide, outcome(soc1) pscore(score_landslide) noreplacement caliper(0.010)
scalar ate_soc1_ls_c = r(att)
scalar se_soc1_ls_c = r(seatt)
scalar low_soc1_ls_c = ate_soc1_ls_c - 1.96 * se_soc1_ls_c
scalar high_soc1_ls_c = ate_soc1_ls_c + 1.96 * se_soc1_ls_c
scalar pval_soc1_ls_c = 2 * (1 - normal(abs(ate_soc1_ls_c / se_soc1_ls_c)))

psmatch2 drought, outcome(soc1) pscore(score_drought) noreplacement caliper(0.020)
scalar ate_soc1_dr_c = r(att)
scalar se_soc1_dr_c = r(seatt)
scalar low_soc1_dr_c = ate_soc1_dr_c - 1.96 * se_soc1_dr_c
scalar high_soc1_dr_c = ate_soc1_dr_c + 1.96 * se_soc1_dr_c
scalar pval_soc1_dr_c = 2 * (1 - normal(abs(ate_soc1_dr_c / se_soc1_dr_c)))

* Dataset for the graph
preserve
clear
set obs 4
```

```
gen outcome = "soc1"

gen shock = ""
replace shock = "landslide" in 1
replace shock = "drought" in 2
replace shock = "landslide" in 3
replace shock = "drought" in 4

gen method = ""
replace method = "NN" in 1/2
replace method = "Caliper" in 3/4

gen x = .
replace x = 1 in 1
replace x = 2 in 2
replace x = 4 in 3
replace x = 5 in 4

gen ate = .
replace ate = ate_soc1_ls_nn in 1
replace ate = ate_soc1_dr_nn in 2
replace ate = ate_soc1_ls_c in 3
replace ate = ate_soc1_dr_c in 4

gen ci_low = .
replace ci_low = low_soc1_ls_nn in 1
replace ci_low = low_soc1_dr_nn in 2
replace ci_low = low_soc1_ls_c in 3
replace ci_low = low_soc1_dr_c in 4

gen ci_high = .
replace ci_high = high_soc1_ls_nn in 1
replace ci_high = high_soc1_dr_nn in 2
replace ci_high = high_soc1_ls_c in 3
replace ci_high = high_soc1_dr_c in 4

* Graph ATET Social1
gen str15 ate_label = ""
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_soc1_ls_nn < 0.01, "***", cond(pval_soc1_ls_nn < 0.05, "**", cond(pval_soc1_ls_nn < 0.1, "*", ""))) in 1
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_soc1_dr_nn < 0.01, "***", cond(pval_soc1_dr_nn < 0.05, "**", cond(pval_soc1_dr_nn < 0.1, "*", ""))) in 2
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_soc1_ls_c < 0.01, "***", cond(pval_soc1_ls_c < 0.05, "**", cond(pval_soc1_ls_c < 0.1, "*", ""))) in 3
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_soc1_dr_c < 0.01, "***", cond(pval_soc1_dr_c < 0.05, "**", cond(pval_soc1_dr_c < 0.1, "*", ""))) in 4

twoway ///
    (scatter ate x if shock == "landslide", msymbol(circle) mcolor(blue) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
    (scatter ate x if shock == "drought", msymbol(diamond) mcolor(green) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
    (rcap ci_low ci_high x if shock == "landslide", lcolor(blue)) ///
    (rcap ci_low ci_high x if shock == "drought", lcolor(green)) ///
    ,   title("Social 1") ///
    xlabel(none) ///
    ylabel(-0.8(0.2)0.8, angle(0) labsize(small) labcolor(black)) ///
    yscale(range(-0.8 0.8)) ///
    ytitle("Average Treatment Effect on the Treated") ///
    yline(0, lcolor(red)) ///
    legend(order(1 "Landslide" 2 "Drought") rows(1)) ///
    xscale(range(1 5.5)) ///
    xsize(6) ysize(4)
```

```
*** ATET Social 2 ***

* NN Matching
psmatch2 landslide, outcome(soc2) pscore(score_landslide) noreplacement neighbor(1) common
scalar ate_soc2_ls_nn = r(att)
scalar se_soc2_ls_nn = r(seatt)
scalar low_soc2_ls_nn = ate_soc2_ls_nn - 1.96 * se_soc2_ls_nn
scalar high_soc2_ls_nn = ate_soc2_ls_nn + 1.96 * se_soc2_ls_nn
scalar pval_soc2_ls_nn = 2 * (1 - normal(abs(ate_soc2_ls_nn / se_soc2_ls_nn)))

psmatch2 drought, outcome(soc2) pscore(score_drought) noreplacement neighbor(1) common
scalar ate_soc2_dr_nn = r(att)
scalar se_soc2_dr_nn = r(seatt)
scalar low_soc2_dr_nn = ate_soc2_dr_nn - 1.96 * se_soc2_dr_nn
scalar high_soc2_dr_nn = ate_soc2_dr_nn + 1.96 * se_soc2_dr_nn
scalar pval_soc2_dr_nn = 2 * (1 - normal(abs(ate_soc2_dr_nn / se_soc2_dr_nn)))

* Caliper Matching
psmatch2 landslide, outcome(soc2) pscore(score_landslide) noreplacement caliper(0.010)
scalar ate_soc2_ls_c = r(att)
scalar se_soc2_ls_c = r(seatt)
scalar low_soc2_ls_c = ate_soc2_ls_c - 1.96 * se_soc2_ls_c
scalar high_soc2_ls_c = ate_soc2_ls_c + 1.96 * se_soc2_ls_c
scalar pval_soc2_ls_c = 2 * (1 - normal(abs(ate_soc2_ls_c / se_soc2_ls_c)))

psmatch2 drought, outcome(soc2) pscore(score_drought) noreplacement caliper(0.020)
scalar ate_soc2_dr_c = r(att)
scalar se_soc2_dr_c = r(seatt)
scalar low_soc2_dr_c = ate_soc2_dr_c - 1.96 * se_soc2_dr_c
scalar high_soc2_dr_c = ate_soc2_dr_c + 1.96 * se_soc2_dr_c
scalar pval_soc2_dr_c = 2 * (1 - normal(abs(ate_soc2_dr_c / se_soc2_dr_c)))

* Dataset for the graph
preserve
clear
set obs 4

gen outcome = "soc2"

gen shock = ""
replace shock = "landslide" in 1
replace shock = "drought" in 2
replace shock = "landslide" in 3
replace shock = "drought" in 4

gen method = ""
replace method = "NN" in 1/2
replace method = "Caliper" in 3/4

gen x = .
replace x = 1 in 1
replace x = 2 in 2
replace x = 4 in 3
replace x = 5 in 4

gen ate = .
replace ate = ate_soc2_ls_nn in 1
replace ate = ate_soc2_dr_nn in 2
replace ate = ate_soc2_ls_c in 3
replace ate = ate_soc2_dr_c in 4

gen ci_low = .
```

```
replace ci_low = low_soc2_ls_nn in 1
replace ci_low = low_soc2_dr_nn in 2
replace ci_low = low_soc2_ls_c in 3
replace ci_low = low_soc2_dr_c in 4

gen ci_high = .
replace ci_high = high_soc2_ls_nn in 1
replace ci_high = high_soc2_dr_nn in 2
replace ci_high = high_soc2_ls_c in 3
replace ci_high = high_soc2_dr_c in 4

* Graph ATET Social2
gen str15 ate_label = ""
replace ate_label = string(ate, "%9.3f") + ///
  cond(pval_soc2_ls_nn < 0.01, "***", cond(pval_soc2_ls_nn < 0.05, "**", cond(pval_soc2_ls_nn < 0.1, "*", ""))) in 1
replace ate_label = string(ate, "%9.3f") + ///
  cond(pval_soc2_dr_nn < 0.01, "***", cond(pval_soc2_dr_nn < 0.05, "**", cond(pval_soc2_dr_nn < 0.1, "*", ""))) in 2
replace ate_label = string(ate, "%9.3f") + ///
  cond(pval_soc2_ls_c < 0.01, "***", cond(pval_soc2_ls_c < 0.05, "**", cond(pval_soc2_ls_c < 0.1, "*", ""))) in 3
replace ate_label = string(ate, "%9.3f") + ///
  cond(pval_soc2_dr_c < 0.01, "***", cond(pval_soc2_dr_c < 0.05, "**", cond(pval_soc2_dr_c < 0.1, "*", ""))) in 4

twoway ///
  (scatter ate x if shock == "landslide", msymbol(circle) mcolor(blue) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
  (scatter ate x if shock == "drought", msymbol(diamond) mcolor(green) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
  (rcap ci_low ci_high x if shock == "landslide", lcolor(blue)) ///
  (rcap ci_low ci_high x if shock == "drought", lcolor(green)) ///
  ,  title("Social 2") ///
  xlabel(none) ///
  ylabel(-0.8(0.2)0.8, angle(0) labsize(small) labcolor(black)) ///
  yscale(range(-0.8 0.8)) ///
  ytitle("Average Treatment Effect on the Treated") ///
  yline(0, lcolor(red)) ///
  legend(order(1 "Landslide" 2 "Drought") rows(1)) ///
  xscale(range(1 5.5)) ///
  xsize(6) ysize(4)

*** ATET Hypothetical 1 ***

* NN Matching
psmatch2 landslide, outcome(hyp1) pscore(score_landslide) noreplacement neighbor(1) common
scalar ate_hyp1_ls_nn = r(att)
scalar se_hyp1_ls_nn = r(seatt)
scalar low_hyp1_ls_nn = ate_hyp1_ls_nn - 1.96 * se_hyp1_ls_nn
scalar high_hyp1_ls_nn = ate_hyp1_ls_nn + 1.96 * se_hyp1_ls_nn
scalar pval_hyp1_ls_nn = 2 * (1 - normal(abs(ate_hyp1_ls_nn / se_hyp1_ls_nn)))

psmatch2 drought, outcome(hyp1) pscore(score_drought) noreplacement neighbor(1) common
scalar ate_hyp1_dr_nn = r(att)
scalar se_hyp1_dr_nn = r(seatt)
scalar low_hyp1_dr_nn = ate_hyp1_dr_nn - 1.96 * se_hyp1_dr_nn
scalar high_hyp1_dr_nn = ate_hyp1_dr_nn + 1.96 * se_hyp1_dr_nn
scalar pval_hyp1_dr_nn = 2 * (1 - normal(abs(ate_hyp1_dr_nn / se_hyp1_dr_nn)))

* Caliper Matching
psmatch2 landslide, outcome(hyp1) pscore(score_landslide) noreplacement caliper(0.010)
scalar ate_hyp1_ls_c = r(att)
scalar se_hyp1_ls_c = r(seatt)
scalar low_hyp1_ls_c = ate_hyp1_ls_c - 1.96 * se_hyp1_ls_c
scalar high_hyp1_ls_c = ate_hyp1_ls_c + 1.96 * se_hyp1_ls_c
scalar pval_hyp1_ls_c = 2 * (1 - normal(abs(ate_hyp1_ls_c / se_hyp1_ls_c)))
```

```
psmatch2 drought, outcome(hyp1) pscore(score_drought) noreplacement caliper(0.020)
scalar ate_hyp1_dr_c = r(att)
scalar se_hyp1_dr_c = r(seatt)
scalar low_hyp1_dr_c = ate_hyp1_dr_c - 1.96 * se_hyp1_dr_c
scalar high_hyp1_dr_c = ate_hyp1_dr_c + 1.96 * se_hyp1_dr_c
scalar pval_hyp1_dr_c = 2 * (1 - normal(abs(ate_hyp1_dr_c / se_hyp1_dr_c)))

* Dataset for the graph
preserve
clear
set obs 4

gen outcome = "hyp1"

gen shock = ""
replace shock = "landslide" in 1
replace shock = "drought" in 2
replace shock = "landslide" in 3
replace shock = "drought" in 4

gen method = ""
replace method = "NN" in 1/2
replace method = "Caliper" in 3/4

gen x = .
replace x = 1 in 1
replace x = 2 in 2
replace x = 4 in 3
replace x = 5 in 4

gen ate = .
replace ate = ate_hyp1_ls_nn in 1
replace ate = ate_hyp1_dr_nn in 2
replace ate = ate_hyp1_ls_c in 3
replace ate = ate_hyp1_dr_c in 4

gen ci_low = .
replace ci_low = low_hyp1_ls_nn in 1
replace ci_low = low_hyp1_dr_nn in 2
replace ci_low = low_hyp1_ls_c in 3
replace ci_low = low_hyp1_dr_c in 4

gen ci_high = .
replace ci_high = high_hyp1_ls_nn in 1
replace ci_high = high_hyp1_dr_nn in 2
replace ci_high = high_hyp1_ls_c in 3
replace ci_high = high_hyp1_dr_c in 4

* Graph ATET Hypothetical1
gen str15 ate_label = ""
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_hyp1_ls_nn < 0.01, "***", cond(pval_hyp1_ls_nn < 0.05, "**", cond(pval_hyp1_ls_nn < 0.1, "*", ""))) in 1
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_hyp1_dr_nn < 0.01, "***", cond(pval_hyp1_dr_nn < 0.05, "**", cond(pval_hyp1_dr_nn < 0.1, "*", ""))) in 2
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_hyp1_ls_c < 0.01, "***", cond(pval_hyp1_ls_c < 0.05, "**", cond(pval_hyp1_ls_c < 0.1, "*", ""))) in 3
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_hyp1_dr_c < 0.01, "***", cond(pval_hyp1_dr_c < 0.05, "**", cond(pval_hyp1_dr_c < 0.1, "*", ""))) in 4

twoway ///
    (scatter ate x if shock == "landslide", msymbol(circle) mcolor(blue) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
    (scatter ate x if shock == "drought", msymbol(diamond) mcolor(green) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
```

```
    (rcap ci_low ci_high x if shock == "landslide", lcolor(blue)) ///
    (rcap ci_low ci_high x if shock == "drought", lcolor(green)) ///
    ,   title("Hypothetical 1") ///
    xlabel(none) ///
    ylabel(-0.8(0.2)0.8, angle(0) labsize(small) labcolor(black)) ///
    yscale(range(-0.8 0.8)) ///
    ytitle("Average Treatment Effect on the Treated") ///
    yline(0, lcolor(red)) ///
    legend(order(1 "Landslide" 2 "Drought") rows(1)) ///
    xscale(range(1 5.5)) ///
    xsize(6) ysize(4)

*** ATET Hypothetical 2 ***

* NN Matching
psmatch2 landslide, outcome(hyp2) pscore(score_landslide) noreplacement neighbor(1) common
scalar ate_hyp2_ls_nn = r(att)
scalar se_hyp2_ls_nn = r(seatt)
scalar low_hyp2_ls_nn = ate_hyp2_ls_nn - 1.96 * se_hyp2_ls_nn
scalar high_hyp2_ls_nn = ate_hyp2_ls_nn + 1.96 * se_hyp2_ls_nn
scalar pval_hyp2_ls_nn = 2 * (1 - normal(abs(ate_hyp2_ls_nn / se_hyp2_ls_nn)))

psmatch2 drought, outcome(hyp2) pscore(score_drought) noreplacement neighbor(1) common
scalar ate_hyp2_dr_nn = r(att)
scalar se_hyp2_dr_nn = r(seatt)
scalar low_hyp2_dr_nn = ate_hyp2_dr_nn - 1.96 * se_hyp2_dr_nn
scalar high_hyp2_dr_nn = ate_hyp2_dr_nn + 1.96 * se_hyp2_dr_nn
scalar pval_hyp2_dr_nn = 2 * (1 - normal(abs(ate_hyp2_dr_nn / se_hyp2_dr_nn)))

* Caliper Matching
psmatch2 landslide, outcome(hyp2) pscore(score_landslide) noreplacement caliper(0.010)
scalar ate_hyp2_ls_c = r(att)
scalar se_hyp2_ls_c = r(seatt)
scalar low_hyp2_ls_c = ate_hyp2_ls_c - 1.96 * se_hyp2_ls_c
scalar high_hyp2_ls_c = ate_hyp2_ls_c + 1.96 * se_hyp2_ls_c
scalar pval_hyp2_ls_c = 2 * (1 - normal(abs(ate_hyp2_ls_c / se_hyp2_ls_c)))

psmatch2 drought, outcome(hyp2) pscore(score_drought) noreplacement caliper(0.020)
scalar ate_hyp2_dr_c = r(att)
scalar se_hyp2_dr_c = r(seatt)
scalar low_hyp2_dr_c = ate_hyp2_dr_c - 1.96 * se_hyp2_dr_c
scalar high_hyp2_dr_c = ate_hyp2_dr_c + 1.96 * se_hyp2_dr_c
scalar pval_hyp2_dr_c = 2 * (1 - normal(abs(ate_hyp2_dr_c / se_hyp2_dr_c)))

* Dataset for the graph
preserve
clear
set obs 4

gen outcome = "hyp2"

gen shock = ""
replace shock = "landslide" in 1
replace shock = "drought" in 2
replace shock = "landslide" in 3
replace shock = "drought" in 4

gen method = ""
replace method = "NN" in 1/2
replace method = "Caliper" in 3/4

gen x = .
```

```
replace x = 1 in 1
replace x = 2 in 2
replace x = 4 in 3
replace x = 5 in 4

gen ate = .
replace ate = ate_hyp2_ls_nn in 1
replace ate = ate_hyp2_dr_nn in 2
replace ate = ate_hyp2_ls_c in 3
replace ate = ate_hyp2_dr_c in 4

gen ci_low = .
replace ci_low = low_hyp2_ls_nn in 1
replace ci_low = low_hyp2_dr_nn in 2
replace ci_low = low_hyp2_ls_c in 3
replace ci_low = low_hyp2_dr_c in 4

gen ci_high = .
replace ci_high = high_hyp2_ls_nn in 1
replace ci_high = high_hyp2_dr_nn in 2
replace ci_high = high_hyp2_ls_c in 3
replace ci_high = high_hyp2_dr_c in 4

* Graph  ATET Hypothetical2
gen str15 ate_label = ""
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_hyp2_ls_nn < 0.01, "***", cond(pval_hyp2_ls_nn < 0.05, "**", cond(pval_hyp2_ls_nn < 0.1, "*", ""))) in 1
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_hyp2_dr_nn < 0.01, "***", cond(pval_hyp2_dr_nn < 0.05, "**", cond(pval_hyp2_dr_nn < 0.1, "*", ""))) in 2
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_hyp2_ls_c < 0.01, "***", cond(pval_hyp2_ls_c < 0.05, "**", cond(pval_hyp2_ls_c < 0.1, "*", ""))) in 3
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_hyp2_dr_c < 0.01, "***", cond(pval_hyp2_dr_c < 0.05, "**", cond(pval_hyp2_dr_c < 0.1, "*", ""))) in 4

twoway ///
    (scatter ate x if shock == "landslide", msymbol(circle) mcolor(blue) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
    (scatter ate x if shock == "drought", msymbol(diamond) mcolor(green) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
    (rcap ci_low ci_high x if shock == "landslide", lcolor(blue)) ///
    (rcap ci_low ci_high x if shock == "drought", lcolor(green)) ///
    ,   title("Hypothetical 2") ///
    xlabel(none) ///
    ylabel(-0.8(0.2)0.8, angle(0) labsize(small) labcolor(black)) ///
    yscale(range(-0.8 0.8)) ///
    ytitle("Average Treatment Effect on the Treated") ///
    yline(0, lcolor(red)) ///
    legend(order(1 "Landslide" 2 "Drought") rows(1)) ///
    xscale(range(1 5.5)) ///
    xsize(6) ysize(4)

*** ATET Hypothetical 3 ***

* NN Matching
psmatch2 landslide, outcome(hyp3) pscore(score_landslide) noreplacement neighbor(1) common
scalar ate_hyp3_ls_nn = r(att)
scalar se_hyp3_ls_nn = r(seatt)
scalar low_hyp3_ls_nn = ate_hyp3_ls_nn - 1.96 * se_hyp3_ls_nn
scalar high_hyp3_ls_nn = ate_hyp3_ls_nn + 1.96 * se_hyp3_ls_nn
scalar pval_hyp3_ls_nn = 2 * (1 - normal(abs(ate_hyp3_ls_nn / se_hyp3_ls_nn)))

psmatch2 drought, outcome(hyp3) pscore(score_drought) noreplacement neighbor(1) common
scalar ate_hyp3_dr_nn = r(att)
scalar se_hyp3_dr_nn = r(seatt)
```

```
scalar low_hyp3_dr_nn = ate_hyp3_dr_nn - 1.96 * se_hyp3_dr_nn
scalar high_hyp3_dr_nn = ate_hyp3_dr_nn + 1.96 * se_hyp3_dr_nn
scalar pval_hyp3_dr_nn = 2 * (1 - normal(abs(ate_hyp3_dr_nn / se_hyp3_dr_nn)))

* Caliper Matching
psmatch2 landslide, outcome(hyp3) pscore(score_landslide) noreplacement caliper(0.010)
scalar ate_hyp3_ls_c = r(att)
scalar se_hyp3_ls_c = r(seatt)
scalar low_hyp3_ls_c = ate_hyp3_ls_c - 1.96 * se_hyp3_ls_c
scalar high_hyp3_ls_c = ate_hyp3_ls_c + 1.96 * se_hyp3_ls_c
scalar pval_hyp3_ls_c = 2 * (1 - normal(abs(ate_hyp3_ls_c / se_hyp3_ls_c)))

psmatch2 drought, outcome(hyp3) pscore(score_drought) noreplacement caliper(0.020)
scalar ate_hyp3_dr_c = r(att)
scalar se_hyp3_dr_c = r(seatt)
scalar low_hyp3_dr_c = ate_hyp3_dr_c - 1.96 * se_hyp3_dr_c
scalar high_hyp3_dr_c = ate_hyp3_dr_c + 1.96 * se_hyp3_dr_c
scalar pval_hyp3_dr_c = 2 * (1 - normal(abs(ate_hyp3_dr_c / se_hyp3_dr_c)))

* Dataset for the graph
preserve
clear
set obs 4

gen outcome = "hyp3"

gen shock = ""
replace shock = "landslide" in 1
replace shock = "drought" in 2
replace shock = "landslide" in 3
replace shock = "drought" in 4

gen method = ""
replace method = "NN" in 1/2
replace method = "Caliper" in 3/4

gen x = .
replace x = 1 in 1
replace x = 2 in 2
replace x = 4 in 3
replace x = 5 in 4

gen ate = .
replace ate = ate_hyp3_ls_nn in 1
replace ate = ate_hyp3_dr_nn in 2
replace ate = ate_hyp3_ls_c in 3
replace ate = ate_hyp3_dr_c in 4

gen ci_low = .
replace ci_low = low_hyp3_ls_nn in 1
replace ci_low = low_hyp3_dr_nn in 2
replace ci_low = low_hyp3_ls_c in 3
replace ci_low = low_hyp3_dr_c in 4

gen ci_high = .
replace ci_high = high_hyp3_ls_nn in 1
replace ci_high = high_hyp3_dr_nn in 2
replace ci_high = high_hyp3_ls_c in 3
replace ci_high = high_hyp3_dr_c in 4

* Graph ATET Hypothetical3
gen str15 ate_label = ""
```

```
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_hyp3_ls_nn < 0.01, "***", cond(pval_hyp3_ls_nn < 0.05, "**", cond(pval_hyp3_ls_nn < 0.1, "*", ""))) in 1
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_hyp3_dr_nn < 0.01, "***", cond(pval_hyp3_dr_nn < 0.05, "**", cond(pval_hyp3_dr_nn < 0.1, "*", ""))) in 2
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_hyp3_ls_c < 0.01, "***", cond(pval_hyp3_ls_c < 0.05, "**", cond(pval_hyp3_ls_c < 0.1, "*", ""))) in 3
replace ate_label = string(ate, "%9.3f") + ///
    cond(pval_hyp3_dr_c < 0.01, "***", cond(pval_hyp3_dr_c < 0.05, "**", cond(pval_hyp3_dr_c < 0.1, "*", ""))) in 4

twoway ///
    (scatter ate x if shock == "landslide", msymbol(circle) mcolor(blue) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
    (scatter ate x if shock == "drought", msymbol(diamond) mcolor(green) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
    (rcap ci_low ci_high x if shock == "landslide", lcolor(blue)) ///
    (rcap ci_low ci_high x if shock == "drought", lcolor(green)) ///
    ,   title("Hypothetical 3") ///
    xlabel(none) ///
    ylabel(-0.8(0.2)0.8, angle(0) labsize(small) labcolor(black)) ///
    yscale(range(-0.8 0.8)) ///
    ytitle("Average Treatment Effect on the Treated") ///
    yline(0, lcolor(red)) ///
    legend(order(1 "Landslide" 2 "Drought") rows(1)) ///
    xscale(range(1 5.5)) ///
    xsize(6) ysize(4)

*** ATET Hypothetical 4 ***

* NN Matching
psmatch2 landslide, outcome(hyp4) pscore(score_landslide) noreplacement neighbor(1) common
scalar ate_hyp4_ls_nn = r(att)
scalar se_hyp4_ls_nn = r(seatt)
scalar low_hyp4_ls_nn = ate_hyp4_ls_nn - 1.96 * se_hyp4_ls_nn
scalar high_hyp4_ls_nn = ate_hyp4_ls_nn + 1.96 * se_hyp4_ls_nn
scalar pval_hyp4_ls_nn = 2 * (1 - normal(abs(ate_hyp4_ls_nn / se_hyp4_ls_nn)))

psmatch2 drought, outcome(hyp4) pscore(score_drought) noreplacement neighbor(1) common
scalar ate_hyp4_dr_nn = r(att)
scalar se_hyp4_dr_nn = r(seatt)
scalar low_hyp4_dr_nn = ate_hyp4_dr_nn - 1.96 * se_hyp4_dr_nn
scalar high_hyp4_dr_nn = ate_hyp4_dr_nn + 1.96 * se_hyp4_dr_nn
scalar pval_hyp4_dr_nn = 2 * (1 - normal(abs(ate_hyp4_dr_nn / se_hyp4_dr_nn)))

* Caliper Matching
psmatch2 landslide, outcome(hyp4) pscore(score_landslide) noreplacement caliper(0.010)
scalar ate_hyp4_ls_c = r(att)
scalar se_hyp4_ls_c = r(seatt)
scalar low_hyp4_ls_c = ate_hyp4_ls_c - 1.96 * se_hyp4_ls_c
scalar high_hyp4_ls_c = ate_hyp4_ls_c + 1.96 * se_hyp4_ls_c
scalar pval_hyp4_ls_c = 2 * (1 - normal(abs(ate_hyp4_ls_c / se_hyp4_ls_c)))

psmatch2 drought, outcome(hyp4) pscore(score_drought) noreplacement caliper(0.020)
scalar ate_hyp4_dr_c = r(att)
scalar se_hyp4_dr_c = r(seatt)
scalar low_hyp4_dr_c = ate_hyp4_dr_c - 1.96 * se_hyp4_dr_c
scalar high_hyp4_dr_c = ate_hyp4_dr_c + 1.96 * se_hyp4_dr_c
scalar pval_hyp4_dr_c = 2 * (1 - normal(abs(ate_hyp4_dr_c / se_hyp4_dr_c)))

* Dataset for the graph
preserve
clear
set obs 4

gen outcome = "hyp4"
```

```
gen shock = ""
replace shock = "landslide" in 1
replace shock = "drought" in 2
replace shock = "landslide" in 3
replace shock = "drought" in 4

gen method = ""
replace method = "NN" in 1/2
replace method = "Caliper" in 3/4

gen x = .
replace x = 1 in 1
replace x = 2 in 2
replace x = 4 in 3
replace x = 5 in 4

gen ate = .
replace ate = ate_hyp4_ls_nn in 1
replace ate = ate_hyp4_dr_nn in 2
replace ate = ate_hyp4_ls_c in 3
replace ate = ate_hyp4_dr_c in 4

gen ci_low = .
replace ci_low = low_hyp4_ls_nn in 1
replace ci_low = low_hyp4_dr_nn in 2
replace ci_low = low_hyp4_ls_c in 3
replace ci_low = low_hyp4_dr_c in 4

gen ci_high = .
replace ci_high = high_hyp4_ls_nn in 1
replace ci_high = high_hyp4_dr_nn in 2
replace ci_high = high_hyp4_ls_c in 3
replace ci_high = high_hyp4_dr_c in 4

* Graph ATET Hypothetical4
gen str15 ate_label = ""
replace ate_label = string(ate, "%9.3f") + ///
   cond(pval_hyp4_ls_nn < 0.01, "***", cond(pval_hyp4_ls_nn < 0.05, "**", cond(pval_hyp4_ls_nn < 0.1, "*", ""))) in 1
replace ate_label = string(ate, "%9.3f") + ///
   cond(pval_hyp4_dr_nn < 0.01, "***", cond(pval_hyp4_dr_nn < 0.05, "**", cond(pval_hyp4_dr_nn < 0.1, "*", ""))) in 2
replace ate_label = string(ate, "%9.3f") + ///
   cond(pval_hyp4_ls_c < 0.01, "***", cond(pval_hyp4_ls_c < 0.05, "**", cond(pval_hyp4_ls_c < 0.1, "*", ""))) in 3
replace ate_label = string(ate, "%9.3f") + ///
   cond(pval_hyp4_dr_c < 0.01, "***", cond(pval_hyp4_dr_c < 0.05, "**", cond(pval_hyp4_dr_c < 0.1, "*", ""))) in 4

twoway ///
   (scatter ate x if shock == "landslide", msymbol(circle) mcolor(blue) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
   (scatter ate x if shock == "drought", msymbol(diamond) mcolor(green) msize(medium) mlabel(ate_label) mlabcolor(black)) ///
   (rcap ci_low ci_high x if shock == "landslide", lcolor(blue)) ///
   (rcap ci_low ci_high x if shock == "drought", lcolor(green)) ///
   ,   title("Hypothetical 4") ///
   xlabel(none) ///
   ylabel(-0.8(0.2)0.8, angle(0) labsize(small) labcolor(black)) ///
   yscale(range(-0.8 0.8)) ///
   ytitle("Average Treatment Effect on the Treated") ///
   yline(0, lcolor(red)) ///
   legend(order(1 "Landslide" 2 "Drought") rows(1)) ///
   xscale(range(1 5.5)) ///
   xsize(6) ysize(4)
```

```
* Merge ATET graphs Spatial1 Spatial2 Temporal1 Temporal2 Social1 Social2 Hypothetical1 Hypothetical2 Hypothetical13
Hypothetical4 (Figure 7)
graph combine ///
   /Users/alexcano86/Desktop/Thesis/Stata/Dissertation/pic/spa1_atet.gph ///
   /Users/alexcano86/Desktop/Thesis/Stata/Dissertation/pic/spa2_atet.gph ///
   /Users/alexcano86/Desktop/Thesis/Stata/Dissertation/pic/temp1_atet.gph ///
   /Users/alexcano86/Desktop/Thesis/Stata/Dissertation/pic/temp2_atet.gph ///
   /Users/alexcano86/Desktop/Thesis/Stata/Dissertation/pic/soc1_atet.gph ///
   /Users/alexcano86/Desktop/Thesis/Stata/Dissertation/pic/soc2_atet.gph ///
   /Users/alexcano86/Desktop/Thesis/Stata/Dissertation/pic/hyp1_atet.gph ///
   /Users/alexcano86/Desktop/Thesis/Stata/Dissertation/pic/hyp2_atet.gph ///
   /Users/alexcano86/Desktop/Thesis/Stata/Dissertation/pic/hyp3_atet.gph ///
   /Users/alexcano86/Desktop/Thesis/Stata/Dissertation/pic/hyp4_atet.gph, ///
   cols(5) ysize(10) xsize(17) ///
         note("* p<0.10, ** p<0.05, *** p<0.010" ///
      "Balancing property satisfied:  YES" ///
      "Common support imposed:    YES" ///
      "Number of Neighbors: 1" ///
      "Caliper for landslides: 0.010" ///
      "Caliper for drought: 0.020" ///
      "Source: Authors.") ///
   title("Average Treatment Effect on the Treated")

*************************************************************************************
***                    Appendix A.2. Rosenbaum Bounds for ATET - Landslides                    ***
*************************************************************************************

qui psmatch2 landslide, outcome(sev1) pscore(score_landslide) noreplacement neighbor(1) common
gen delta = perc_sev_agri - _perc_sev_agri if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 landslide, outcome(sev1) pscore(score_landslide) caliper(0.010) noreplacement
gen delta = perc_sev_agri - _perc_sev_agri if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 landslide, outcome(sev2) pscore(score_landslide) noreplacement neighbor(1) common
gen delta = perc_sev_nare - _perc_sev_nare if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 landslide, outcome(sev2) pscore(score_landslide) caliper(0.010) noreplacement
gen delta = perc_sev_nare - _perc_sev_nare if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 landslide, outcome(sev3) pscore(score_landslide) noreplacement neighbor(1) common
gen delta = perc_sev_farmers - _perc_sev_farmers if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 landslide, outcome(sev3) pscore(score_landslide) caliper(0.010) noreplacement
gen delta = perc_sev_farmers - _perc_sev_farmers if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 landslide, outcome(vul1) pscore(score_landslide) noreplacement neighbor(1) common
gen delta = perc_vul1 - _perc_vul1 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
```

```
qui psmatch2 landslide, outcome(vul1) pscore(score_landslide) caliper(0.010) noreplacement
gen delta = perc_vul1 - _perc_vul1 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 landslide, outcome(vul2) pscore(score_landslide) noreplacement neighbor(1) common
gen delta = perc_vul2 - _perc_vul2 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 landslide, outcome(vul2) pscore(score_landslide) caliper(0.010) noreplacement
gen delta = perc_vul2 - _perc_vul2 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 landslide, outcome(vul3) pscore(score_landslide) noreplacement neighbor(1) common
gen delta = perc_vul3 - _perc_vul3 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 landslide, outcome(vul3) pscore(score_landslide) caliper(0.010) noreplacement
gen delta = perc_vul3 - _perc_vul3 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 landslide, outcome(spa1) pscore(score_landslide) noreplacement neighbor(1) common
gen delta = geo_distance1 - _geo_distance1 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 landslide, outcome(spa1) pscore(score_landslide) caliper(0.010) noreplacement
gen delta = geo_distance1 - _geo_distance1 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 landslide, outcome(spa2) pscore(score_landslide) noreplacement neighbor(1) common
gen delta = geo_distance2 - _geo_distance2 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 landslide, outcome(spa2) pscore(score_landslide) caliper(0.010) noreplacement
gen delta = geo_distance2 - _geo_distance2 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 landslide, outcome(temp1) pscore(score_landslide) noreplacement neighbor(1) common
gen delta = temp_distance1 - _temp_distance1 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 landslide, outcome(temp1) pscore(score_landslide) caliper(0.010) noreplacement
gen delta = temp_distance1 - _temp_distance1 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 landslide, outcome(temp2) pscore(score_landslide) noreplacement neighbor(1) common
gen delta = temp_distance2 - _temp_distance2 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 landslide, outcome(temp2) pscore(score_landslide) caliper(0.010) noreplacement
gen delta = temp_distance2 - _temp_distance2 if _treat==1 & _support==1
```

```
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 landslide, outcome(soc1) pscore(score_landslide) noreplacement neighbor(1) common
gen delta = social_distance1 - _social_distance1 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 landslide, outcome(soc1) pscore(score_landslide) caliper(0.010) noreplacement
gen delta = social_distance1 - _social_distance1 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 landslide, outcome(soc2) pscore(score_landslide) noreplacement neighbor(1) common
gen delta = social_distance2 - _social_distance2 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 landslide, outcome(soc2) pscore(score_landslide) caliper(0.010) noreplacement
gen delta = social_distance2 - _social_distance2 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 landslide, outcome(hyp1) pscore(score_landslide) noreplacement neighbor(1) common
gen delta = hypothetical_distance1 - _hypothetical_distance1 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 landslide, outcome(hyp1) pscore(score_landslide) caliper(0.010) noreplacement
gen delta = hypothetical_distance1 - _hypothetical_distance1 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 landslide, outcome(hyp2) pscore(score_landslide) noreplacement neighbor(1) common
gen delta = hypothetical_distance2 - _hypothetical_distance2 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 landslide, outcome(hyp2) pscore(score_landslide) caliper(0.010) noreplacement
gen delta = hypothetical_distance2 - _hypothetical_distance2 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 landslide, outcome(hyp3) pscore(score_landslide) noreplacement neighbor(1) common
gen delta = hypothetical_distance3 - _hypothetical_distance3 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 landslide, outcome(hyp3) pscore(score_landslide) caliper(0.010) noreplacement
gen delta = hypothetical_distance3 - _hypothetical_distance3 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 landslide, outcome(hyp4) pscore(score_landslide) noreplacement neighbor(1) common
gen delta = hypothetical_distance4 - _hypothetical_distance4 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 landslide, outcome(hyp4) pscore(score_landslide) caliper(0.010) noreplacement
gen delta = hypothetical_distance4 - _hypothetical_distance4 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)
```

```
************************************************************************************
***                Appendix A.3. Rosenbaum Bounds for ATET - Droughts              ***
************************************************************************************

drop delta
qui psmatch2 drought, outcome(sev1) pscore(score_drought) noreplacement neighbor(1) common
gen delta = perc_sev_agri - _perc_sev_agri if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 drought, outcome(sev1) pscore(score_drought) caliper(0.020) noreplacement
gen delta = perc_sev_agri - _perc_sev_agri if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 drought, outcome(sev2) pscore(score_drought) noreplacement neighbor(1) common
gen delta = perc_sev_nare - _perc_sev_nare if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 drought, outcome(sev2) pscore(score_drought) caliper(0.020) noreplacement
gen delta = perc_sev_nare - _perc_sev_nare if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 drought, outcome(sev3) pscore(score_drought) noreplacement neighbor(1) common
gen delta = perc_sev_farmers - _perc_sev_farmers if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 drought, outcome(sev3) pscore(score_drought) caliper(0.020) noreplacement
gen delta = perc_sev_farmers - _perc_sev_farmers if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 drought, outcome(vul1) pscore(score_drought) noreplacement neighbor(1) common
gen delta = perc_vul1 - _perc_vul1 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 drought, outcome(vul1) pscore(score_drought) caliper(0.020) noreplacement
gen delta = perc_vul1 - _perc_vul1 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 drought, outcome(vul2) pscore(score_drought) noreplacement neighbor(1) common
gen delta = perc_vul2 - _perc_vul2 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 drought, outcome(vul2) pscore(score_drought) caliper(0.020) noreplacement
gen delta = perc_vul2 - _perc_vul2 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 drought, outcome(vul3) pscore(score_drought) noreplacement neighbor(1) common
gen delta = perc_vul3 - _perc_vul3 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 drought, outcome(vul3) pscore(score_drought) caliper(0.020) noreplacement
gen delta = perc_vul3 - _perc_vul3 if _treat==1 & _support==1
```

```
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 drought, outcome(spa1) pscore(score_drought) noreplacement neighbor(1) common
gen delta = geo_distance1 - _geo_distance1 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 drought, outcome(spa1) pscore(score_drought) caliper(0.020) noreplacement
gen delta = geo_distance1 - _geo_distance1 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 drought, outcome(spa2) pscore(score_drought) noreplacement neighbor(1) common
gen delta = geo_distance2 - _geo_distance2 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 drought, outcome(spa2) pscore(score_drought) caliper(0.020) noreplacement
gen delta = geo_distance2 - _geo_distance2 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 drought, outcome(temp1) pscore(score_drought) noreplacement neighbor(1) common
gen delta = temp_distance1 - _temp_distance1 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 drought, outcome(temp1) pscore(score_drought) caliper(0.020) noreplacement
gen delta = temp_distance1 - _temp_distance1 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 drought, outcome(temp2) pscore(score_drought) noreplacement neighbor(1) common
gen delta = temp_distance2 - _temp_distance2 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 drought, outcome(temp2) pscore(score_drought) caliper(0.020) noreplacement
gen delta = temp_distance2 - _temp_distance2 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 drought, outcome(soc1) pscore(score_drought) noreplacement neighbor(1) common
gen delta = social_distance1 - _social_distance1 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 drought, outcome(soc1) pscore(score_drought) caliper(0.020) noreplacement
gen delta = social_distance1 - _social_distance1 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 drought, outcome(soc2) pscore(score_drought) noreplacement neighbor(1) common
gen delta = social_distance2 - _social_distance2 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 drought, outcome(soc2) pscore(score_drought) caliper(0.020) noreplacement
gen delta = social_distance2 - _social_distance2 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)
```

```
drop delta
qui psmatch2 drought, outcome(hyp1) pscore(score_drought) noreplacement neighbor(1) common
gen delta = hypothetical_distance1 - _hypothetical_distance1 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 drought, outcome(hyp1) pscore(score_drought) caliper(0.020) noreplacement
gen delta = hypothetical_distance1 - _hypothetical_distance1 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 drought, outcome(hyp2) pscore(score_drought) noreplacement neighbor(1) common
gen delta = hypothetical_distance2 - _hypothetical_distance2 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 drought, outcome(hyp2) pscore(score_drought) caliper(0.020) noreplacement
gen delta = hypothetical_distance2 - _hypothetical_distance2 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 drought, outcome(hyp3) pscore(score_drought) noreplacement neighbor(1) common
gen delta = hypothetical_distance3 - _hypothetical_distance3 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 drought, outcome(hyp3) pscore(score_drought) caliper(0.020) noreplacement
gen delta = hypothetical_distance3 - _hypothetical_distance3 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 drought, outcome(hyp4) pscore(score_drought) noreplacement neighbor(1) common
gen delta = hypothetical_distance4 - _hypothetical_distance4 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)

drop delta
qui psmatch2 drought, outcome(hyp4) pscore(score_drought) caliper(0.020) noreplacement
gen delta = hypothetical_distance4 - _hypothetical_distance4 if _treat==1 & _support==1
rbounds delta, gamma(1 (0.5) 2)
```

A.3: Questionnaire

We are conducting a study on adaptation to climate change in the central region of Colombia. The questions in the questionnaire are mostly multiple-choice. The information you provide is strictly confidential and will be used only for the purposes of the study and will not be shared with anyone outside the project. The estimated time to answer the questionnaire is 30 minutes. We appreciate your participation.

Municipality: __________________
Village: __________________

Emergency:
☐ None
☐ Landslide
☐ Drought

Farm Id: _____

I. General Farmer Information:

1. Your position on the farm(s):
   ☐ Owner
   ☐ Tenant
   ☐ Manager
   ☐ "Agregado"
   ☐ Other ¿which one? _______________

2. What is your age? ________ years

3. Which gender do you identify with?
   ☐ Masculine
   ☐ Feminine
   ☐ Other

4. What is your marital status?
   ☐ Single
   ☐ Married
   ☐ Living together
   ☐ Divorced
   ☐ Separated
   ☐ Widowed

II. General Information on the Farm:

5. What is the size of the farm? ______
   Measurement Unit:
   ☐ Hectares

☐ Cuadras
☐ Square meters

6. Do you own the farm?
☐ Yes
☐ No

7. Do you have crops?
☐ Yes
☐ No (If your answer is no, skip to question 5)

8. Please state the five (5) main crops grown on your farm and the area planted:
Crop 1: _____________ Area _____ ☐ Hect ☐ Cuadras ☐ m^2
Crop 2: _____________ Area _____ ☐ Hect ☐ Cuadras ☐ m^2
Crop 3: _____________ Area _____ ☐ Hect ☐ Cuadras ☐ m^2
Crop 4: _____________ Area _____ ☐ Hect ☐ Cuadras ☐ m^2
Crop 5: _____________ Area _____ ☐ Hect ☐ Cuadras ☐ m^2

9. Do you have animals?
☐ Yes
☐ No (If your answer is no, skip to question 7)

10. What type of animals are they and how many do you have?
Cows: ☐ Yes ☐ No How many? ________
Pigs: ☐ Yes ☐ No How many? ________
Chickens: ☐ Yes ☐ No How many? ________
Another: ☐ Yes ☐ No Which one? ________ How many? _____
Another: ☐ Yes ☐ No Which one? ________ How many? _____
Another: ☐ Yes ☐ No Which one? ________ How many? _____

11. How many people work on the farm (including family)? _________

12. On your farm is there a spring or do you have access to a stream or river?
☐ Yes
☐ No

13. On your farm is there a forest, part of a forest or a guadual?
☐ Yes
☐ No

III. Psychological Distance

With your finger indicate how much you agree with the following statements. 1 is “completely disagree” and 5 is “completely agree”.	**1**	**2**	**3**	**4**	**5**
Climate change is affecting this village.					

Climate change is indeed affecting other villages, but NOT this village.					
The effects of climate change are happening right now.					
The effects of climate change are going to happen in the future, but they are NOT happening right now.					
Climate change is going to affect farmers like me.					
Climate change is going to affect other farmers but not me.					
Climate change is already affecting me.					
I am not sure that climate change is really happening.					
Landslides are a consequence of climate change.					
Droughts are a consequence of climate change.					

IV. Perceptions

With your finger indicate how negative you think the consequences of climate change are about: 1 is "not at all serious" and 5 is "very serious".	**1**	**2**	**3**	**4**	**5**
Your farm's agricultural operations.					
The natural resources of the village.					
Other farmers in the village.					

With your finger indicate how much this concerns you on a weekly basis: 1 is "very little" and 5 is "a lot".	**1**	**2**	**3**	**4**	**5**
Thinking about climate change.					
Being affected by the negative effects of climate change.					
Negative effects on their agricultural activities.					

V. Perceived Costs

With your finger indicate how much you agree with the following statements: 1 is "completely disagree" and 5 is "completely agree".	**1**	**2**	**3**	**4**	**5**
Taking measures to mitigate the negative effects of climate change costs a lot of money.					
Taking action to mitigate the negative effects of climate change takes a long time.					

Even if I had the money and the time, I do not want to change the way I work to mitigate climate change.					

14. What things limit you when making decisions on your farm (e.g., money, time, size of the farm, number of workers, climate)?

____

____

____

VI. Efficiencies

Protection of Water Sources					
Do you protect water sources on your farm?	☐ Yes ☐ No				
With your finger indicate how much you agree with the following: 1 is “very little” and 5 is “very much”.	**1**	**2**	**3**	**4**	**5**
Protecting water sources helps climate change do less damage to my farm.					
If you could, you are able to protect water sources.					
How much do you want to protect water sources?					
Why?					

Agroforestry or Agrosilvopastoral Practices					
Do you do agroforestry or agrosilvopastoral practices?	☐ Yes ☐ No				
With your finger indicate how much you agree with the following: 1 is “very little” and 5 is “very much”.	**1**	**2**	**3**	**4**	**5**
Agroforestry or agrosilvopastoral practices help to reduce the damage caused by climate change on my farm.					
If you could, you are capable of agroforestry or agrosilvopastoral practices.					
How much do you want to have agroforestry or agroforestry practices?					
Why?					

Soil Coverage					
Do you have plants or cover crops on your farm?	☐ Yes ☐ No				
With your finger indicate how much you agree with the following:	**1**	**2**	**3**	**4**	**5**

1 is “very little” and 5 is “very much”.					
Having soil covers helps to reduce the damage climate change can do on my farm.					
If you could, you are able to have soil covers.					
How much do you want to have soil cover?					
Why?					

Retaining walls (bioengineering) or “Trinchos”					
Do you have retaining walls or trinchos on your farm?	☐ Yes ☐ No				
With your finger indicate how much you agree with the following: 1 is “very little” and 5 is “very much”.	**1**	**2**	**3**	**4**	**5**
Having retaining walls or trinchos helps to reduce the damage climate change can do on my farm.					
If you could, you are able to have retaining walls or trinchos.					
How much do you want to have retaining walls or “trinchos”?					
Why?					

Diversify off-farm income					
Do you have other income outside the farm?	☐ Yes ☐ No				
With your finger indicate how much you agree with the following: 1 is “very little” and 5 is “very much”.	**1**	**2**	**3**	**4**	**5**
Having off-farm income helps to make climate change less damaging to my farm.					
If you could, you are able to have off-farm income as protection from climate change.					
How much do you want to have off-farm income as protection from climate change?					
Why?					

Borrow money from a financial institution or purchase some type of insurance					
Do you have a loan with any financial institution or any type of insurance that protects you from weather events?	☐ Yes ☐ No				
With your finger indicate how much you agree with the following: 1 is “very little” and 5 is “very much”.	**1**	**2**	**3**	**4**	**5**
Borrowing money from financial institutions or having insurance will help to reduce the damage					

climate change will do to my farm.					
If you could, you are able to borrow money from financial institutions or have insurance against weather events.					
How much do you want to borrow money from financial institutions or have insurance against weather events?					
Why?					

Borrowing money from a family member, friend, or neighbor					
Have you ever borrowed money from a family member, friend or neighbor as a result of a weather event?	☐ Yes ☐ No				
With your finger indicate how much you agree with the following: 1 is "very little" and 5 is "very much".	**1**	**2**	**3**	**4**	**5**
Borrowing money from family, friends or neighbors helps to make climate change do less damage to my farm.					
If you could, you are able to borrow money from family, friends or neighbors to protect yourself from weather events.					
How much do you want to borrow money from family, friends or neighbors to protect yourself from weather events?					
Why?					

VII. Financial Literacy[1]

15. Risk Diversification: Suppose you have some money. Is it safer to put your money into one single business or investment, or into multiple businesses or investments?
    a. One business or investment
    b. Multiple businesses or investments
    c. Don't know
    d. Chose not to answer

16. Inflation: Suppose that over the next 10 years, prices of the things you buy double. If your income also doubles, will you be able to buy less than you can buy today, the same as today, or more than today?
    a. Less
    b. The same
    c. More
    d. Don't know
    e. Chose not to answer

[1] S&P's Ratings Services, Gallup, Inc., the World Bank Development Research Group, and the Global Financial Literacy Excellence Center on the S&P Global FinLit Survey. https://gflec.org/sp-global-finlit-survey-methodology/)

17. Numeracy (Interest): Suppose you need to borrow 100,000 pesos and are offered two loan options. One charges 3% interest. The other requires you to pay back 105,000 pesos. Which one do you prefer?
    a. 105,000 pesos
    b. 100,000 pesos plus 3 percent
    c. Don't know
    d. Chose not to answer

18. Compound Interest: Suppose you deposit money in the bank for two years and the bank agrees to add 15% annually to your account. Will the bank add more money to your account in the second year than in the first, or the same amount both years?
    a. More
    b. The same
    c. Don't know
    d. Chose not to answer

VIII. General Farmer Information

19. How many years of formal education have you completed so far? _______________

20. What is your highest level of education attained?

☐ None
☐ Primary school
☐ High School
☐ Technician or technologist
☐ University
☐ Graduate

21. How many people live on the farm? _______________
22. How many years have you lived in the municipality? _______________

23. What is your monthly income?

☐ Less than 1 smmlv[2].
☐ Between 1 and up to 2 smmlv.
☐ Between 2 and up to 4 smmlv.
☐ 4 smmlv or more.

24. Does all of your income come from the farm?

☐ Yes (If yes, go to question 22)
☐ No

25. Please indicate what other sources of income you have:

☐ Work on other farms.
☐ Non-agricultural work.
☐ Leases
☐ Remittances.
☐ Other ¿which one? ___________

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[2] Salario Mínimo Mensual Legal Vigente (Minimum Legal Monthly Salary in Effect in English).

26. Are you generally a risk[3]-averse person, i.e. you try to avoid risk, or are you a risk-seeker, i.e. you are willing to take risk? Please, on a scale of 1 to 10, where 1 is that you do not like risk at all and 10 is that you like risk a lot, say how you perceive yourself to be.

1	2	3	4	5	6	7	8	9	10

[3] Risk has to do with uncertainty or not being sure what the outcome of something is going to be. For example, you plant a crop, but you are not sure if the harvest will be as expected because there may be pests, bad weather, or the soil or seeds were not the best. Or for example you expect to sell the crop at a price, but there is no certainty that when you go to sell that will be the price.
Source: Economic Research Service, U.S. Department of Agriculture. https://www.ers.usda.gov/topics/farm-practices-management/risk-management/risk-in-agriculture/

A.4: Semi-Structured Interviewed Protocol

In-depth Interview Guide for Farmers on Climate Change Perceptions and Adaptive Behavior

This semi-structured interview protocol was used to explore farmers' experiences, perceptions, and responses related to climate change. The interview is divided into thematic sections: general background, vulnerability, climate change perception, adaptive behavior, and open reflections. Interviews were conducted in Spanish and later transcribed and translated for analysis.

A. General Background

Objective: Understand the respondent's history, context, and social dynamics in the community.

1. At what age did you begin working in agriculture?
2. Have you always lived in this region? If not, where else have you lived?
3. Since you started working in agriculture, how has farming changed? For example, the crops you grow, how you plant, the use of fertilizers or pesticides.
4. In this village, how is the relationship between farmers? Is there any kind of association? Do people talk to each other, or only with neighbors? Do you have a WhatsApp® group?

B. Perceived Vulnerability

Objective: Capture concerns, exposure to climate risks, and access to support mechanisms.

5. In general, what worries you the most at this moment?
6. Have you experienced any extreme weather events, such as droughts, floods, landslides, strong winds, hailstorms, or frost? What do you remember about it?
7. How did this event affect you personally and in your farm work?
8. Did you receive any kind of assistance? What did they give you? From whom? How was it distributed?
9. Are you worried that this kind of event could happen again?
10. Do you know someone else who experienced an extreme weather event? What do you remember about it? How did it affect them personally and their farm work? Did they receive any assistance? From whom? How was it distributed?

C. Climate Change Perception

Objective: Understand how farmers perceive and interpret climate change and its effects.

11. Since you began working in agriculture, have you noticed any changes in the climate? If yes, how has it changed?
12. Do you think these climate changes have been good or bad for you?
13. If you think they have been good, why?
14. If you think they have been bad, why?

D. Adaptive Behavior

Objective: Identify individual and collective actions taken in response to climate change.

15. What have you done to take advantage of the "good" climate changes? Why did you decide to do that?
16. What have you done to cope with the "bad" climate changes? Why did you decide to do that?
17. Have you ever talked about climate change with other people? With whom and why? What did you discuss? Did you decide to take any action as a result? What kind of action?
18. Have you observed what other farmers are doing to adapt to climate change? What have you seen them do?
19. Have you adopted or replicated anything they are doing? Why or why not?
20. If you had the financial resources, what would you like to change on your farm?
21. Why would you like to make that change?
22. If you were the leader of your village, what would you change to improve living conditions in your community?

E. Final Reflections

Objective: Provide space for additional experiences and suggestions.

23. Would you like to share a personal story about your experience with climate change that we haven't talked about yet?
24. Is there anything else you think is important that we haven't discussed and that could improve your quality of life on the farm?