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Are Risk Attitudes and Rainfall Variability Determinants of Diversification? Evidence from Rondonia, Brazil

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ARE RISK ATTITUDES AND RAINFALL VARIABILITY DETERMINANTS OF DIVERSIFICATION? EVIDENCE FROM RONDONIA, BRAZIL

by

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Risk exposure and management are inherent to smallholder farmers. One of the risks they face is climate change. Climate change decreases rainfall, increases frequency of drought, adds heat stress to crops from higher temperatures, and leads to higher rainfall variability. The threat of rainfall variability causes higher production in some years and lower in others. Even if the average income remains the same, people's welfare is reduced by the variability and the size of the loss will depend on their attitudes towards risk.

Diversification is one adaption strategy that may help reduce climate risk. Diversified farmers produce multiple types of crops, sell things like milk and livestock, or look to off-farm sources like jobs or rental income. Rainfall variability is one risk that may continue to grow as the earth faces higher rates of climate change. It is useful to understand how farmers adapt to this risk as they face potentially even higher variabilities in their seasonal rainfall. Looking into how households make decisions based on their own risk tolerance and increasing environmental risk will aid policy makers in crafting policy to alleviate the burden on smallholder farmers.

Farmer's likelihood to adopt a diversification strategy in the face of increased rainfall variability could depend on their attitudes towards risk. People will have different risk tolerance, with some more naturally open to risks, others more averse. This paper uses Ordinary Least Squares and Poisson regression analysis to answer how rainfall variability and risk attitudes impact diversification.

The results of this analysis show that both risk attitudes and rainfall variability have a statistically significant impact on the diversification level of smallholder farmers in Rondônia, Brazil. Additionally, I find that the rainfall variability during the dry season as well as the length of the dry season are more important in determining diversification than rainfall variability during the entire year or the wet season. I find that the interaction between risk attitudes and rainfall variability is significant, but the effects are not significantly different from one another. These results suggest that as we continue to see increased climate change, we will see farmers move towards diversification.

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1. Introduction

Understanding how farmers make decisions regarding their land use is of interest to both policy makers and scientific communities (Nguyen et al., 2016). This importance stems from the need to ensure global food security as the population continues to grow. This remains one of the largest challenges in development (de Janvry & Sadoulet, 2010). The crop production of smallholder farmers in developing nations is directly impacted by climate variability (Thulstrup, 2015). Climate change is leading to an increase in extreme weather events that affect farmers who depend on agricultural production for their sustained livelihoods (McCord et al., 2015). One way that farmers can protect themselves from climate variability is to diversify their income sources (Mitter et al., 2015). Farmers diversify their income and reduce production risks through constructing a diverse portfolio of activities and assets (Hussein & Nelson, 1999; Ellis, 2000). Studies have found that this strategy allows farmers to reduce risks of food and nutrition insecurity (Mango et al., 2018) as well as to help offset the risks of climate change and market price (McNamara & Weiss, 2005). However, the degree of diversification is different from farmer to farmer (Birthal et al., 2014) because of differences in the way they perceive climate change and the production capacity (Stuart et al., 2014; Arouri et al., 2015). For this reason, it is useful to understand factors that impact farmers decision making and their perceptions of climate risks to create future policies to protect smallholder farmers. My work will specifically illuminate the relationship between risk attitudes, rainfall variability and farmers diversification decisions in Rondônia, Brazil.

A better understanding of the effect of rainfall on diversification will offer the foundation into understanding how farmers are adapting to climate change. Understanding this effect will help to predict when and where we will start to see higher rates of diversification due to changing levels of rainfall variability. People naturally vary in how willing they are to accept or seek out risk. This risk willingness differs between farmers. Examining its impact on diversification decisions will help to understand why we may not see all farmers adopt a diversification strategy in the face of increased climate risks. Understanding what determines their behavior is the first step in finding a way to protect their livelihoods for future generations.

This study aims to answer two questions. First, how rainfall variability and the relative risk tolerance of individual farmers impact diversification decisions? Research has argued that diversification may be a good insurance mechanism for farmers facing production risk through crop failure due to increased rainfall variability (Bezabih & Sarr, 2012). Therefore, I hypothesize that increased rainfall variability will be associated with increased levels of diversification as farmers attempt to shield themselves from the potential loss of production and income. Previous research has found that climate change and rainfall variability can impact farm income which leads to falling below the threshold of survival (Mirza 2003, Kahan 2008, Perry et al., 2004, Ndamani & Watanabee 2015). A decrease in annual production lowers farmers' incomes and can further threaten their stability. This increase of climate risks impacts farmers differently dependent on their risk attitudes. There is a growing body of literature surrounding how farmers respond and adapt to increased climate risks. Ali (2019) finds that a risk averse farmer who faces increased rainfall variability will allocate less labor into farming activities and instead move into other sources of income. This conclusion supports my hypothesis that relatively risk intolerant farmers will have a higher level of diversification than farmers who are more risk accepting. Understanding how changes in rainfall impact diversification decisions made by farmers can provide useful information for how to promote food production and fight against poverty in developing nations (Nguyen et al., 2016).

Standard economic theory states that the tendency to diversify income portfolio is driven by the individual risk preferences of the decision markers (Bezabih and Sarr, 2012). Research has found that in general, farmers will show some degree of risk aversion (OECD, 2009; Sulewski & Kloczko-Gajewska 2014; Meuwissen et al., 2001). I hypothesize that farmers who are less willing to take risks will tend to exhibit higher levels of diversification. This strategy offers lower variability in income. However, because a farmer is participating in additional activities outside of the one with the highest income return, they may receive lower income on average. A farmer who dislikes risks and variability should be willing to make this tradeoff.

Second, I aim to answer whether the impact of rainfall variability depends on the farmers general willingness to take risks. Fafchamps (1992) argues that risk exposure will affect farmers production choices and will depend on farmers attitudes towards risks. For that reason, I believe that increases in rainfall variability should have the highest impact on farmers who are relatively less risk tolerant.

Previous research has focused on the relationship between risk aversion and the level of crop diversification seen within a farming household (e.g., Bezabih & Sarr, 2012; Sarwosri & Musshoff, 2020). Others have focused outside of crop portfolios and looks at the impact of risk attitudes on farmers' decision to pursue income in off-farm activities like working in town, owning their own business, or managing rental properties (e.g., Krause 2019, Alemayehu 2018). The goal of this paper is to combine the previous research areas and adopt a broader definition of diversification to include crops, production of other goods, and any income obtained through off-farm work. This study expands on the work of Bezabih and Sarr (2012). They focused on climate risk in the form of rainfall and individual risk preferences' impact on crop diversification decisions. I will investigate specifically the impact of individual risk preferences and rainfall variability on all three types of diversification: crop, other on-farm production, and off-farm. This work will contribute to the literature on farm management as well as climate change through a better understanding into how rainfall variability and risk attitudes impact the diversification levels of smallholder farmers. In addition, I examine the interaction between risk attitudes and rainfall variability to determine whether increased rainfall variability has a greater effect dependent on farmers' individual risk attitudes.

This study expands the existing literature in terms of geographic area. Most of the existing literature is focused on smallholder farmers who reside in Africa (e.g Bizabih & Sarr, 2012; Alemayehu et al., 2018; Makate et al., 2016; Asravor, 2018; Ochieng et al., 2020), or India (e.g., Bandyopadhyay & Skoufias, 2015; Skoufias 2017; Sarwosri & Musshoff, 2020). Relatively no research has been done concerning the smallholder farmers of South America. South America is an area very susceptible to the impacts of climate change and home to many agrarian farmers.

To answer these questions, I use a data set from a survey conducted in 2019 by the Connections Between Water and Rural Production Project. This data covers smallholder farmers located in Rondônia, Brazil. This data set contains 1,267 observations from farming households who answered a question regarding their general willingness to take risks, as well as other questions regarding crop portfolio, non-agricultural production, lot, and household characteristics as well as a variety of other questions. I use this data to generate a diversification index, modeled after Simpson's Diversification Index. I then run Ordinary Least Squares and Poisson regressions to estimate the effect of risk attitudes and the variation of rainfall on the index. To test whether the impact of rainfall variability varies dependent on risk attitudes, I run additional regressions with an interaction term.

The findings of this analysis suggest that both rainfall variability and relative risk tolerance contribute to an increased level of diversification for smallholder farmers in Rondônia, Brazil. The effect of relative willingness to take risks is less significant compared to the effect of rainfall variability. In addition, I find that the rainfall variability during the dry season as well as the length of the dry season are more important in determining diversification decisions than rainfall variability during the entire year or the wet season. Additionally, I find that the interaction between risk attitudes and rainfall variability are not significantly different from one another. Therefore, the impact of increased rainfall variability does not vary based on a respondent's risk attitudes.

There are two important implications of this work. First, increased climate risks, measured by rainfall variability, are causing farmers to increase their rates of diversification. This means that they are not pursuing the higher average income associated with specialization. The lower income levels associated with diversification prevent farmers from being able to reinvest their income into newer and more productive technologies. This slows the progress of the agricultural industry and keeps the farmers at lower income and production levels. Second, this research shows that farmers are diversifying because they dislike the variability income that is associated with specialization. To alleviate some of that variability, policy makers could explore insurance mechanisms like crop insurance that would protect the farmers from income loss and reduce the need for diversification.

The paper is structured as follows: Section 2 sets up the theoretical model used for this analysis. Section 3 discusses the previous literature regarding the impact of relative risk attitudes and rainfall on diversification decisions. The data and study region are described in Section 4.

Section 5 lays out the empirical methodology. Section 6 details the results of regression analysis and Section 7 discusses the conclusions that can be made from my analysis.

2. Theoretical Model

Small-scale farmers tend to adopt different farming strategies with the goal of maintaining their livelihoods. Two opposing strategies that are often debated are diversification and specialization. Specialization is defined as the process of concentrating resources (labor, capital, and land) on producing one good (Abson, 2019). Under this strategy, farmers typically produce high value crops (HVCs) (Ali and Abedullah, 2002, Barghouti et al., 2004, Joshi et al., 2004, Weinberger and Lumpkin, 2007). The argument for this strategy is that by specializing in high value crops, farmers will be able to maximize their average profit and consumption at the end of a cropping season and lower the poverty rate among households (Birthal et al., 2015). However, this strategy also increases variability for farmers. Some seasons they will lose part or all their crops due to outside factors like climate, market prices, etc. Under a diversification strategy, farmers will grow multiple crops or participate in multiple sources of income to reduce risks and variability in income (Hussein & Nelson, 1999). Under this model, farmers can choose from a variety of income options. The main three being: crop, other on-farm activities like livestock and other forest products, and off-farm work. This lowers their average profit and consumption, but also reduces their variability. This is because they have other sources of income to fall back on if one fails during a season. Having multiple sources of income is only helpful for reducing risk if the variation in those sources is uncorrelated or at least not highly correlated. For production of crops, the variation may have a higher rate of correlation. Crops will tend to need similar amounts of inputs like sunlight, rainfall, fertilization ect. However, diversifying into agroforestry, livestock, or off-farm income will likely have a lower correlation as the inputs vary. Having uncorrelated income sources will have greater benefits for the farmer and result in higher rates of risk reduction.

These farm management strategies could be pursued in an attempt by the household to either increase average profit and consumption or to reduce variability depending on their individual preferences. A specialization strategy implies higher levels of risk. A household that grows only one high value product faces a higher chance of losing their entire consumption if it is a bad season. A diversified household will allocate resources into activities that do not produce the highest rate of expected consumption return. However, they are more protected from risk which could provide the household with higher levels of stability and certainty. The following section will construct a farm household model to understand the household's decisions, and the benefits of certainty.

2.1: Farm Household Model

Following the model in Caviglia-Harris (2004), the production decisions of the farming household are modeled in the expected utility maximization framework. Smallholder farmers seek to maximize their utility due to market imperfections and leisure choices that can involve tradeoffs between consumption and leisure time. According to this model, a household will maximize its expected utility based on the consumption of goods (C), and leisure (L_L) through the choice variables: labor (L) and land allocation (D). The labor time of the household is split between three possible activities: agriculture (L_A), off-farm or wage employment (L_W) and leisure (L_L). The household's utility function can be modeled by:

$$U=U\ (C, L_L; H)\}$$

Where C is the household's consumption of goods, L_L is leisure and H is a variety of household characteristics, including risk attitudes. Their utility function is constrained by the budget for household consumption, which is a function of agricultural revenue ($P_A Q$), input costs ($P_N N$)and off-farm income ($L_W W$).

Max (L, D) E {U (C, L_L; H)}

Subject to C $\leq$ $((P_A Q \ - P_N N) \ + \ L_W W; \Psi)$

L = $\Sigma L_{Ai} + L_W + L_L$

D = ΣD_i

Where E is the expectations operator, U is the households utility function, D is the household land endowment, and where *i* are the different possible uses of land e.g., crops, pasture, forest. L is household labor endowment, divided between different on farm activities, like crops, livestock, and other production (L_{Ai}), wage labor (L_W), and leisure (L_L). N is equal to agricultural inputs, P_N is a matrix of input prices, W is the wage for off-farm labor, H is the household characteristics, $P_A$is a matrix of agricultural good prices, Q is a matrix of quantities of agricultural goods harvested (agricultural production), and Ψ is the degree of risk impacting agricultural production and labor opportunities.

Due to the household labor constraint, off-farm labor serves as a substitute for agricultural production. The household may participate in different activities such as cropping, other on-farm production, or finding work off the farm. The total output of the farm will be dependent on what they decide to allocate their labor to. Their decision lies in where to allocate their labor and land.

In this model, farming households will decide on a combination of labor, leisure, and land-use to maximize their utility (U). Risk, arises due to outside factors like price variability, health, and climate change risks like increased rainfall variability. Diversification offers risk averse households a lower variability in consumption. Environmental risk poses the threat of exterminating farmers' crops or resulting in lower yields. One way to reduce this risk is by diversifying crops and / or other on-farm production like livestock to include a greater variety of goods (crop and production diversification) or to diversify their income sources through participation in off-farm labor markets (off-farm diversification). This is a tradeoff and while it does reduce variability it may also reduce the total consumption of the household.

Under a specialization strategy a farmer will only grow one crop of the highest value. This will increase their average production which in turn increases their average income. In some years, however, outside factors like market changes or climate risks will cause the farmer to not be able to sell this crop. So, while specialization is the strategy that offers the highest level of average production and income, it carries a higher level of risk.

Farmer's willingness to take risks will impact whether they value the higher average income and production under specialization or the lower variability under diversification. A farmer who is more willing to take risks in theory prefers a specialization strategy because it offers them the highest level of consumption and utility. This is because they are less concerned with the potential risk of losing crops. Farmers who are less willing to take risks, however, are more likely to pick a diversification strategy, despite the lower levels of income and consumption, because in return they receive higher levels of certainty and less risk. Whether or not farmers are willing to make this tradeoff will depend on how they value consumption and variability in their utility function. In both cases, farmers are trying to maximize their utility. How they decide to do this will depend on their individual risk attitudes.

Climate changes, like rainfall variability, increase the risks faced by smallholder farmers. Without consistent rain, the risk of losing crops is even higher. Based on these assumptions, I hypothesize that levels of diversification should increase both when willingness to take risks decreases and rainfall variability increases. In addition, I hypothesis that the impact of increased rainfall variability should have a higher impact on the diversification levels of farmers who are less willing to take risks than on the farmers who responded that they are more willing to take risks. This paper will explore these assumptions to evaluate the strength of these hypothesizes and the extent of the relationship between risk attitudes, rainfall variability and diversification.

3. Literature Review

Agricultural production is usually a risky business, and those risks can be particularly burdensome to smallholder farmers in developing countries (Hazell and Norton, 1986). Other research has studied some of the general characteristics of farms belonging to risk averse individuals like they tend to be the smallest farms in the study area and on average use more pesticides (Sulewski & Kloczko-Gajewska 2014; Pan et al., 2020). Risk aversion can also determine things like involvement in agri-environmental programs and whether some of the family works in town (Van Winsen et al., 2016; Dörschner & Musshoff 2013). The more relevant finding, however, is that most risk averse farmers do tend to opt for a “mixed farm” or diversification strategy (Sulewski & Kloczko-Gajewska 2014).

Farmers need to adopt risk management and risk coping strategies. Hazell and Norton (1986) found that farmers typically prefer farm plans that provide a certain level of security even if that means they must sacrifice higher levels of income. In the farming risk literature, the risk-balancing hypothesis states that whenever there are changes in risk conditions, expected utility maximizing farmers might opt to make offsetting adjustments in the firm's financial structure (Gabriel and Baker; Barry; Barry and Robinson). Escalante and Barry (2001) find that highly risk averse farmers do tend to opt for integrated risk-management plans. They find that these plans are largely based on diversification principles and are made up of a combination of risk-reducing and profit generating strategies. Their research concludes that as farmers become increasingly risk averse, they will opt for a more diversified production portfolio. This results in the least variability and still sustains strong profitability (Escalante & Barry 2001).

One source of risk that smallholder farmers face most frequently is climate. Smallholder farmers living in relatively poor countries are some of the most vulnerable to climate change. As climate change continues to increase, it is important to understand how farmers adapt to these increased risks as they will undoubtedly continue to battle the uncertainty of climate change. Climate risks may present themselves in a variety of forms. One of the most detrimental changes to farmers is water and rainfall. Water related risks may take the form of flash floods, reduced water availability, and higher rainfall variability. Studies have found that areas which see abnormal increases in rainfall see increases in pest resurgence which can damage crops and reduce level of consumption (Tefera 2012). Farmers have seen an increase in pre-harvest crop losses due to these pests and delayed planting times due to increased flooding. In addition, they've seen increased post-harvest losses from poor storage and livestock death (Waha et al., 2012). A reduction in the level of rainfall per year can result in other losses for farmers. Inadequate levels of rainfall can lead to reduced crop harvests as they are not receiving enough rain to reach full growing potential or dying off midseason. It can also lead to decreased livestock productivity. This results in partial or total crop failure (Jones and Thornton 2003; Tubiello et al. 2007; Mader et al. 2009; Knox et al. 2012).

In the face of increased climate risk, farmers may adopt different farming strategies to protect themselves. Diversification is one farming strategy that has been explored as an adaptation to increasing climate risk. Existing studies have found that as rainfall patterns become more variable and water resources are depleted, the risks associated with a less diversified crop portfolio are bound to increase (Ochieng et al., 2020). Much research has been done to test this theory in practice. The existing research has found diversification to be a beneficial strategy for battling increased climate variability.

Researchers have found that increased climate variability is pushing smallholder farmers into diversification. Skoufias et al. (2017) found a strong correlation between rainfall variability and off-farm income diversification. They argue that this is an example of an ex-ante push factor rather than the pull of higher potential earnings of the non-agricultural sector. Push factors force households to allocate labor and time to more activities as a means of survival or as a coping strategy (Haggblade 2007). The pursuit of off-farm income diversification has been argued to be an essential piece for smallholder farmers facing the risks of rainfall variability (Asravor 2018). Bandyopadhyay et al. (2015) comes to a similar conclusion. They state that while off-farm diversification is typically viewed as a pull factor, their analysis shows that households in Bangladesh are being pushed into off-farm income diversification as an adaptation strategy against the risk of local rainfall variability. These findings suggest that the decision to diversify is a survival led decision, and that it may be one of the few strategies smallholder farmers have to combat climate risks.

Bezabih and Sarr (2012) also measure the impact of rainfall variability on the diversification decisions of smallholder farmers. They find that spring rainfall is crucial to the cropping decisions of farmers and that summer rainfall has less of an impact. They hypothesize that this is because spring rainfall, more than summer rainfall, greatly impacts the early growing stages of crops. My research will expand on their study through an understanding of how rainfall variability during key periods impacts the diversification decisions of smallholder farmers in Rondônia, Brazil. Their study is unique because it is one of the few studies that incorporates individual risk preferences as a determinant for diversification. They conduct a hypothetical risk experiment using a lottery choice design like that of Holt and Laury (2002) to elicit risk preferences. Their study finds weak evidence that personal risk aversion is an important determinant of crop diversification. This relationship has received little attention (Alemayehu et al., 2018). I hope to add to the understanding of how willingness to take risks impacts diversification of not only crops but of all activities. This understanding could aid policy makers looking to increase the livelihoods of relatively poor smallholder farmers.

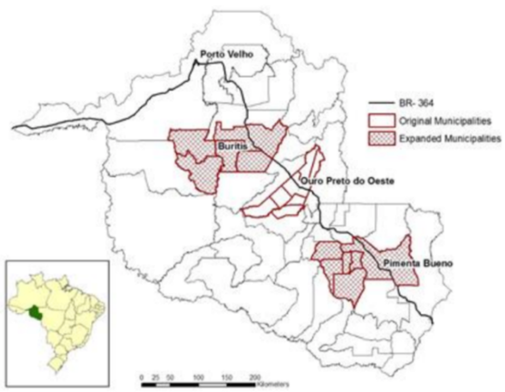
Bellon et al. (2015) argue that diversification is a valuable component of smallholder farming systems and is crucial for improving farmers' well-being. Researchers have found that diversification is a successful method of reducing risk for those who pursue it. Research has shown that diversification could help to offset the costs of rainfall variability among smallholder farmers in developing countries (Bradshaw 2004; Lin 2011; Makate et al. 2016; Ochieng et al., 2020). For example, Ochieng (2020) found that higher temperatures and decreased rainfall were positively associated with increased crop diversification in rural Kenya. They found that farmers opted for more diversified crop portfolios to reduce the risk of possible crop failures due to droughts. However, they only investigate rainfall's impact on crop diversification, omitting both other on-farm production and off-farm work. Other benefits of crop diversification in response to rainfall variability are providing insurance against the risk of crop failure and expanding the production possibility set for farmers and stabilizing incomes (Samuelson 1967; Meert et al., 2005, Lin 2011, Subhatu et al., 2015; Makate et al., 2016). Diversification's ability to reduce the risk of lost income also improves food security (Barrett & Reardon, 2000; Korir et al., 2005). In practice, research has found that a more diversified crop portfolio is significantly and positively associated with self-consumption (Bellon et al., 2020). While a farmer may be able to reach higher levels of average consumption under specialization, this strategy comes with high risk. Other studies have also confirmed that diversification leads to higher levels of food security (Haggblade 2007).

Diversification has been found to increase the household's income through an increase in household employment (Vyas, 1996). There is a severe problem of both seasonal unemployment and underemployment in the agricultural sector. The addition of other activities like dairy farming or working off the farm allows the employment level to increase. Bellon et al. (2020) echoed these results and found that the level of cash income for a farming household was significantly and positively associated with a more diverse crop portfolio. Off-farm diversification has been shown to increase income, which helps farmers purchase production inputs and assets (Woldehanna & Oskam, 2001). Using this increase in income to reinvest in the farm can help to increase production output, and again work to increase the household's consumption. In addition, an increase in income can help alleviate financial stress and allow for more leisure time. Both helps to decrease household risk and increase household utility.

4. Data

This study uses farm level survey data from Rondônia, Brazil. Rondônia is an Amazonian state in the southwestern region of Brazil, as shown in Figure 1. The Water Production Connections team conducted the survey and shared background research and information. The survey data covers three field sites made up of crop land, mature forest, secondary forest, and pastureland (Namata et al., 2009; Roberts et al., 2002). These sites were selected to capture differences in precipitation patterns, climate, soils, and biophysical factors while holding socioeconomic conditions relatively constant. The three sites cover the Northwestern region, the Southeast region, and the Central region of Ouro Preto do Oeste.

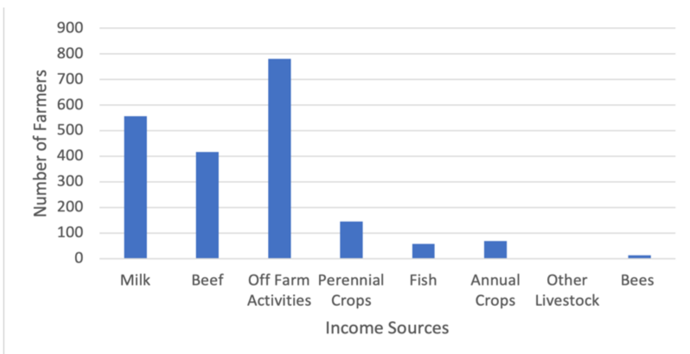
Figure 1: Map of Study Region



This survey was designed to collect both lot and household characteristics, which would allow for analysis of household decision making (Harris and Caviglia-Harris, 2005). Households were questioned about income, wealth, household characteristics and land use. It was stratified such that the sample from each municipality was representative of the population and so there was variation in topography and other geographical characteristics (Caviglia-Harris et al., 2009). This study focuses only on the survey responses that were collected in 2019, however surveys were completed in previous years in the Central Ouro Preto do Oeste region.

The oldest municipalities in this study were founded in the 1970s and the youngest in the 1990s. The households that were surveyed are all similar in terms of their production portfolios, level of income, education, and health status. Smallholder farmers within the study area primarily focus on the production of milk and beef. 556 households in the study sold milk, and 416 households sold beef. These were the two highest categories for on-farm production. A large portion of the sample relied on income from working off the farm as well. 781 households received some of their income from off farm activities. The number of farmers participating in each income source is shown in Figure 2.

Figure 2: Distribution of Farmers in Each Income Source



The primary objective of the 2019 survey was to understand farmers' experience and responses to water scarcity. Rainfall data was collected and added to the dataset following the procedure set forth in Ye Mu et al., 2020. To understand farmers' experience and response, a question was added to the survey asking about general willingness to take risks. The question asks respondents to rate themselves on a scale from 0 -10, 0 being not at all willing to take risks and 10 being extremely willing to take risks. This question is self-reported and based on the interpretation made by each respondent, which may differ from person to person. This question offers insight into the relative risk attitudes of the respondents and will be used for the proceeding analysis. For this reason, this study only uses data from 2019 when the risk question was asked.

This study is a cross-sectional analysis of survey data from 2019 on 1,326 households in Rondônia, Brazil. Because I aim to answer whether risk attitudes impact diversification decisions, any household that did not respond to this question was dropped from analysis. 1,267 households responded to the risk question. Table 1 shows an average comparison between households that did and did not respond to the risk question.

Table 1: Characteristics of Nonresponse and Response Households

Characteristics	**Did Not Respond to Risk Question**	**Responded to Risk Question**	**T-test**
Lot Size	96.1	100.1	0.89
Family Members Living on Lot	3.9	3.7	0.59
Education Level of Household Head	3.96	4.6	0.39
Wealth	8.4	12.1	0.00

There may be some potential for bias due to the qualities of households that did and did not answer the risk question. As shown in Table 1, households that did not answer the question tend to have households' heads with lower levels of education. This could potentially be correlated with their decisions to diversity. Nonresponse families also tend to be less wealthy than those who did response, which could also bias this study. The T-test statistic shows that there is no significant difference between nonresponse and response households for lot size, number of family members living on the lot, or education level. However, the two groups are significantly different in their wealth.

3.1: Dependent Variable

The main dependent variable is the level of diversification shown by each household. Diversification levels have been measured in the literature using indices. The Margalef index used in Astravor (2018), has been mainly used in agrobiodiversity and can account for the area cultivated with different crop varieties on the farm. Other studies have opted for the Shannon Index of Diversification, which quantifies the degree of diversification (e.g., Schwarzw & Zeller, 2005). This index considers both the number of income sources and their evenness and increases continuously with higher levels of diversity.

Considering the objective of expanding the definition of diversification to include three categories, crop, other on-farm production, and off-farm work, I opt for Simpson's Index of Diversification. Simpson's Index provides a more precise measure of diversification based on proportions of income rather than absolute counts (Ochieng et al., 2020). In comparison to the Shannon Index, the Simpson Index ranges between 0 and 1, where 0 is complete specialization and 1 would equal infinite number of activities. The Simpson Index is defined as:

$$SID = 1 - \sum_{n=1}^{i} P_i^2$$

Where P_i is the proportion of income generated from source *i*, which includes crop production, other on-farm production and off-farm work.

There are 30 potential sources of income for households in the sample: 23 different crops, milk, cattle, other livestock, fish, bees, off farm activities and other sources. The other sources category encompasses government payments such as pensions, and other government programs. Rondônia has two predominant government programs, the Bolsa Escola which is a school grant program and the Bolsa Familia which is a family grant program. The other sources are included in the calculation for total household income but are not included as a measure of diversification. The survey asked participants whether they received income from each of the 30 potential sources within the last year.

Diversification is a long-term adaptation and requires enough transitional costs that farmers are not changing their portfolio very much from year to year. Some farming decisions are made over short time periods. For example, a drought year could cause farmers to import feed for cattle or sell some animals. Alternatively, changing farm portfolios is a significant investment of time and money as farmers may decide to convert forest to crop land, bring in new crops, raise more animals etc. They will likely make this decision based on long term climate conditions and expectations, rather than after one bad rain season. Some diversification habits are easier than others, like finding work off the farm. Others, like converting forest, take significantly longer. Easier movements may be made based on rainfall in the last few years whereas harder movements may be made based on rainfall in the last few decades.

This description of Simpson's diversification index is the one used for all following results and conclusions. For robustness, I define the index two additional ways. The first, was to group crops into annual and perennial resulting in only 9 different income sources. The second, was to leave off-farm work out of the diversification index all together. The thought behind this approach was that families who are less willing to take risks may avoid a strategy like off-farm work because it could increase their risks. Off-farm work would be a new strategy with unknown outcomes. Families less willing to take risks may prefer to diversify into activities they already understand like adding further crops or on-farm production. The main reason for including off-farm work as a type of diversification is that other studies typically study crop diversification and off-farm diversification separately. The mean of the diversification index is higher when off-farm is excluded. This is because removing off-farm income will lower average diversification for farmers who have both on-farm and off-farm activities but will raise the average because households who are fully specialized in off-farm activities drop out of the sample. As shown in

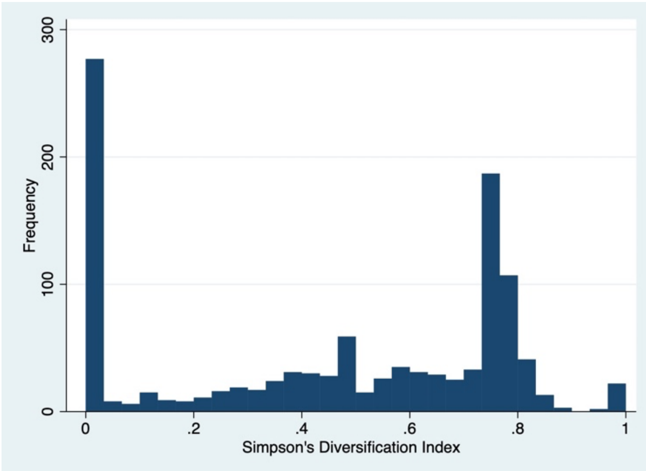
Figure 2, there are many households who specialize in off-farm activities, which explains why the mean is higher for SDI: off-farm excluded. Changing the specification of the index did not make any significant impact on the results of the regression models. The results using both specifications can be found in the appendix.

Table 2: Simpson's Diversification Index

	Mean	SD
SDI: 23 income sources	.4558667	.3189588
SDI: 9 income sources / grouped crops	.4415325	.3147467
SDI: Off-farm excluded	.6429413	.3888012
N	1,127	

Table 2 shows the mean and standard deviation of the three specification of Simpson's diversification index. The frequency chart of the 23 income source index is shown in Figure 3. A large portion of farmers in Rondônia are completely specialized, while the rest fall somewhere between 0 and 1 on the diversification scale. The average farmer falls somewhere in the middle with a mean of 0.456. Of the specialized households, most sold only milk or only cattle. 109 households specialized in the production of milk, and 49 specialized in raising cattle. 37 households focused all their labor into off-farm work. The other income sources saw less specialization. 15 in crop production, 7 in fish and none in other livestock or bees.

Figure 3: Distribution of Simpson's Diversification Index



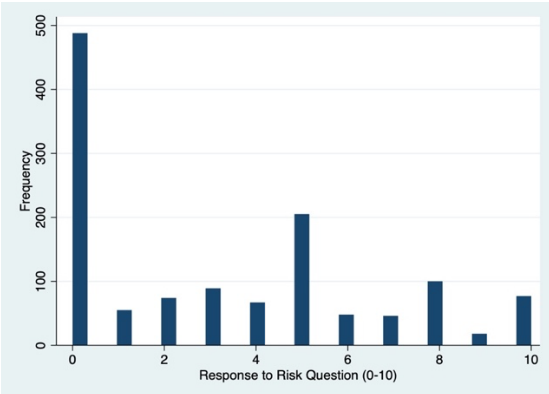
3.2 Independent Variables

3.2.1: Risk Variable

The first explanatory variable of interest in this study is the responses to the willingness to take risks question. Some studies try to measure risk preferences using methods like those used in Holt and Laury (2002). This method (HL) is an experimental lottery often with paid incentives. It consists of a series of questions asking participants how they would act in situations with different levels of risk and different payoffs. This has been called the gold standard for risk preference elicitation (Anderson and Mellor, 2009). For this study however, we don't attempt to measure risk preferences but instead ask respondents about their attitudes towards risk. Previous studies have verified the behavioral validity of a survey question (Dohmen et al., 2011). Dohmen et al. (2011) test the behavioral validity of a general risk willingness question through a comparison between those responses and how the respondent acted during a paid lottery experiment like Holt and Laury's. They find that the general willingness question was significant in all contexts with a relatively large coefficient and goodness of fit. Other studies have echoed these results and concluded that a self-assessment question is reasonably correlated with actual risk aversion (Nielsen et al., 2013; Hardeweg et al., 2013; Gloede et al., 2011; Vieider et al., 2015). The benefit of a general risk question like this one is first that it is simple to understand. The problem with methods like Holt and Laury is that they are often complicated and confusing. This leads to unusable data as participants get confused and make mistakes in their responses. Additionally, an experiment like this is hard to execute in the field and often suffers from errors made by the surveyor. A general question is a beneficial way to understand relative risk tolerances of a sample. Additionally, a question like this has no domain specificity which is another strength for analyses like this one. For my analysis, this is a fitting measure as I am not concerned with "true" risk aversion but rather relative risk tolerance. The question, translated from Portuguese, reads "Please tell me how much you would say you are or are not willing to take risks in general. To answer, use a scale from 0 to 10, where 0 means you are 'not willing at all to take risks' and 10 means that you are 'very willing to take risks'. You can use any number between 0 and 10 to indicate your answer". This wording matches the question posed in Dohmen et al. (2011) almost exactly. They asked, "How willing are you to take risk, in general". They also ask their participants to rank themselves on a scale from 0 to 10.

1,267 households responded to the risk question. The frequency in responses to the question is shown in Figure 4. The mean of the responses to the risk question is 3.24, which is a lower sample mean than has been found in other studies (Hardeweg et al., 2013; Dohmen et al., 2011). This is largely due to the large number of people who responded to the question with an answer of 0, not at all willing to take risks. Dohmen et al., 2011 did not have a high number of responses of zeros. Only roughly 7% of their participants answered that they were not at all willing to take risks which would explain why their mean was higher at 4.76.

Figure 4: Distribution of Responses to the Risk Question



It is possible that we see many responses of 0 because survey respondents did not fully understand the question and selected 0 out of confusion. However, it could be that there are truly this many people who define themselves as not at all willing to take risks in Rondônia, Brazil. We also see a large spike at responses of "5" in the self-assessment. Due to the qualitative nature of this question, this cannot be interpreted as perfect risk neutrality (Gloede et al., 2011). Research has shown there is a tendency for participants to select the easily identifiable middle category when given questions regarding their risk preferences (Nielson et al., 2013; Dohmen et al., 2011; Hardeweg et al., 2013). This is a limitation of the 0-10 self-selection scale. To answer whether relative willingness to take risks determines diversification decisions, I will use the raw responses to the question. For robustness, I compare these results with results from regressions using the categorization of the risk variable which can be found in the Appendix. The second question I aim to answer is whether the effect of rainfall variability is different for farmers with different relative risk tolerances. To do this, I break the responses into three categories: zero willingness to take risks (response = 0), low willingness to take risks (response = 1-4), and high willingness to take risks (response > 5).

3.2.2 Rainfall Variables

Rainfall data is typically collected in one of two ways. One method is to use satellite data and the other is to use rainfall gauges placed strategically around the study area. The Climate Hazards Group Infrared Precipitation (CHIRP) combined with gauge data (CHIRPS) are satellite-based rainfall measurements with both spatial and temporal resolution (Funk et al., 2015). Various validations of this method have been done (Shrestha et al., 2017; Rivera et al., 2018). CHIRPS has been found to be one of the best products for hydro-meteorological studies (Hessels 2015). The issue arises with rainfall measurement using CHIRPS in the Brazilian Amazon. CHIRPS measurements seem to underestimate extreme rainfall (Cavalcante et al., 2020). The other method for measuring rainfall is a rain gauge network located over the Amazon basin (Ye Mu et al., 2021). The issue with rain gauges is there are significant spatial and temporal gaps. Cavalcante et al. (2020) had access to only a few rain gauges and had significant gaps in data surrounding important agricultural regions like Rondônia.

To combat these issues, I use the rainfall dataset described in Ye Mu et al. (2021). Spatial patterns and trends in monthly rainfall estimates were documented using satellite-based rainfall estimates (CHIRPS). These were then calibrated and validated with a network of rain gauges located across the state of Rondônia. This blended method of the two measures of rainfall was found to have improved accuracy during months with extremely high or low rainfall. (Ye Mu et al., 2021).

To answer what the impact is of rainfall variability on diversification, I look at rainfall through five key time periods. The whole year, the dry season (June, July and August), the wet season (January, February and March), in May and in September. May and September are the start and the end of the dry season. In theory it may matter not only how dry the dry season is but also how long it lasts. The summary statistics for rainfall over these five time periods is shown in Table 3.

Table 3: Summary Statistics of Rainfall During Five Time Periods (mm)

	mean	min	max
Yearly Rainfall	2145.90	1848	2385
Dry Season Rainfall	57.66	12	107
Wet Season Rainfall	977.26	780	1183
May Rainfall	61.81	34	93
September Rainfall	56.34	37	82
N	1217		

Farmers make decisions based on their personal observations. For that reason, I took the rainfall variability, measured as standard deviation, of rainfall since each respondent first moved to their property. The rainfall data begins in 1981, so for any farmer that moved to their property before this date, the standard deviation is taken from 1981 to 2019. Table 4 shows the average rainfall variability in each of the five key time periods. As a robustness check, I used the standard deviation of rainfall from 1981 to 2019, in the last 10 years and in the last 5 years rather than since the time the farmer moved to their property. The results of those regressions can be found in the appendix.

Table 4: Standard Deviation of Rainfall Since Farmers Moved to Their Property (mm)

	mean	min	max
Yearly Rainfall	184.44	32.19	303.35
Dry Season Rainfall	29.08	.71	42.98
Wet Season Rainfall	105.04	11.50	245.37
May Rainfall	36.38	1.41	80.01

September Rainfall	32.60	2.12	58.84
N	1217		

3.3 Control Variables

To measure the effects of relative risk preferences and rainfall variability, the model must control for other factors that could influence household diversification and may be correlated with risk preferences or rainfall. The control variables fall into two broad categories: household characteristics and lot characteristics.

Household characteristics encompass characteristics of the farming household that may impact their decision to diversify. “Family” refers to the number of household family members that are currently living on the lot. It does not account for family members that have moved off the lot and now reside elsewhere. It is controlled for because households with larger families have more labor which could impact diversification. The 2019 survey did not report the age of the female or male household head. To control for age, Table 5 reports the age categories for the female and male household head. This variable is = 1 if the household head is not elderly (15-59 years old) or 0 if they are elderly (60+). The age of the household head could potentially influence the decision towards diversification. The education level of household members could also impact the decision to diversify. More educated household members may have a better understanding of the tradeoffs between diversification and utility, rainfall risk and their own risk aversion. Three measures of household education are controlled for. The education level in years of the female household head (Edu (F)), the education level of the male household head (Edu (M)), and the education level of the most educated household member (Most Edu). The most education a household head could have is 14 years. The most educated household member on average has 4.6 years of education, which is relatively low compared to the maximum number.

Another important household characteristic that must be controlled for is their wealth. Households with higher levels of wealth could be less risk averse due to their increased financial security, and therefore less diversified. Wealth is a concept that does not come with a simple form of measurement. For my purposes, the number of durable goods owned by the household can be used as a proxy to capture household wealth. The list of durable goods the household may own was provided in the survey. It is possible that a household may own other goods that were not listed.

Table 5: Summary Statistics of Control Variables

	mean	min	max	sd
Family	3.726125	0	15	2.16
Edu(F)	3.563439	0	14	3.95
Edu(M)	3.471764	0	14	3.24
Most Edu	4.577834	0	14	5.27
Age Cat(F)	1.07433	1	2	0.26
Age Cat(M)	1.254501	1	2	0.44
Durables	12.07656	0	67	6.30
Lot Size	100.6035	.2	3146	220.82
Year Acquire	1995.14	1960	2019	13.29
N	1267			

In terms of lot characteristics, this model controls for lot size. To measure lot size, the survey asked participants to self-report the area of the lot in hectares. It stands to reason that a larger plot of land would have more crop or on-farm production diversification due to the additional space available. Through the addition of lot size as a control variable, diversification decisions no longer depend on how much land a farmer has. In addition, this model will also control for the year the household head or family acquired the lot. Households that have had their lot for longer periods of time may have had more of an opportunity to diversify and slowly increase their portfolio. To ensure that the model is measuring the correct relationship, we must control for time the family has owned the land.

5. Methods

I aim to estimate the effect of rainfall variability and relative risk attitudes on the diversification practices of smallholder farmers in Rondônia, Brazil. To do this I first estimate what the effect of rainfall variability and risk attitudes is on the Simpson Diversification Index independently but conditional on one another. To do this, I use five periods of rainfall variability: yearly, dry season, wet season, May, and September. I estimate five regressions, one with each of the different time periods for rainfall variability. I will also consider the impact of self-assessed risk attitudes on the index. For the initial regressions, I use the raw risk variable. The variable takes a value of 0 – 10 depending on the respondents answer to the willingness to take risks assessment question. The equation for these five regressions is as follows:

$$Index_i = \beta_0 + \beta_1 rain_i + \beta_2 risk_i + \Sigma\beta_j controls_{ji} + \mu_i$$

For the initial regression, I used rainfall variability and risk to estimate their effects on diversification individually. It is possible that there is an interaction between variation of rainfall and relative risk tolerance. The impact of rainfall variability on diversification may have a different impact dependent on the respondent’s willingness to take risks. To estimate this relationship, I break the raw risk variable into three categories. No willingness to take risks (answer = 0), low willingness to take risks (answer = 1-4) and high willingness to take risks (answer > 5). This breakdown of the risk variable keeps the sample sizes of the three categories relatively similar, with an average of 429 respondents in each category. I then run five separate regressions, one with each period of rainfall variability. These results will show whether the effect of rainfall variation is different based on which of the risk categories a respondent belongs to. This equation includes the same control variables as equation 1. The difference is in the categorization of the risk variable and the inclusion of an interaction term between rainfall variability and the risk categories. The equation for these regressions is as follows:

$$Index_i = \beta_0 + \beta_1 rain_i + \Sigma\beta_k riskcat_{ki} + \Sigma\beta_i rain_i * riskcat_{ki} + \Sigma\beta_j controls_{ji} + \mu_i$$

I run both ordinary least squares and Poisson regressions. I use a Poisson specification because the distribution is nonlinear and non-zero. I also ran additional regressions using different specifications of the diversification index, as well different specifications of the risk and rainfall variables. Those results can be found in the appendix.

The goal of this study is to expand on the existing literature surrounding the determinants of diversification for smallholder farmers using both relative risk preferences and rainfall patterns as key factors. It is important to note some possible sources of bias and endogeneity problems. While studies have found that self-identifying one's risk attitudes is a valid measure of how they are likely to behave (Dohmen et al., 2011; Nielson et al., 2013; Hardeweg et al., 2013; Gloede et al., 2011), there is potential for the coefficients on risk to be biased. This is due to possibilities of lack of understanding of the question or an inadequacy in ability to identify one's own risk attitudes. Other unobservable characteristics that could be correlated with risk preferences and diversification are things like open mindedness of the household head, entrepreneurial spirit, and other personal characteristics. Open mindedness as well as entrepreneurial spirit are likely positively correlated with people's willingness to take risks. In other words, more open-minded entrepreneurial people will be more willing to take risks. That would mean that based on my hypothesis, these people would be less diversified. Therefore, these factors would have a positive bias on the overstate the role of risk attitudes.

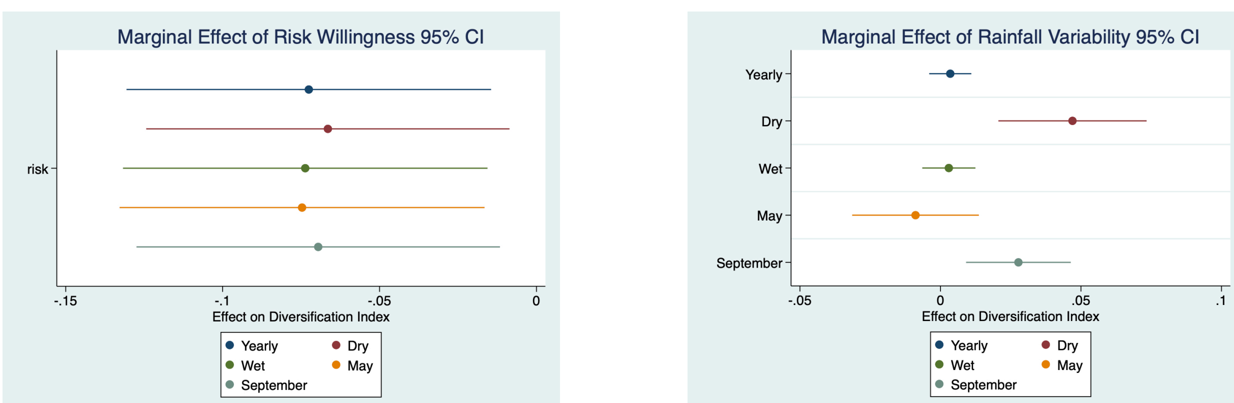
Farming households cannot control rainfall variability. However, they can choose areas with higher or lower variable rainfall. This choice is limited to a degree because families were randomly assigned property when the region was settled. Some properties have been bought and sold since then which could create a spatial bias. This choice would be negatively correlated with rainfall variability as farmers choose places with more consistent rainfall. This would create a negative bias and understate the roll of rainfall variability. Choices about where to locate could have some correlation with other spatial patters like distance to roads and urban centers. In addition, patterns of higher or lower rainfall could correlate with unobservable characteristics such as soil quality and terrain which could determine how long the land has been settled and the diversification level of the household. These are important to keep in mind and mean that a cross-section analysis cannot be considered completely random and there is source for bias in my results.

6. Results

6.1 Ordinary Least Squares & Poisson: No Interaction

Table 6 shows ordinary least squares regression results of the effect of relative risk attitudes and each of the five rainfall time periods on Simpson's Diversification Index. Under this specification, risk is a continuous variable taking a value from 0 to 10. This provides a basic understanding of the relationships that exist between these key variables. Figure 5a shows that the risk coefficient is negative and significant in all cases because the confidence intervals lay to the left of and do not include zero. Figure 5b shows that of the five key rainfall time periods, only dry season rainfall (regression 2) and rainfall in September (regression 5) show positive and statistically significant coefficients. There is no effect for yearly rainfall variability, wet season variability or variability in May. Regression 2 shows the coefficient on dry season rainfall variability is statistically significant and shows that for a 10 mm increase in dry season rainfall variability a farmer's index score increases by 0.0545. The standard deviation of dry season rainfall variability is 7.21 mm, so a 10 mm increase is only slightly outside of this range. The diversification index ranges from 0 to 1 so an increase of 0.05 is about a 5-percentage point increase in diversification level of the farmer. The standard deviation of September rainfall variability is higher at 10.36 mm. The coefficient for September rainfall variability is similar in significance to the dry season but shows a smaller effect. For a 10 mm increase in September rainfall variability a farmer's index score increases by 0.0337. The standard deviation of the diversification index is 0.32, so while these are statistically significant effects, they are not relatively large changes in the index value. These results indicate that the dry season and September rainfall are the key periods in which farmers are observing rainfall and making diversification decisions. These results also show that an increase in response to the risk question (moving towards more willing to take risks) is associated with a decrease in the farmers diversification index score in all five of the regression models. Because the risk question measures relative risk aversion, it's hard to tell what the practical impact of a one unit increase in risk willingness is. The standard deviation in the risk response is 3.28, so a one-unit increase is a realistic degree of variation in risk attitudes for examining the size of the effects. The size of the effect is different between the five models but on average a one unit decrease in willingness to take risks is associated with a 0.007 point increase in diversification index score. Again, the standard deviation of the diversification index is 0.32, so while these are statistically significant effects, they are not relatively large changes in the index value. This supports the initial hypothesis that relatively more risk averse farmers should tend have higher levels of diversification. Regressions 2 and 5 finds average yearly rainfall to be negative and significant. The three other regression models show a positive coefficient on average yearly rainfall, but no statistical significance. In Regression 2, an increase in average yearly rainfall of 10 mm per year is associated with a farmers diversification score decreasing by 0.00229. This finding shows that as rainfall increases, farmers are less likely to be diversified. If climate change continues to cause drier years (less average yearly rainfall) and higher rainfall variability we will see these two effects work together to further raise diversification levels.

Figure 5a & 5b:



Regarding control variables, five show statistical significance. The education level of the female household head shows negative impact on diversification level. In other words, as the education level of the female head increases, the diversification index score will decrease. Age category of both the female and male head have a positive effect on diversification so as the heads get older the household sees an increase in diversification level. As the size of the lot the household owns increases, the household is less likely to be diversified and the longer the family has been on their lot, the less likely they are to be diversified.

Table 6: OLS Regression - No Interaction - Risk as Continuous

	(1) Per Year	(2) Dry Season	(3) Wet Season	(4) May	(5) Sept
Risk	-0.00736** (-2.48)	-0.00684** (-2.32)	-0.00747** (-2.52)	-0.00750** (-2.53)	-0.00718** (-2.43)
Std Dev Yearly Rainfall	0.000381 (0.99)				
Avg Yearly Rainfall	-0.0000823 (-0.63)	-0.000229* (-1.69)	-0.0000745 (-0.57)	-0.0000336 (-0.24)	- 0.000227* (-1.65)
Family	0.00916 (1.45)	0.00947 (1.50)	0.00883 (1.40)	0.00911 (1.44)	0.00919 (1.46)
Education (F)	-0.00624** (-2.05)	-0.00625** (-2.06)	-0.00604** (-1.98)	-0.00625** (-2.06)	-0.00642** (-2.11)
Education (M)	0.00224 (0.66)	0.00220 (0.65)	0.00222 (0.66)	0.00226 (0.67)	0.00234 (0.69)
Most Educated	-0.000250 (-0.11)	-0.000485 (-0.22)	-0.000352 (-0.16)	-0.000266 (-0.12)	-0.000373 (-0.17)
Female Age Category	0.143*** (3.90)	0.145*** (3.96)	0.146*** (3.97)	0.143*** (3.90)	0.140*** (3.80)
Male Age Category	0.199*** (8.60)	0.200*** (8.66)	0.199*** (8.61)	0.199*** (8.59)	0.197*** (8.52)
Durable Goods	-0.0000922 (-0.04)	-0.000276 (-0.13)	-0.00000486 (-0.00)	-0.0000757 (-0.04)	- 0.0000483 (-0.02)

Lot Size	-0.000105* (-1.75)	-0.000107* (-1.79)	-0.000102* (-1.70)	-0.000105* (-1.76)	- 0.000107* (-1.80)
Year Acquire	-0.00191** (-2.37)	-0.000739 (-0.66)	-0.00203** (-2.49)	-0.00193** (-2.38)	-0.00328** (-2.27)
Dry Season		0.00545*** (3.85)			
Wet Season			0.000328 (0.68)		
May Rainfall				-0.000779 (-0.63)	
Sept Rainfall					0.00337*** (3.32)
_cons	0.575** (2.25)	0.769*** (3.02)	0.596** (2.34)	0.579** (2.24)	0.816*** (3.15)
N	1073	1073	1073	1073	1073

statistics in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Because the distribution is nonlinear and non-negative, Ordinary Least Squares may not be the best fit. Therefore, I also run the model under a Poisson specification. Table 7 shows that the effect of risk is negative and significant in all cases showing that for an increase in willingness to take risks there will be a decrease in the value of the diversification index. The coefficient on dry season rainfall variability is positive and significant. This shows that for a 10 mm increase in dry season rainfall variability there will be a 0.12 increase in diversification index value. The coefficient on September rainfall is also positive and significant. For a 10 mm increase in September rainfall variability there will be an 0.07 increase in the diversification index value. Again, the standard deviation of the diversification index is 0.32, so while these are statistically significant effects, they are not relatively large changes in the index value. The coefficients on average yearly rainfall are statistically significant for the Dry season and

September model, and the coefficients on yearly rainfall variability, wet season variability and variability in May show no statistical significance.

Poisson - No interaction - Risk as Continuous

	(1) Per Year	(2) Dry Season	(3) Wet Season	(4) May	(5) Sept
SDI					
Risk	-0.0162**	-0.0150**	-0.0165**	-0.0165**	-0.0158**
	(0.00678)	(0.00673)	(0.00678)	(0.00677)	(0.00670)
Std Dev Yearly Rainfall	0.000833 (0.000884)				
Avg Yearly Rainfall	-0.000178 (0.000280)	-0.000484* (0.000281)	-0.000161 (0.000281)	-0.0000723 (0.000299)	-0.000492* (0.000291)
Dry Season		0.0121*** (0.00321)			
Wet Season			0.000707 (0.00106)		
May Rainfall				-0.00169 (0.00265)	
Sept Rainfall					0.00746*** (0.00229)
_cons	-0.530	-0.143	-0.484	-0.521	-0.0163
	(0.554)	(0.534)	(0.550)	(0.557)	(0.551)
N	1073	1073	1073	1073	1073

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

6.2 Ordinary Least Squares & Poisson: Interaction

My hypothesis is that changes in rainfall variability will impact farmers' diversification decisions differently based on their risk attitudes. Rainfall variability in this case is a higher risk to farmers. Increases in variability should have a higher impact on farmers who are less willing to take risks. Table 8 shows an OLS model with an interaction term between rainfall and risk. The variation in dry season rainfall is significant for all three levels of risk willingness. For people who answered with 0, no willingness to take risks, a 10 mm increase in dry season rainfall variability is associated with a 0.0482 increase in their diversification index. The effect of a 10 mm increase in dry season rainfall variability is the highest in the low willingness to take risks category, affecting a 0.0619 increase in index score. The people most willing to take risks see a 0.0556 increase in their diversification index when dry season rainfall variability increases by 10 mm. The variation of rainfall in September is only significant for the category of people the most willing to take risks. A 10 mm increase in September rainfall variability will increase the diversification index of people the most willing to take risks by 0.0444. Contrast commands showed that the p value was 0.9253 and 0.6093 respectively for the interactions in the dry season and September regressions under OLS. This again shows that the degree to which a farmer diversifies in response to rainfall variability does not vary with their attitude towards risk.

Table 8: OLS: Effects of Rainfall Variability by Risk Category

	(1) Per Year	(2) Dry Season	(3) Wet Season	(4) May Rainfall	(5) Sept Rainfall
1. No willingness to take risks	0.000301 (0.47)	0.00482** (2.17)	-0.0000722 (-0.09)	-0.00137 (-0.70)	0.00243 (1.52)
2. Low willingness to take risks	0.000455 (0.56)	0.00619** (2.18)	0.000699 (0.74)	-0.000484 (-0.20)	0.00264 (1.32)
3. High willingness to take risks	0.000460 (0.77)	0.00556** (2.51)	0.000527 (0.66)	-0.000438 (-0.24)	0.00444*** (2.88)
N	1073	1073	1073	1073	1073

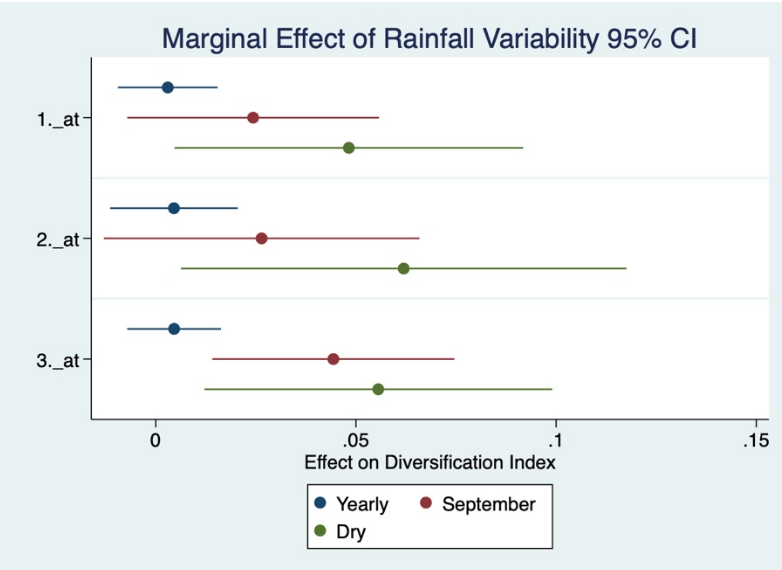
statistics in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Figure 6 shows the marginal effect of a 10 mm increase in rainfall variability in the entire year, dry season, and September at the 95% confidence interval per the OLS equation. 1 is people who answered that they had no willingness to take risks, 2 is low willingness and 3 is high willingness. This figure shows that the dry season rainfall variability has a larger effect than

September variability. The overlapping confidence intervals show that the effect of rainfall variability is not significantly different for different risk willingness categories.

Figure 6: Marginal Effect of Rainfall Variability: OLS



1 = No willingness to take risks, 2 = low willingness to take risks,
3= high willingness to take risks

Table 9 shows the interaction equation ran under a Poisson specification. The variation in dry season rainfall is again significant for all three levels of risk willingness. For people who answered with 0, no willingness to take risks, a 10 mm increase in dry season rainfall variability is associated with a 0.042 increase in their diversification index score. The effect of a 10 mm increase in dry season rainfall variability is the highest in the high willingness to take risks category. A 10 mm increase is associated with a 0.053 increase in the diversification index for people with high willingness to take risks. The middle category, people with low willingness to take risks, see a 0.048 increase in their diversification index score when dry season rainfall variability increases by 10 mm. In the September rainfall regression, only the low and high willingness categories are significant. Here a 10 mm increase in September rainfall variability is associated with a 0.028 increase in actual index score for people with low willingness and a 0.38 increase for those with high willingness. I ran contrast commands to test whether the effects were significantly different from one another and like in the OLS model they were not. This further confirms that the effect of rainfall variability does not change significantly based on how willing a person is to take risks.

Table 9: Poisson - With interaction - Risk as Category

	(1)	(2)	(3)	(4)	(5)
	Per Year	Dry Season	Wet Season	May	Sept
main					
1. No willingness to take risks	0.000239	0.00423^{**}	0.00000827	-0.00144	0.00163
	(0.000624)	(0.00214)	(0.000712)	(0.00174)	(0.00154)
2. Low willingness to take risks	0.000350	0.00481^{***}	0.000321	-0.000867	0.00281^{***}
	(0.000402)	(0.00145)	(0.000485)	(0.00114)	(0.00100)
3. High willingness to take risks	0.000445	0.00531^{**}	0.000592	-0.000366	0.00384^{**}
	(0.000588)	(0.00221)	(0.000757)	(0.00171)	(0.00150)
N	1073	1073	1073	1073	1073

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

7. Conclusions

I investigate whether relative risk tolerance and rainfall variability over five key time periods impact the diversification decisions of smallholder farmers in Rondônia, Brazil. Ordinary Least Squares as well as Poisson regressions show a strong correlation between rainfall variability and diversification as well as risk attitudes and diversification. I also investigate the effect of risk attitudes and rainfall conditional on one another and how they interact. Interaction regressions show that the impact of increased rainfall variability is significant over all three risk willingness levels. However, these effects are not statistically different from one another which shows that the impact of rainfall variability does not differ based on a person’s willingness to take risks. Previous research surrounding determinants of diversification have focused on household and farm characteristics with fewer considering rainfall variability. Other works have used risk elicitation methods to study the impact of risk aversion on crop diversification decisions (Sarworsi & Musshoff, 2020; Bezabih & Sarr, 2012). To my knowledge, no other study has used a relative risk attitude measure through the form of a survey question. In addition, this study is unique in its expanding definition of diversification to include crop, on-farm production, and off-farm work.

My findings suggest that rainfall variability increased the level of diversification seen in a household. I hypothesized that increased rainfall variability should increase the level of diversification used by the household due to the increased risks posed by variability rainfall. Specifically, for Rondônia, the variability of the dry season as well as how long the dry season lasts (September rainfall) has a higher impact than the variability in the wet season or throughout the entire year. The dry season is a key period as it highly influences the success of different crops. September is the end of the dry season. Its significance tells us that it is not only the “dryness” of the dry season that matters, but also the length. If higher levels of rainfall variability continue into the month of September, this has a significant impact on diversification decisions.

I also find evidence to support the initial hypothesis that relative willingness to take risks impacts the diversification decisions of farmers in Rondônia. I hypothesized that farmers who are less willing to take risks should be more diversified, as a specialization strategy poses the risk of losing their entire income. The results from both the OLS and the Poisson regressions show the coefficients on risk for all five rainfall regressions as negative and significant. This suggests that decreased willingness to take risks will increase the level of diversification. Previous studies using an experiment to elicit risk attitudes have found that the link between risk aversion and specifically crop diversification is weak (Bezabih and Sarr 2012). Others have found that risk-averse farmers are less likely to partake in risky but potentially more rewarding strategies like specialization (Alemayehu et al., 2018).

I find no evidence that the impact of rainfall variability is different for people with different willingness to take risks. This could in part be due to the nature of self-selecting one's willingness to take risks. People may perceive their willingness to take risks one way and respond to the question accordingly but behave quite differently in risky situations. This interaction could be explored further with experiment driven risk data rather than a self-selection question to determine whether there is truly no relationship between rainfall variability and willingness to take risks.

Climate change continues to be an issue for the Amazonian region with increased extreme rainfall events and flooding (Dalagnol et al., 2022) to record breaking warming and extreme periods of drought (Jimenez-Munoz et al., 2016.) These findings suggest that as we continue to see increased climate change and rainfall variability, we will continue to see farmers turn to a diversification strategy. This may have important implications as farmers move away from growing crops and move into other areas like off-farm work. Already in this sample close to 800 farmers receive some income from off-farm work, with 37 only working off the farm. If climate change increases and makes cropping less viable for smallholder farmers city centers will continue to grow as people look to gain other employment. This change will also impact the security of food in these areas as less farmers grow and sell their crops. Financial and social inequality can worsen climate-related food insecurity. Smallholder farmers like those in Brazil are already poor and often food insecure. One lost cropping season due to climate change can move them from struggling to failing. This research serves as another warning into the increased dangers to people and their livelihoods at the hands of climate change. It is increasingly important to work to migrate these changes and protect the small farms in charge of our food supply.

The need for farmers to diversify in the face of increased climate risks results in a tradeoff. Farmers who are diversifying are giving up higher average incomes in exchange for lower variability to protect themselves. This means that the need to diversify prevents potentially predictable movements into specialization of high value goods. In the case of Rondônia those high value goods would be the production of beef, fish, and coffee. The need for diversification as a method of protection prevents farmers from pursing the higher average income associated with a specialization strategy and may continue to keep small holder farmers in a position of poverty. Due to lower average incomes, farmers are unable to reinvest into newer and more productive technologies thus slowing the progress of the agricultural industry. Finding ways to protect farmer's will be an important task for policy makers in Rondônia, Brazil. These findings show that farmers are diversifying because they dislike the variability in income associated with specialization. One way for policy makers to reduce that variability and promote higher rates of specialization would be to institute insurance mechanisms like crop insurance. In Brazil in 2018, almost 60% of the population had no access to rural insurance contracts for crop, livestock, or forest products (Souza & Assunção, 2020). This insurance mechanism could be expanded to further protect the smallholder farmers of Brazil.

My findings also leave questions to be addressed through further research. First, additional research is needed into other types of investments farmers or policy makers could use to diminish the risk of rainfall variability. For example, if cattle are suffering a lack of drinking water due to inadequate rain, would an investment in a drinking water pond be beneficial for the farm and reduce these risks? Additionally, while my findings help illuminate what increased climate risks will mean for farmers in the form of higher rates of diversification, research is needed on the implications for land use. It stands to reason that a more diversified farmer is likely to preserve some of the forest to be used for agroforestry. This may mean a lower rate of deforestation for Brazil as farmers would be using the forest instead of clearing it to make room for more crop land. So, while specialization benefits the farmer with higher average income, it may have negative impacts on the land. Balancing the costs and benefits of these two strategies will be increasingly important for Brazil as well as other agricultural nations as climate change continues to be a threat.

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APPENDIX: ADDITIONAL REGRESSION TABLES

Tables 1 – 7: Grouped Diversification Index

These regressions were run with what I named the grouped diversification index. This means that crops were not broken down into 22 specific crops but were categorized as annual and perennial. Tables 1 and 2 show standard OLS regression results using the grouped index first with risk as a continuous variable and then broken into the three risk categories.

Table 1: OLS Regression Results - No Interaction - Grouped Index – Risk as Continuous

	(1) Per Year	(2) Dry Season	(3) Wet Season	(4) May	(5) Sept
Risk	-0.00743**	-0.00683**	-0.00752**	-0.00752**	-0.00724**
	(-2.54)	(-2.35)	(-2.57)	(-2.57)	(-2.49)
Std Dev Yearly Rainfall	0.000371 (0.98)				
Avg Yearly Rainfall	-0.0000925	-0.000263**	-0.0000805	-0.0000662	-0.000245*
	(-0.72)	(-1.97)	(-0.63)	(-0.48)	(-1.80)
Dry Season		0.00622***			
		(4.47)			
Wet Season			0.000162		
			(0.34)		
May Rainfall				-0.000239	
				(-0.20)	
Sept Rainfall					0.00351***
					(3.50)
_cons	0.582**	0.798***	0.610**	0.608**	0.830***
	(2.31)	(3.18)	(2.43)	(2.38)	(3.25)
N	1073	1073	1073	1073	1073

t statistics in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 2: OLS Regression Results - No Interaction - Grouped Index – Risk as Category

	(1)	(2)	(3)	(4)	(5)

	Per Year	Dry Season	Wet Season	May	Sept
Risk	-0.0331***	-0.0300***	-0.0335***	-0.0334***	-0.0315***
	(-3.03)	(-2.76)	(-3.06)	(-3.06)	(-2.90)
Std Dev Yearly Rainfall	0.000368				
	(0.97)				
Avg Yearly Rainfall	-0.0000911	-0.000259*	-0.0000795	-0.0000646	-0.000239*
	(-0.71)	(-1.94)	(-0.62)	(-0.47)	(-1.77)
Dry Season		0.00612***			
		(4.40)			
Wet Season			0.000173		
			(0.36)		
May Rainfall				-0.000245	
				(-0.20)	
Sept Rainfall					0.00343***
					(3.43)
_cons	0.589**	0.800***	0.616**	0.614**	0.831***
	(2.34)	(3.20)	(2.46)	(2.41)	(3.26)
N	1073	1073	1073	1073	1073

t statistics in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 3 shows results from an OLS regression, again using the grouped diversification index.

This equation includes an interaction term between the risk categories and rainfall variability.

Table 3: OLS Regression Results - With Interaction Term - Grouped Index – Risk as Category

	(1)	(2)	(3)	(4)	(5)
	Per Year	Dry Season	Wet Season	May	Sept
main					
1. No Willingness to Take Risks	0.000516	0.00477**	0.000478	-0.00107	0.00189
	(0.83)	(2.32)	(0.65)	(-0.59)	(1.27)
2. Low willingness to take risks	0.000784	0.00612***	0.000172	-0.000285	0.00338***
	(0.98)	(4.39)	(0.36)	(-0.23)	(3.38)

3. High Willingness to take risks	0.0000753 (0.13)	0.00747*** (3.65)	-0.000135 (-0.18)	0.00129 (0.46)	0.00637*** (2.74)
N	1073	1073	1073	1073	1073

t statistics in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

I also ran regressions under a Poisson specification with the grouped diversification index. Tables 4 and 5 show the results under Poisson first with risk as continuous and second with risk as a three-level category.

Table 4: Poisson Regression Results - No Interaction - Grouped Index – Risk as Continuous

	(1) Per Year	(2) Dry Season	(3) Wet Season	(4) May	(5) Sept
GSDIndex					
Risk	-0.0169 (0.0142)	-0.0155 (0.0142)	-0.0172 (0.0142)	-0.0172 (0.0142)	-0.0165 (0.0141)
Std Dev Yearly Rainfall	0.000837 (0.00182)				
Avg Yearly Rainfall	-0.000207 (0.000613)	-0.000572 (0.000631)	-0.000180 (0.000612)	-0.000148 (0.000652)	-0.000547 (0.000650)
Dry Season		0.0144** (0.00689)			
Wet Season			0.000362 (0.00227)		
May Rainfall				-0.000534 (0.00578)	
Sept Rainfall					0.00803 (0.00490)
_cons	-0.506 (1.200)	-0.0711 (1.190)	-0.441 (1.193)	-0.446 (1.214)	0.0408 (1.222)
N	1073	1073	1073	1073	1073
adj. R^2					

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 5: Poisson – Without Interaction – Grouped Index – Risk as Category

	(1) Per Year	(2) Dry Season	(3) Wet Season	(4) May	(5) Sept
GSDIndex					
Risk	-0.0743	-0.0669	-0.0751	-0.0751	-0.0707
	(0.0521)	(0.0522)	(0.0521)	(0.0521)	(0.0521)
Std Dev Yearly Rainfall	0.000830				
	(0.00182)				
Avg Yearly Rainfall	-0.000204	-0.000561	-0.000178	-0.000144	-0.000533
	(0.000612)	(0.000631)	(0.000611)	(0.000652)	(0.000649)
Dry Season		0.0141^{**}			
		(0.00690)			
Wet Season			0.000384		
			(0.00227)		
May Rainfall				-0.000547	
				(0.00578)	
Sept Rainfall					0.00785
					(0.00490)
_cons	-0.492	-0.0671	-0.429	-0.434	0.0375
	(1.199)	(1.188)	(1.192)	(1.213)	(1.219)
N	1073	1073	1073	1073	1073

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 7 shows the results from a Poisson regression with the interaction between risk level and rainfall variability.

Table 7: Poisson Regression Results - With Interaction - Grouped Index – Risk as Category

	(1) Per Year	(2) Dry Season	(3) Wet Season	(4) May	(5) Sept
main					
1. No Willingness to Take Risks	0.000602	0.00486	0.000485	-0.00107	0.00190
	(0.46)	(1.04)	(0.30)	(-0.26)	(0.57)

2. Low Willingness to Take Risks	0.000369 (0.46)	0.00639** (2.07)	0.000154 (0.15)	-0.000238 (-0.09)	0.00356 (1.63)
3. High Willingness to Take Risks	0.000166 (0.15)	0.00770* (1.72)	-0.000132 (-0.09)	0.000480 (0.14)	0.00499 (1.61)
N	1073	1073	1073	1073	1073

t statistics in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Tables 8 – 10: Diversification Index without off-farm work included

Theoretically, a farmer may answer that they are more willing to take risks if they know that they have another source of income not tied to their farmland. That implies there may be a correlation between risk response and off-farm work. I created a third specification of Simpson's Diversification Index in which off-farm work is not included as a measure of diversification and is instead used as a control variable. Tables 8 and 9 show the results of OLS regressions using this specification with risk as continuous and risk as a category respectively. Removing off-farm income will lower average diversification for farmers that have on-farm and off-far activities, but will raise the average if households fully specialized in off farm work because they drop out of the sample.

Table 8: OLS Regression Results - No Interaction - No Off-farm Index – Risk as Continuous

	(1) Per Year	(2) Dry Season	(3) Wet Season	(4) May	(5) Sept
Risk	-0.00946** (-2.50)	-0.00940** (-2.50)	-0.00991*** (-2.62)	-0.00997*** (-2.64)	-0.00981*** (-2.60)
Std Dev Yearly Rainfall	0.000980* (1.95)				

Avg Yearly Rainfall	-0.000254 (-1.53)	-0.000379** (-2.21)	-0.000224 (-1.36)	-0.000178 (-1.01)	-0.000354** (-2.02)
Dry Season		0.00586*** (3.23)			
Wet Season			0.000573 (0.91)		
May Rainfall				-0.000797 (-0.50)	
Sept Rainfall					0.00310** (2.37)
_cons	0.848*** (2.62)	1.100*** (3.40)	0.912*** (2.83)	0.911*** (2.78)	1.121*** (3.41)
N	1003	1003	1003	1003	1003

t statistics in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 9: OLS Regression Results - No Interaction - No Off-farm Index – Risk as categorical

	(1) Per Year	(2) Dry Season	(3) Wet Season	(4) May	(5) Sept
Risk	-0.0273** (-2.55)	-0.0272** (-2.55)	-0.0285*** (-2.67)	-0.0287*** (-2.69)	-0.0283*** (-2.66)
Std Dev Yearly Rainfall	0.000975* (1.94)				
Avg Yearly Rainfall	-0.000252 (-1.52)	-0.000378** (-2.20)	-0.000223 (-1.35)	-0.000177 (-1.01)	-0.000353** (-2.02)
Dry Season		0.00586*** (3.23)			
Wet Season			0.000566 (0.89)		
May Rainfall				-0.000789 (-0.49)	
Sept Rainfall					0.00310** (2.37)
_cons	0.849***	1.101***	0.914***	0.912***	1.123***

	(2.62)	(3.41)	(2.83)	(2.79)	(3.41)
N	1003	1003	1003	1003	1003

t statistics in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 10 shows the OLS regression on the index with off farm as a control and includes the interaction between risk level and rainfall variability.

Table 10: OLS Regression Results - With Interaction Term - No Off-farm Index – Risk as Categorical

	(1) Per Year	(2) Dry Season	(3) Wet Season	(4) May	(5) Sept
main					
1. No Willingness to Take Risks	-0.0000806	0.00240	0.000358	-0.00268	-0.000230
	(-0.10)	(0.94)	(0.40)	(-1.19)	(-0.13)
2. Low Willingness to Take Risks	0.00107	0.00265	0.000258	-0.000571	0.000464
	(1.09)	(1.53)	(0.44)	(-0.38)	(0.37)
3. High Willingness to Take Risks	0.000705	0.00290	0.000158	0.00365	0.00185
	(0.97)	(1.14)	(0.17)	(1.06)	(0.64)
N	1003	1003	1003	1003	1003

t statistics in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Tables 11 – 12: Poisson Regression Results

Tables 11 and 12 show the Poisson regression results for Diversification Index without the inclusion of off farm work with risk as continuous and as a category respectively.

Table 11: Poisson Regression Results - No Interaction - No Off-farm Index – Risk as Continuous

	(1) Per Year	(2) Dry Season	(3) Wet Season	(4) May	(5) Sept
SDI3new					
Risk	-0.0192	-0.0190	-0.0201	-0.0202	-0.0198
	(-1.38)	(-1.37)	(-1.45)	(-1.45)	(-1.43)

Std Dev Yearly Rainfall	0.00196 (1.07)				
Avg Yearly Rainfall	-0.000501 (-0.84)	-0.000736 (-1.20)	-0.000445 (-0.75)	-0.000354 (-0.56)	-0.000702 (-1.11)
Dry Season		0.0118* (1.76)			
Wet Season			0.00112 (0.50)		
May Rainfall				-0.00157 (-0.27)	
Sept Rainfall					0.00622 (1.30)
_cons	-0.0126 (-0.01)	0.456 (0.39)	0.126 (0.11)	0.123 (0.10)	0.534 (0.45)
N	1003	1003	1003	1003	1003

t statistics in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 12: Poisson – No Interaction – No Off-farm Index – Risk as categorical

	(1) Per Year	(2) Dry Season	(3) Wet Season	(4) May	(5) Sept
SDI3new riskcat	-0.0546 (-1.40)	-0.0540 (-1.39)	-0.0572 (-1.47)	-0.0575 (-1.48)	-0.0565 (-1.46)
Std Dev Yearly Rainfall	0.00195 (1.07)				
Avg Yearly Rainfall	-0.000497 (-0.83)	-0.000733 (-1.19)	-0.000442 (-0.74)	-0.000352 (-0.55)	-0.000699 (-1.10)
Dry Season		0.0118* (1.76)			
Wet Season			0.00110 (0.49)		
May				-0.00154	

Rainfall				(-0.27)	
Sept Rainfall					0.00622 (1.30)
_cons	-0.0108 (-0.01)	0.458 (0.39)	0.128 (0.11)	0.125 (0.11)	0.534 (0.45)
N	1003	1003	1003	1003	1003

t statistics in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 13 shows Poisson results for the same index specification but includes the interaction between risk level and rainfall variability.

Table 13: Poisson Regression Results - With Interaction - No Off-farm Index – Risk as a Category

	(1) Per Year	(2) Dry Season	(3) Wet Season	(4) May	(5) Sept
main					
1. No willingness to take risks	0.000516 (0.36)	0.00316 (0.62)	0.00142 (0.79)	-0.00330 (-0.78)	0.000713 (0.20)
2. Low willingness to take risks	0.000901 (0.99)	0.00476 (1.46)	0.000400 (0.35)	-0.00118 (-0.44)	0.00218 (0.96)
3. High willingness to take risks	0.00122 (0.93)	0.00609 (1.27)	-0.000456 (-0.26)	0.000595 (0.15)	0.00341 (1.03)
N	1003	1003	1003	1003	1003

t statistics in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Tables 14: Regression Results Using Rainfall Variability over All Years, Last 10 Years and Last 5 Years

These regressions were run using the standard deviation of rain over the entire time (1981 – 2019), the last 10 years and the last 5 years. It was later decided that diversification decisions would likely depend more on how a farmer observed rainfall since they moved to their property, and less on what the variability had been during these three time periods.

Table: 14 OLS: Rainfall Variability over 3 Periods

	(1) All Years	(2) Last 10	(3) Last 5
Risk	-0.00271	-0.00273	-0.00261
	(-0.71)	(-0.72)	(-0.69)
Variability: All Years	-0.0000916		
	(-0.10)		
Average: All Years	0.0000856		
	(0.35)		
Variability: Last 10 Years		-0.0000344	
		(-0.05)	
Average: Last 10 years		0.000135	
		(0.34)	
Variability: Last 5 Years			-0.000474
			(-1.13)
Average: Last 5 Years			0.000210
			(0.52)
_cons	0.306	0.194	0.123
	(0.78)	(0.22)	(0.15)
N	684	684	684

t statistics in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$