**LUÍS ALBERTO CAMPOS SCHMIDT**

# A SHOT OF RESILIENCE: EVALUATING THE POTENTIAL OF PARAMETRIC DROUGHT INSURANCE FOR NON IRRIGATED COFFEE CROPS IN SOUTHERN MINAS GERAIS

Thesis submitted to the Applied Economics Postgraduate Program of the Universidade Federal de Viçosa in partial fulfillment of the requirements for the degree of *Doctor Scientiae*.

Advisor: Marcelo José Braga

Co-advisor: Mateus Pereira Lavorato

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*Once again to Erica*

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# Abstract


SCHMIDT, Luís Alberto Campos, D.Sc. Universidade Federal de Viçosa, February, 2024. **A shot of resilience: evaluating the potential of parametric drought insurance for non irrigated coffee crops in southern Minas Gerais**. Advisor: Marcelo José Braga. Co-advisor: Mateus Pereira Lavorato.

Coffee production in Brazil, particularly in the South/Southwest region of Minas Gerais, faces challenges due to increasing drought frequency and severity. This study investigates the feasibility of parametric drought insurance as a risk management tool for non-irrigated coffee growers in this region. We analyze historical coffee yield data and weather data to assess the effectiveness of parametric drought insurance in reducing risk exposure. Different payout structures are proposed, considering trigger levels, payout intervals, and the unique biennial bearing cycle of coffee trees. The performance of these contracts is evaluated under different scenarios to account for premium loading and government subsidies. Results demonstrate the potential of parametric drought insurance to mitigate income volatility during dry years. The financial safety net provided by the insurance can be particularly beneficial for risk-averse coffee growers. Furthermore, our findings suggest that parametric insurance might require continued subsidies to achieve widespread adoption, especially considering risk-averse farmers who are more sensitive to basis risk. By estimating the relationship between drought indices and yields across different yield distribution quantiles for various municipalities over time, this study provides a more robust understanding of how droughts affect yields at different points in the distribution. Subsequently, this study evaluates the effectiveness of the proposed insurance product from the perspective of coffee farmers through efficiency analysis. First, we compare the final wealth trajectories of farmers with and without insurance, considering downside risks measured by mean-semivariance. Second, we evaluate whether the insurance offers an attractive risk-return trade-off for different risk aversion profiles using Stochastic Efficiency with Respect to a Function (SERF). This study contributes to advancements in agricultural risk management strategies by offering a comprehensive analysis of parametric drought insurance for tree crops, particularly coffee. It offers valuable insights for policymakers and insurance providers seeking to enhance risk management strategies for coffee growers in Brazil.



Keywords: Parametric drought insurance. Coffee production. Agricultural risk management. Basis risk. Panel Quantile Regression. Efficiency analysis.

# Resumo

SCHMIDT, Luís Alberto Campos, D.Sc. Universidade Federal de Viçosa, fevereiro de 2024. **A shot of resilience: evaluating the potential of parametric drought insurance for non irrigated coffee crops in southern Minas Gerais**. Orientador: Marcelo José Braga. Coorientador: Mateus Pereira Lavorato.

A produção de café no Brasil, especialmente na região Sul/Sudoeste de Minas Gerais, enfrenta desafios devido ao aumento da frequência e severidade das secas. Este estudo investiga a viabilidade do seguro paramétrico contra secas como ferramenta de gerenciamento de risco para a cafeicultura não-irrigada nesta região. Dados históricos da produção de café e dados meteorológicos foram utilizados para avaliar a eficácia do seguro paramétrico na redução da exposição ao risco de secas. Diferentes estruturas de indenização foram propostas, considerando diferentes níveis de gatilho, intervalos de indenização e a bienalidade dos cafeeiros. O desempenho destes contratos foi avaliado sob diferentes cenários para considerar o prêmio comercial e subsídios governamentais. Os resultados demonstram o potencial do seguro paramétrico contra secas para mitigar a volatilidade dos rendimentos durante os anos secos. A segurança financeira proporcionada pelo seguro pode ser particularmente benéfica para os cafeicultores avessos ao risco. Além disso, as conclusões sugerem que o seguro paramétrico pode exigir a continuidade dos subsídios para alcançar uma adoção abrangente, especialmente considerando os produtores mais sensíveis ao risco de base. Ao estimar a relação entre os índices de seca e as produtividades em diferentes quantis de distribuição para vários municípios ao longo do tempo, este estudo fornece uma compreensão mais robusta de como as secas afetam as produtividades em diferentes pontos da distribuição. Posteriormente, este estudo avalia a eficácia do seguro proposto na perspectiva dos cafeicultores por meio de análises de eficiência. Primeiro, comparou-se as trajetórias de renda dos agricultores com e sem seguro, considerando os riscos medidos pela média-semivariância. Em segundo, foi avaliado se o seguro oferece uma compensação atraente entre risco e retorno para diferentes perfis de aversão ao risco usando Eficiência Estocástica com Respeito a uma Função (SERF). Este estudo contribui para avanços nas estratégias de gestão de riscos agrícolas, oferecendo uma análise abrangente do seguro paramétrico contra secas para culturas perenes, especialmente café. Ele também fornece informações para formuladores de políticas e seguradoras que buscam aprimorar estratégias de gestão de risco para a cafeicultura no Brasil.

Palavras-chave: Seguro paramétrico contra secas. Produção de café. Gestão de riscos agrícolas. Risco de base. Regressão quantílica em painel. Análise de eficiência.

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# List of abbreviations and acronyms

| | |
|---|---|
| BRAC | Break-even Risk Aversion Coefficients |
| BR-DWGD | Brazilian Daily Weather Gridded Data |
| CAGR | Compound Annual Growth Rate |
| CRRA | Constant Relative Risk Aversion |
| CE | Certainty Equivalents |
| CECAFE | Council of Coffee Exporters of Brazil |
| CEF | Conditional Expectation Function |
| CEPEA | Center for Advanced Studies on Applied Economics |
| CGSR | Interministerial Management Committee for Rural Insurance |
| CONAB | National Supply Company |
| CQF | Conditional Quantile Function |
| DARA | Decreasing Absolute Risk Aversion |
| EMBRAPA | Brazilian Agricultural Research Company |
| GDP | Gross Domestic Product |
| IBGE | Brazilian Institute of Geography and Statistics |
| IPCC | Intergovernmental Panel on Climate Change |
| MAPA | Ministry of Agriculture and Livestock |
| MCL | Maximum Compensation Limit |
| MG | Minas Gerais |
| MMSE | Minimum Mean Square Error |
| MSE | Mean Square Error |
| OLS | Ordinary Least Squares |
| PAM | Municipal Agricultural Production |
| PAP | Agricultural and Livestock Plan |

| | |
|---|---|
| PAPI | Paper-And-Pencil Interview |
| PROAGRO | Program to Guarantee Agricultural and Livestock Activity |
| PRONAF | National Program for the Support of Family Farming |
| PRONAMP | National Support Program for Medium Rural Producers |
| PSR | Rural Insurance Premium Subsidy Program |
| R1 | Reproductive Stage 1 |
| R2 | Reproductive Stage 2 |
| R1R2 | Reproductive Stage 1 and 2 |
| SEAF | Family Farming Insurance |
| SERF | Stochastic Efficiency with Respect to a Function |
| SEU | Subject Expected Utility |
| SPI | Standardized Precipitation Index |
| SPEI | Standardized Evapotranspiration Precipitation Index |
| USDA | United States Department of Agriculture |
| WMO | World Meteorological Organization |
| ZARC | Agricultural Risk Zoning |

# Contents

# 1 Introduction

## 1.1 Background

Agricultural activity is strongly characterized by its dependence on biological processes and natural resources – water availability, climate behavior and soil quality –, which makes it an activity with a range of inherent risks. Development of technologies and growing demand for food placed agriculture into modern, specialized and globalized markets. When agricultural production were extensive and diversified, capital investments and general expenses by producers were lower, as well as the magnitude of the risks associated to the activity. Nevertheless, producers saw their risk exposure multiply over the decades: overspecialized and capital-intensive production is more susceptible to market and climate events, meaning that producers are more vulnerable and require the use and the understanding of more complex risk management tools (EMBRAPA, 2018; BUAINAIN et al., 2014).

In the agricultural sector, a definition of risk can be associated to negative and unpredictable results derived from biological, climatic, regulatory or market variables. Risks related to agricultural activities are usually classified into diverse and often interconnected categories, such as production risks, market risks and business-related risks. Indeed, for many farmers, production and price are two variables that reflect the main sources of uncertainty. Production risk is an evident and straightforward type of risk to understand, where climatic events, wildfires, animal and plant diseases are all exogenous events – or risk factors[1] – that can have significant impact on production and yields (OECD, 2011; ARIAS et al., 2015).

Climate uncertainty is an intrinsic risk to the sector. In recent decades, changes in climate have already impacted natural and human systems on all continents and recent climate-related extremes, such as heat waves, droughts and floods reveal significant vulnerability and exposure of some ecosystems. Accounting for more than 20% of Brazilian GDP and employment, Brazilian agribusiness, and especially farmers and small-scale producers, is even more susceptible to climate shocks. Although global warming is usually referred to as the average increase on earth surface's temperature, it does not imply that regional impacts are uniform. In Brazil, as exposed in IPCC (2014), major impacts attributed to climate change are on food production, livelihoods, health and/or economics (eastern and southern regions) and on rivers, lakes, floods and/or droughts (northern region). IPCC's report also attributes impacts on terrestrial ecosystems and wildfires as minor contributions of climate change on center-western region of the country.

In practice, the aforementioned impacts of climate change in Brazil translates

[1] Arias et al. (2015) compiled eight different risk factors into the three risk categories. Besides production, risk factors associated to market risk can be commercialization and foreign trade. Risk factors related to the business can be logistics and infrastructure, contracts, politics and institutions.

to (i) reduced water availability and increased flooding and landslides, (ii) reduced food production and food quality and (iii) spread of vector-borne diseases. In terms of geography, rural areas are expected to experience major impacts on water availability and supply, food security, infrastructure and agricultural incomes, including shifts in the production areas of food and non-food crops around the world. From a demography perspective, such impacts are very likely to slow down economic growth and make poverty reduction more difficult (IPCC, 2014).

These consequences raise concerns about future pathways to adaptation, mitigation and sustainable development policies in Brazil. As a consequence, agricultural systems around the world face accumulating economic, ecological and societal challenges, which raises concerns about their resilience (the ability to cope with change and uncertainty and the capacity to adapt) to shocks and stresses. Adaptation strategies can improve socioeconomic welfare in the near term and existing or innovative economic instruments, such as insurance schemes, can foster adaptation by anticipating and reducing climate impacts and by increasing resilience (IPCC, 2014; MEUWISSEN et al., 2019; OECD, 2021).

Farmers have several tools to try to cope with extreme weather events, be it through on-farm risk management strategies or through risk-sharing options on public and private markets. Normal variations in production and prices do not generally require any policy response and should be directly managed by farmers as part of their normal business strategy. For example, farmers can reduce risk exposure with the adoption of anti-hail netting structures, irrigation equipment and production and income diversification. Because such strategies either require direct expenditures or induce opportunity costs, they have the disadvantage of increasing production costs (VROEGE, 2020; VROEGE; FINGER, 2020).

A holistic framework could be described as one where public policy enables market solutions and risk is managed at different levels: (i) frequent and limited losses are managed at farm level since they are part of the normal business environment, (ii) larger and infrequent risks that are beyond farm-based risk management are addressed by market mechanisms, and (iii) very large and rare risks that can lead to market failure require government intervention. At the intermediate level, market tools to manage risk could be insurance products, financial markets solutions such as forward and futures contracts and co-operative arrangements among farmers (OECD, 2011; HOHL, 2019).

In Brazil, agricultural policy is broad and multifaceted, but its essence rests on rural credit, risk management tools and programs to support commercialization and supply chains. Among these initiatives, the Brazilian Crop Insurance Program (PSR) stands out as a crucial policy for risk management in agriculture. This program allows farmers to obtain insurance at a reduced cost through premium subsidies offered by the government.

While most resources from PSR are allocated to the southern region and for grain crops, it's important to note that the geographical distribution of PSR enrollment reflects market demand rather than a direct allocation of resources by the government. The government's role lies primarily in subsidizing a portion of the premiums for insurance products offered by the private market (BUAINAIN et al., 2014; MAPA, 2023).

In the last decades, different types of agricultural insurance products have been developed to adapt to different contexts and risks. Two main categories can be defined to cover the existing range of products. Indemnity-based schemes depend on measured losses at the individual level and therefore require on-site damage assessment. They are more common in developed economies and, in emerging countries, they occur in countries with strong public welfare systems, developed agricultural markets, and larger farm sizes. However, this kind of insurance scheme is costly and time consuming in all its life cycle (underwriting, claim and payment).

In order to overcome the challenges posed by traditional indemnity-based insurances, economic literature has seen a marked increase in index-based insurance as a financial risk management tool for agricultural risks in the 2000s, more markedly from 2015 on. Index-based products have been developed as an alternative in developing contexts where indemnity-based solutions are challenging to implement. In this case, the indemnification process is not based on actual losses experiences, but on a pre-defined amount set by contract that depends on the realization of the contracted index (ABDI et al., 2022; MIRANDA; FARRIN, 2012).

Among the main agricultural activities in the country, coffee farming is a cornerstone of the Brazilian economy and generates significant employment and income, particularly in the state of Minas Gerais. However, coffee growers in Minas Gerais face increasing challenges due to climate change, particularly the increased frequency and severity of droughts. These droughts have caused substantial losses for coffee growers in recent years, threatening the sustainability of the coffee sector and the livelihoods of those who depend on it (IBGE, 2022).

Traditional crop insurance products have not been effective in addressing the specific risks faced by coffee growers due to the unique characteristics of coffee production. Coffee is a perennial crop with a biennial phenology, the many development stages of coffee trees are susceptible in different ways to climate shocks. Nonetheless, the strongest climatic limitations of coffee are frost and drought, although drought episodes are more common than frosts. Hence, drought is considered the major environmental stress affecting coffee production in most coffee-growing countries (DAMATTA; RAMALHO, 2006).

Additionally, traditional insurance products often require complex claims processes and rely on subjective yield assessments, which can be inaccurate and time-consuming. Parametric drought insurance offers a potential solution to these challenges. Parametric drought insurance utilizes weather index-based payouts, eliminating the need for complex claims processes and subjective yield assessments. By using weather data as a proxy for yield losses, parametric drought insurance can provide coffee growers with timely and transparent payouts during periods of drought. Even so, little focus and research has been put into developing solutions such as index-based insurance for the coffee sector.

In the academic literature, the most frequently studied crops are temporary crops, with special emphasis on wheat, maize, rice, cotton and soybean. As to underlying indices, rainfall-based and temperature-based data were most prevalent in weather index insurance. An additional improvement for index insurances emerged with the use of satellite-based indices, which are expected to reduce costs and basis risk without increasing asymmetric information. Thus, vegetation indices were also popular choices in the literature (VROEGE et al., 2019; FAO, 2021; ABDI et al., 2022).

Insurance applications for tree crops, such as coffee crops, are scarce in the literature, although many studies have been published that investigate the effect of climate change on perennial crops, including coffee (CASTILLO et al., 2020; CEBALLOS-SIERRA; DALL'ERBA, 2021; KATH et al., 2021). Concerning insurance for tree crops, Kölle et al. (2020) offers one exception, but they assess the hedging effectiveness of satellite-based weather index insurance for perennial non-irrigated olive trees in Spain. In addition to the study developed in this thesis, we are aware of only other two studies on parametric coffee insurance. In one of them, Adriana & Penagos-Londoño (2022) examined the possible spread of weather index insurance programs for Arabica Coffee in Colombia according to the wet and dry crop seasons. In an application to Brazil, Branco (2023) designed a parametric drought insurance for coffee, but considered a probabilistic index rather than a climate variable: they predicted the likelihood of extreme weather based on the Generalized Distribution of Extreme Values and correlated those predictions to crop losses through a logistic model.

## 1.2 Problem statement

Non-irrigated coffee growers in Minas Gerais, Brazil, face financial risks due to drought. Traditional crop insurance products have not been effective in addressing these risks, as they often require complex claims processes and rely on subjective yield assessments. Additionally, the Brazilian insurance market is heavily reliant on government programs for premium subsidies, which hinders the expansion of insurance coverage across the country, as the availability of subsidies is constrained by federal budget limitations.

## 1.3 Objectives

This thesis aims to develop and evaluate parametric drought insurance products as a robust risk management tool for non-irrigated coffee farmers in the South/Southwest region of Minas Gerais, Brazil. By leveraging historical data and exploring different insurance models, this research seeks to contribute to increasing the resilience of the coffee sector in the face of increasingly severe and frequent climate events. To achieve the general objective, this thesis pursues the following specific goals:

- Assess the potential of parametric drought insurance: We will analyze historical coffee yield data and weather data to evaluate the effectiveness of parametric drought insurance in reducing risk exposure for non-irrigated coffee growers in the study region.
- Design effective insurance products: Building on the potential identified, we will propose different payout structures for parametric drought insurance contracts. These structures will consider factors such as trigger levels and payout intervals, tailoring the insurance to the specific needs and risks of coffee growers.
- Evaluate performance under different scenarios: We will assess the performance of these proposed insurance contracts under various pricing scenarios, considering factors such as historical drought frequency and severity, premium loading, and potential premium subsidies.
- Identify an appropriate insured period: Taking into account the unique phenology of coffee trees, particularly their biennial bearing cycle, we will investigate the relationship between coffee yields and climate data. This will help identify an appropriate phenological period (insured window) for measuring the underlying index used in the insurance contracts.

## 1.4 Hypothesis

The hypotheses tested in this thesis are:

- Parametric drought insurance can reduce the risk exposure of non-irrigated coffee growers in the South/Southwest of Minas Gerais, Brazil
- Parametric drought insurance can reduce income volatility in dry years for non-irrigated coffee growers in the South/Southwest of Minas Gerais, Brazil, by providing a financial safety net that stabilizes their income during periods of drought
- Parametric drought insurance can contribute to reducing the dependency of the Brazilian insurance market on government programs for premium subsidies by providing a more affordable and efficient risk management tool for coffee growers

- While parametric drought insurance may be less effective for tree crops like coffee compared to seasonal crops due to the longer production cycle and biennial bearing, the development of such a product is feasible and can provide benefits for coffee growers in reducing risk exposure and improving financial resilience

## 1.5 Contribution

As academic and empirical contribution, this thesis intends to fill a gap in the literature and expand the frontier of knowledge about agricultural insurance in Brazil. To that end, we wish to answer the question whether it is possible to structure a feasible index-based insurance for Brazilian coffee growing that is effective in reducing wealth volatility caused by yield losses in years of severe droughts. International studies about agricultural insurance are concentrated in eastern Europe and Africa, followed by the USA and Asia. There is little research applied to Latin America, and ex-ante evaluations of insurance schemes just started to emerge in Brazil. This thesis will contribute by designing and assessing the viability of innovative insurance for coffee growers. It is more than a contribution of just adding a new activity to the research area, but rather of thinking in solutions for perennial cropping systems, which can not be adapted to climate change as easily as in systems with annual crops. The underlying index choice is also novel in the region, since we do not know of other studies using index-based application of insurance for coffee growers in Brazil. If solutions proposed in the thesis prove feasible, there could be a reduction in premium values, leading to lower subsidies requirements from the government, therefore increasing the likelihood of increased usage of agricultural insurance by coffee growers in Brazil, which would ultimately reduce farmer's risk exposure and improve their expected utility, welfare and resilience.

# 2 Coffee Landscape: Risk, Resilience, and the Role of Parametric Insurance in Minas Gerais, Brazil

Brazil is well known for its farming vocation as it figures as a world top producer of agricultural products and by-products and commodities in general. Hence, primary sector activities are of greatest importance for Brazilian development and growth. The country is responsible for more than a quarter of world production of orange, orange juice, soybeans oilseed and coffee. Also, it accounts for 10%-20% of what is produced in the world of other commodities, such as sugar, meat, milk powder, cotton, corn and other soybeans and cotton by-products. Not only is Brazil a top producer, but it is also a leading commodities exporter, including more than half of global shipments of soybean oilseed and orange juice and more than 20% of global exports of meat, sugar, coffee and cotton (USDA, 2024).

According to calculations from the Center for Advanced Studies on Applied Economics at the University of São Paulo (CEPEA/USP), Brazilian agribusiness has been responsible for nearly one fourth, on average, of the country's gross domestic product (GDP) since 1994. In 2023, Brazilian agribusiness produced close to US$ 500 billion, which accounted for nearly 24% of Brazilian GDP, and employed more than 28 million people, or 27% of the country's labor market. Beyond the national front, agricultural exports have been pivotal in the country's trade balance and economic stability. In 2023, agribusiness exports reached a historic high of US$ 166.55 billion, being responsible for 49 per cent of the total Brazilian export basket that year. The sector has also delivered an astounding surplus of nearly US$ 150 billion, effectively offsetting the deficit coming from industry and services. What is more relevant is that agricultural sales have consistently guaranteed trade balance surpluses for over a decade. From these revenues, nearly 5% of total agricultural sales were originated in the coffee sector. In 2023, Brazilian coffee was shipped to more than 120 countries and reached more than US$ 8 billion in foreign exchange revenue (CEPEA, 2024a; CEPEA, 2024b; COMEXSTAT, 2024; CECAFE, 2024).

## 2.1 Coffee economy in Minas Gerais and its relevance for the region

Among the most relevant agricultural activities, coffee is a cornerstone of the Brazilian economy and generates significant employment and income, particularly in the state of Minas Gerais. While it is present in 17 states across all geographical regions in Brazil, 87% of mapped coffee fields are restricted to Minas Gerais (56%), Espírito Santo (20%) and São Paulo (11%). Not only the production exists in different regions, but it is also marked by heterogeneity of productivity, farm size and technology, among other things, as well as by the existence of two main different species, namely *Coffea Arabica* and *Coffea Canephora*. In relation to Brazilian totals, 79% of coffee crops and 76% of coffee production consist of Arabica varieties. Except for the state of Espírito Santo, all main producing regions are

Table 1 – Coffee production in the mesoregions of Minas Gerais in 2020.

| Country, State and Mesoregion | Area | Production | Production/Brazil | Production/MG |
|---|---|---|---|---|
| Brazil | 1.898.239 | 3.700.231 | 100% | - |
| Minas Gerais | 1.054.911 | 2.064.689 | 55.8% | 100% |
| South/Southwest of Minas Gerais | 446.484 | 939.723 | 25.4% | 45.5% |
| Triângulo Mineiro/Alto Paranaíba | 192.409 | 364.986 | 9.9% | 17.7% |
| Matas de Minas | 202.544 | 361.965 | 9.8% | 17.5% |
| West of Minas Gerais | 76.485 | 142.179 | 3.8% | 6.9% |
| Vale do Rio Doce | 66.448 | 109.688 | 3% | 5.3% |
| Campo das Vertentes | 23.892 | 45.854 | 1.2% | 2.2% |
| Northwest of Minas Gerais | 17.744 | 43.805 | 1.2% | 2.1% |
| North of Minas Gerais | 8.475 | 25.452 | 0.7% | 1.2% |
| Jequitinhonha | 16.477 | 25.369 | 0.7% | 1.2% |
| Vale do Mucuri | 2.453 | 2.954 | 0.1% | 0.1% |
| Belo Horizonte Metropolitan Area | 944 | 1.404 | 0% | 0.1% |
| Center of Minas Gerais | 556 | 1.310 | 0% | 0.1% |

*Source:* Prepared by the author with data from IBGE (2022).
*Note:* Total area expressed in hectares. Total production expressed in tons. Average productivity expressed in 60kg bags per hectare.

formed by Arabica coffee trees. In Minas Gerais, there are four main producing regions throughout the state: (i) South/Southwest of Minas Gerais; (ii) Cerrado Mineiro[2], which covers the regions of Triângulo Mineiro, Alto Paranaíba, part of Alto São Francisco and part of the Northwest region of the state; (iii) Chapada de Minas, in Jequitinhonha Valley at the Northeast region of the state; and (iv) Matas de Minas, located at the East of the state (IBGE, 2022; RIBEIRO et al., 2022).

The relevance of the four main producing regions is exhibited in Table 1, which shows that more than 80% of the coffee from the state is harvested there. Coffee is specially prevalent in the South/Southwest region, where it accounts for 45.5% of the production in Minas Gerais and more than 24% of total Brazilian production. Although coffee farming has been developing over the State, southern Minas Gerais is historically a suitable location for the activity, where both the climate and topography are favorable to coffee growing, besides appropriate mild temperatures varying between 18$^o$C and 20$^o$C and moderate water deficit. Even though, farmers in the region have experienced some crops with frustrating results from the activity due to lack of rainfall and severe droughts in the last decade. Besides that, one negative characteristic is that the region is subject to frost in the winter due to altitudes as high as 1,400 meters. Overall, the region counts with a solid infrastructure, investments in research and the largest coffee farmers' cooperative in the country.

More than establishing the economic significance of coffee production in the region

[2] The delimited region "Região do Cerrado Mineiro" is the area defined by ordinance n$^o$ 165/95, dated April 27, 1995 of the Instituto Mineiro de Agropecuária.

with cold statistics, we highlight that the economic welfare of the state is closely linked to the success of the coffee sector. Firstly, it is an important source of employment in the region, providing jobs for both farmers and those involved in processing, transporting and marketing coffee. Secondly, the income generated by the coffee sector supports local commerce and services, such as retail stores, restaurants and hotels. Finally, the coffee sector contributes to government tax revenues, which are used to finance public services such as education, health and infrastructure. Therefore, we emphasize the importance of effective risk management solutions for coffee farmers in the region, such as parametric drought insurance.

## 2.2 Historical development of agricultural insurance in Brazil

Brazilian agricultural policy is broad and multifaceted, but its essence rests on rural credit, risk management tools and programs to support commercialization and supply chains. Federal government resources are allocated to policies through the annual Agricultural and Livestock Plan (PAP), also known as Plano Safra[3]. Among others initiatives, Plano Safra concedes rural credit to family farmers and small-holders through the National Program for the Support of Family Farming – PRONAF, to medium sized producers through the National Support Program for Medium Rural Producers – PRONAMP and to other farmers outside of these programes as well.

Brazilian government has also developed crop insurance subsidy and disaster risk management programmes, which include the Crop Insurance Program – PSR[4] and the Program to Guarantee Agricultural and Livestock Activity – PROAGRO. These programs are also supported through Plano Safra. Alongside with other initiatives, PSR and PROAGRO are two of the most relevant agricultural policies dedicated to risk management.

PROAGRO is a federal government program that guarantees the payment of rural financing for agricultural funding when the supported crop incurs losses due to weather events or uncontrolled pests and diseases. It was created for farmers contracting rural credit and offers partial compensation for bank debts on working capital loans indemnifying losses of own resources invested in production. In short, it insures farmer's debt and prevents him from defaulting; yet, it does not guarantee any income to the producer. Most resources from this programme are allocated to the southern region for grain crops, mainly soybeans.

Small-scale family farms can benefit from two other programmes: the PROAGRO-Mais or family agriculture insurance (SEAF); and the crop guarantee programme in the north-east of the country (Garantia Safra). Garantia Safra (GS) aims to guarantee

3 Harvest Plan, in english.
4 A more precise yet longer translation for PSR would be Rural Insurance Premium Subsidy Program.

minimum conditions of survival for family farmers in the semi-arid. It also does not insure the farmer according to its relative losses, rather it is a disaster risk reduction tool that pays a fixed amount of money to each vulnerable family after severe crop losses due to droughts or floods. SEAF is a multi-peril insurance designed to support family farmers that are integrated to the market. However, it can not be directly purchased by producers at their will, rather it is tied to PRONAF's agricultural funding credit line.

Differently, the traditional insurance scheme available in Brazil is the PSR, a government initiative that aims to make crop insurance more accessible to farmers. PSR operates by directly subsidizing a portion of the insurance premium charged to rural producers, both large and small-scale. This financial assistance helps to reduce the overall cost of insurance, encouraging farmers to participate in risk management strategies. Essentially, PSR bridges the gap between traditional crop insurance, where farmers take on the full premium cost, and the desired outcome of broader insurance adoption amongst Brazilian farmers (BUAINAIN et al., 2014; OECD, 2021).

Whilst the above programs exist to help farmers transfer risk to third parties, one governmental initiative to mitigate production risks can be highlighted: the Agricultural Risk Zoning (ZARC). The tool is a study conducted by the Brazilian Agricultural Research Corporation (Embrapa) and was first published for 1996's wheat crop. Currently conducted by Decree n$^o$ 9,841/2019, the program compiles agricultural zoning of climatic risks for more than 40 temporary and permanent crops and is available in all Brazilian states. ZARC's purpose is to improve the quality and availability of data and information on agroclimatic risks in Brazil, with emphasis on supporting the formulation, improvement and implementation of public management programs and policies. The study is designed with the objective of minimizing the risks related to adverse weather phenomena and allows each municipality to identify the best time for planting crops, in different types of soil and cultivar cycles. Compliance with zoning is required to access concessional rural credit, subsidised insurance programmes and PROAGRO.

Private rural insurance history in Brazil dates back to mid-1950s[5], when agricultural insurance was institutionalized to the preservation of crops and herds against the eventuality of risk that is peculiar to them. While Decree-Law N$^o$ 73/1966 is still the current legal framework for private insurance industry, Law N$^o$ 10,823/2003[6] paved the path to the advent of the Rural Insurance Premium Subsidy Program (PSR). PSR's guidelines are to promote universal access to rural insurance, ensure the role of rural insurance as an instrument for the stability of agricultural income and induce the use of appropriate technologies and modernize the management of the agricultural enterprise. The law also

[5] Agricultural insurance was instituted by Law N$^o$ 2,168, dated January 11, 1954 and regulated by Decree N$^o$ 35,370, dated June 12, 1954.

[6] Law N$^o$ 10,823, dated December 19, 2003 provided for the economic subsidy to the Rural Insurance premium and Decree N$^o$ 5,121, dated June 29, 2004 regulated it.

created the Interministerial Management Committee for Rural Insurance (CGSR), which was designated to define the Program's guidelines and priorities. The Committee is also responsible for overseeing and coordinating the resources allocated to the PSR, that is, to receive and consider proposals regarding the percentage of the premium or the maximum value of the rural insurance subsidy (OZAKI, 2005).

In practice, PSR's operationalization begins with Brazilian National Congress defining the budget to subsidize insurance premiums in the harvest year. At the other end, producers are responsible for contracting a rural insurance policy and requesting a subsidy from the federal government through the insurance companies authorized to operate within the Program. Insurers, in turn, submit the contracted policies to MAPA's appreciation. If there are no restrictions and if resources are available, the government grants the subsidy, transfers part of the premium amount to insurers, who deduct the amount charged from beneficiaries at the time of contracting, a portion identical to the value of the subsidy (MAPA, 2022b).

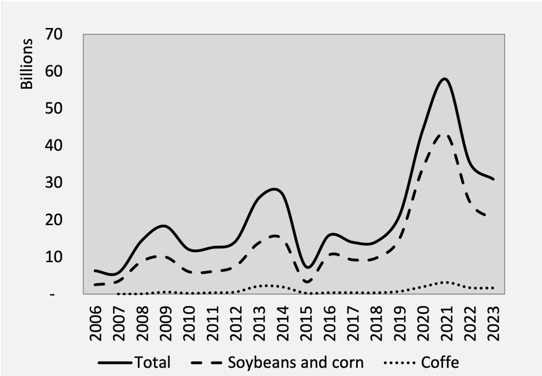
## 2.3 Overview of PSR's performance

PSR began to operate at the end of 2005 and full-year numbers are available from 2006 on. Figure 1 showcases the evolution of main performance indicators from the beginning of the program until 2023, including specific trajectories of insurance contracts for soybeans and corn as well as for coffee. In terms of total liability and total premiums, one can observe how values grew more smoothly at the first decade of the program. In fact, total liability for all cultivars presented a compound annual growth rate (CAGR) of 10% in the entire period of the program. As to total premiums charged by the insurance companies, values increased 18% per year, on average. According to MAPA (2022b), many other performance indicators increased in the past years and record numbers of more than 100,000 insured producers were reached in 2020 and 2021. Yet, due to severe weather and challenging macroeconomic conditions with high inflation and high commodity prices, the insurance uptake showed a weak performance since 2020 with increasing premium rates as a consequence of increasing risks.

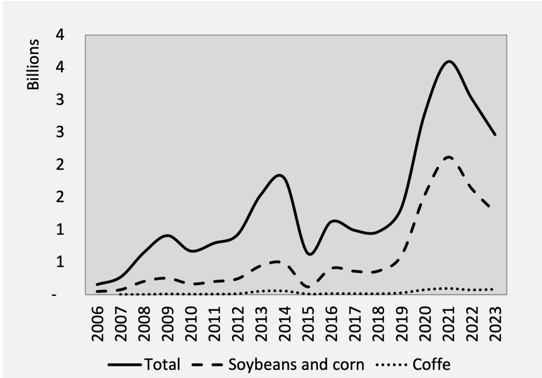
Despite the absolute size that PSR has reached and the steep curves of its performance indicators presented in Figure 1, which is most desirable for such an impactful program, it has been concentrated in a few activities. In fact, from the more than 60 activities available to be insured in 2021, 96% of total subsidies were allocated to 11 of them. Insurances for soybeans and corn alone accounted for 75% of total subsidies and liabilities. The third activity in line is coffee and it appears with a modest 5% share of subsidies and liability (MAPA, 2022a; MAPA, 2022b).

Total insured area increased for the third year in a roll in 2021 and set a new record of almost 14 million hectares. Besides such expansion and the accelerated growth in other

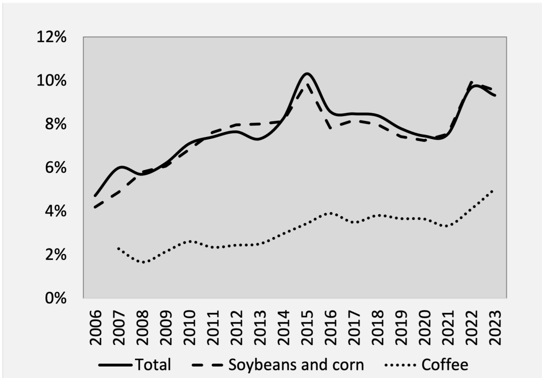
Figure 1 – Performance Indicators from Crop Insurance Program (PSR), constant values



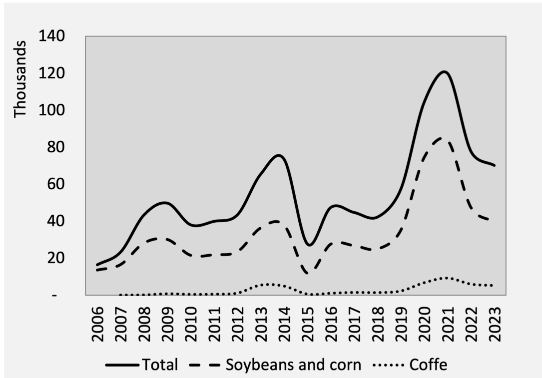

(a) Total liability in R$ (MAPA, 2023).




(b) Total premium in R$ (MAPA, 2023)




(c) Premium rates (MAPA, 2023)




(d) Total insured producers (MAPA, 2023)

performance indicators, crop insurance in Brazil was still far from its potential. Official data from PSR and Municipal Agricultural Production (PAM) showed that total insured area reached the record of 16% of total planted area in that period, whereas in 2022 and 2023 it dropped back to the average coverage of the previous years at around 10%. For soybeans and corn, a record 29% of total crop area was insured in 2020, while the average coverage disregarding record seasons of 2020/2021 has been around 18%. Coffee growers insured a record 15% of total coffee fields area in 2021, but the average insured area has been only 5% of total crops before and after the 2020/2021 crops (IBGE, 2022; MAPA, 2022a). More mature markets insure a great parcel of their planted areas. In the United States, more than 290 million acres are insured under the federal crop insurance program, including more than 80% of the acres of major field crops planted in the United States (USDA, 2020).

Although representing only a small fraction of PSR's subsidies, coffee is the fourth largest Brazilian agricultural production and, together with soybeans, corn and sugar cane, makes up 70% of total production value. From 2018 through 2022, total value of coffee production averaged more than R$ 30 billion, nearly 6% of the production from all Brazilian agriculture in the period. Nevertheless, coffee production is geographically concentrated and 89% of all Brazilian coffee comes from the southeastern region, albeit production exists at smaller scales in 17 of 27 federative units. In the region, production concentrates even more: the state of Minas Gerais originated 68% of all produced value of coffee in the country in 2020. Again, three mesoregions out of 12 are responsible for 81% of coffee value in the state: South/Southwest of Minas responds to 45.6%, Triângulo Mineiro/Alto Paranaíba to 18.3% and Zona da Mata to 17.5%. Similar geographic concentration occurs with subsidized insurance purchases under PSR. In 2022, Minas Gerais was responsible for 70% of total coffee liabilities, 83% of which were concentrated in the three above mentioned mesoregions (IBGE, 2022; MAPA, 2023).

As to concentration, Table 2 explores the geographical distribution of coffee crop insurance purchases in Minas Gerais across various administrative levels. Liability and premium columns represent the share of each region within its corresponding higher geographical level, indicating the concentration of total insured value or total premium paid for crop insurance within that region. The average rate column reflects the average premium rate paid by farmers within each geographical level. Minas Gerais concentrates a significant portion of Brazil's coffee insurance market, holding 70% of the total insured value and contributing 64% of the total premium paid for these policies. The average premium rate across the state is 3.5%. However, a closer look reveals a geographical skew towards specific regions. The four main mesoregions - South/Southwest of Minas Gerais, Triângulo Mineiro/Alto Paranaíba, West of Minas and Matas de Minas - concentrate a substantial 92% of both liability and premium volume. This high concentration likely reflects an increased level of perceived risk in these regions, potentially due to factors like weather patterns or soil conditions. This connection between concentration and risk is further supported by the premium rates. These four mesoregions experience higher rates than the state's average, with the South/Southwest region having the highest at 4.4%.

Delving deeper within the state, the data unveils a further concentration within specific microregions and municipalities. Notably, half of the top ten microregions and municipalities with the highest insurance uptake are situated in the South/Southwest region, with the remaining half concentrated in Triângulo Mineiro/Alto Paranaíba. This pattern aligns with the mesoregion data. Furthermore, a similar trend emerges when examining individual municipalities. Most of the top municipalities exhibit premium rates exceeding the state average. In Patrocínio, for instance, premium rates were a significant 42% higher than the state's average rate. However, it's important to acknowledge the significant variation in premium rates across the state. The data indicates a wide range, with observed minimum and maximum rates hovering around 1% and 10%, respectively. This highlights the need to consider not just regional trends, but also the specific risk profiles at the micro-level when designing and implementing crop insurance programs.

Although coffee represents less than 5% of total PSR liabilities and premiums and

Table 2 – Share of Crop Insurance Purchases by Geographical Level

| Region | Liability | Premium | Average rate |
|---|---|---|---|
| Minas Gerais | 70% | 64% | 3.5% |
| Mesoregions | | | |
| South/Southwest of Minas Gerais | 49% | 48% | 4.4% |
| Triângulo Mineiro/Alto Paranaíba | 27% | 27% | 3.8% |
| West of Minas Gerais | 9% | 9% | 3.9% |
| Matas de Minas | 7% | 8% | 3.0% |
| Other mesoregions | 8% | 8% | 2.6% |
| Microregions | | | |
| Varginha | 23% | 23% | 4.4% |
| Patrocínio | 14% | 14% | 4.8% |
| Passos | 7% | 8% | 4.3% |
| Alfenas | 7% | 6% | 4.6% |
| São Sebastião do Paraíso | 6% | 5% | 4.4% |
| Patos de Minas | 6% | 6% | 3.6% |
| Manhuaçu | 5% | 5% | 2.7% |
| Uberlândia | 4% | 4% | 3.8% |
| Araxá | 3% | 4% | 3.2% |
| Oliveira | 3% | 3% | 4.1% |
| Other microregions | 22% | 23% | 3.5% |
| Municipalities | | | |
| Patrocínio | 5% | 6% | 5% |
| Campos Gerais | 5% | 6% | 4.7% |
| Três Pontas | 4% | 5% | 4.8% |
| Boa Esperança | 4% | 4% | 4.5% |
| Araguari | 4% | 3% | 3.4% |
| Piumhi | 3% | 2% | 3.3% |
| Ibiraci | 3% | 3% | 5.2% |
| Monte Carmelo | 2% | 3% | 4.8% |
| Serra do Salitre | 2% | 3% | 4.7% |
| Carmo da Cachoeira | 2% | 1% | 3.3% |
| Other municipalities | 65% | 63% | 3.7% |

*Source:* Prepared by the author with data from MAPA (2023).
*Note:* Liability and Premium represent the share of each region within its respective geographical level. Average rate displays the average premium rate paid within each geographical level.

slightly more than 1% of total insured area in Brazil, insurance for the activity grew at a faster than average pace since the beginning of the program. For better assessment, Table 3 brings numbers of coffee plantation insurance policies alone, which debuted in 2007. Compared to total policies and to the ones for soybeans and corn, the difference is remarkable: total amount of liability and premiums from coffee growers expanded at a 45%

Table 3 – Coffee Insurance Performance Indicators from Crop Insurance Program (PSR)

| Year | Insured area (ha) | Liability (R$) | Premium (R$) | Subsidy (R$) | Policies | Insured producers |
|---|---|---|---|---|---|---|
| 2007 | 376 | 4,469,428 | 97,199 | 38,880 | 22 | 19 |
| 2008 | 6,861 | 52,072,153 | 684,318 | 273,727 | 125 | 98 |
| 2009 | 37,473 | 551,456,631 | 8,347,415 | 3,338,966 | 920 | 713 |
| 2010 | 18,511 | 203,901,999 | 4,189,924 | 1,675,970 | 475 | 388 |
| 2011 | 29,044 | 379,164,263 | 6,551,956 | 2,620,782 | 624 | 484 |
| 2012 | 45,910 | 563,135,987 | 11,676,223 | 4,670,489 | 1,255 | 1,073 |
| 2013 | 214,044 | 2,163,444,375 | 51,601,476 | 24,332,212 | 7,253 | 5,408 |
| 2014 | 193,060 | 1,948,457,253 | 55,001,770 | 25,680,234 | 6,566 | 4,872 |
| 2015 | 23,080 | 255,509,172 | 8,030,662 | 3,571,309 | 615 | 511 |
| 2016 | 37,727 | 399,078,907 | 14,417,890 | 6,488,048 | 1,200 | 1,004 |
| 2017 | 37,708 | 388,437,656 | 13,423,293 | 6,040,474 | 1,678 | 1,451 |
| 2018 | 32,890 | 359,302,253 | 12,062,389 | 5,421,756 | 1,602 | 1,355 |
| 2019 | 72,163 | 727,118,044 | 25,252,380 | 8,088,593 | 2,828 | 2,197 |
| 2020 | 165,112 | 1,985,002,116 | 74,057,467 | 18,012,783 | 8,691 | 6,691 |
| 2021 | 269,210 | 3,178,026,782 | 93,856,358 | 37,068,962 | 12,351 | 9,203 |
| 2022 | 126,246 | 1,725,258,743 | 70,638,160 | 27,932,697 | 7,120 | 5,927 |
| 2023 | 93,821 | 1,670,237,008 | 81,679,492 | 32,155,266 | 6,335 | 5,191 |
| CAGR | 41% | 45% | 52% | 52% | 42% | 42% |
| 2007-2020 | 60% | 60% | 67% | 60% | 58% | 57% |
| 2020-2023 | -17% | -6% | 3% | 21% | -10% | -8% |

*Source:* Prepared by the author with data from MAPA (2022a).
*Note:* All columns represent total values, not averages from each year. Monetary values are adjusted for inflation.

and 52% compound annual rate, respectively. However, crop insurance has been showing a weak performance since 2020 due to subsequent severe climatic events, increasing premium rates as a consequence of increasing risks and challenging macroeconomic conditions. In the 2020-2023 period, insured coffee area declined 17% per year and premium rates increased 11% per year, on average. In difficult scenarios like this, alternative risk management instruments for coffee farming can promote insurance uptake by farmers and induce market development.

Given the economic relevance of coffee for Brazilian agribusiness and economy, as well as the growth of PSR's performance indicators, it seems plausible to infer that farmer's interest for this kind of protection exist. This is especially true when considering the recent increase of coffee's insured area, liability and subsidies, all of them more than doubled every year, on average, since 2018. Such increases in insurance purchases can be explained, at least partially, by the intense droughts occurred in the period. According to NASA (2020), the second most severe drought in South America since 2002 took place from 2019 to 2020. This was measured in terms of extent, duration and volume of water lost during the drought. In 2021, as available in NASA (2021), prolonged dry conditions have caused the worst drought in central and southern Brazil in almost a century. Nevertheless, even accounting for the recent expansion of insurance purchases by coffee growers, one should reflect on the reasons why demand has been so low even after 15 years of PSR's existence.

Part of the issues of limited demand and low acceptance by farmers is that it largely depends on the insurance scheme in place. Also crucial is the concept insurable risk, which derives from three characteristics: the likelihood of the event must be readily quantifiable, the damage it causes must be easy to attribute and value, and neither the occurrence of the event nor the damage it causes should be affected by the farmer's behaviour. Traditional indemnity-based approaches to crop insurance, as is the case of Brazilian PSR, is inherently expensive, plagued by moral hazard, adverse selection, and high loss adjustment costs. An additional characteristic of insurance in general is that its demand is inherently influenced by current economic conditions and, as a special case in Brazil, its expansion relies on the availability of federal public budget to subsidize insurance premiums[7]. Finally, coffee is a perennial crop and the phenology of coffee trees is complex and detailed, which results in insurance products that are not necessarily entirely adherent to coffee farmers necessities[8].

## 2.4 Phenology of coffee and climate relationship

For the purpose of understanding how climate fluctuations can affect coffee production, it is key to understand coffee tree's phenological cycle and how it drives the plant's biennial bearing. Unlike most crops, coffee takes two years rather than one to complete the entire phenological cycle of frutification[9]. The first year is the vegetative year, when vegetative branches formation occurs, followed by the formation of leaf buds, induction from leaf to floral buds and floral buds maturation. Vegetative year ends with floral gems remaining quiescent in a necessary dry spell before the start of the rains. Water shock, caused by rain or irrigation, is the main factor in triggering flowering. The second phenological year begins with flowering, followed by grain formation, which precedes grain expansion and grain filling until it reaches the expected size. Finally, fruit ripeness takes place. Although schematized in a linear fashion, the two coffee phenological years occur simultaneously, which explains the biennial bearing (or biennial harvest) of coffee trees. Biennial bearing means that crop load alternates from years of high productivity to years with low productivity. This phenomenon occurs independently of weather and climate and is due to plant resources allocation in the productive year (resources mostly applied to the production of the crop at the expense of vegetative growth) and in the vegetative year (resources mostly applied to making up for the vegetative shortfall at the expense of flower and fruit production) (CAMARGO; CAMARGO, 2001; SAKIYAMA, 2015).

Due to the complex phenology of coffee, the many development stages of coffee trees are susceptible in different ways to climate shocks. Also, the kind and magnitude of each event can cause losses to either current and next-season harvests. Nonetheless, the strongest climatic limitations of coffee are frost and drought. For instance, a relatively high air temperature during blossoming, especially if associated with a prolonged dry

[7] Appendix A presents an overview on the relationship between macroeconomic situation and crop insurance performance and discusses how the federal public budget is a determining factor for the expansion of agricultural insurance in Brazil.

[8] Appendix B details the Brazilian agricultural insurance market for coffee.

[9] A schematization of the phenological stages of the Arabica coffee tree is shown in Appendix C.

season, may cause abortion of flowers, which would likely impact only the current harvest. In general, drought episodes are more common than frosts[10], so drought is considered the major environmental stress affecting coffee production in most coffee-growing countries. Specifically, Arabica coffee is feasible in areas with average annual temperature range between $18^oC$ and $23.5^oC$, annual water stress below 150mm and annual rainfall range between 1200 and 1800mm. Coffee plants are susceptible to drought damage throughout their growth cycle, but the impact is most severe during the bean-filling stage. During this phase, the plants struggle to balance the carbon demands of fruit development with the reduced production of energy from photosynthesis. As the weight of the beans increases, the stress from drought intensifies. This can lead to extensive leaf loss, branch dieback, and misshapen fruits, ultimately diminishing the quality of the coffee beans (SEDIYAMA et al., 2001; DAMATTA; RAMALHO, 2006; CAMARGO, 2010; DAMATTA et al., 2018).

Another climate stress in coffee is related to low temperatures, which have an overall negative impact on coffee trees due to a depressing effect on photosynthetic performance. This jeopardizes the development of both vegetative and reproductive cycles and causes losses to both current and subsequent seasons. In addition, when temperature reaches 3-$4^oC$, it can provoke chlorophyll loss (mostly in leaf margins) and leaf necrosis. Although less frequent than drought in general, frost (negative temperatures) is a concern to farmers in the center-south region of Brazil. Frost may strongly compromise the economic viability of the crop, since its impacts include destruction of leaves and fruits in arabica coffee, eventually requiring drastic pruning or complete tree removal. For instance, the occurrence of a severe frost on mid-1970s caused the loss of significant areas of cultivation in the state of Paraná, wich experienced a 60% decrease on its production until 1990 (DAMATTA; RAMALHO, 2006; BRAGA et al., 2021).

Although coffee growing is an activity exposed to different climatic risks at different times of the year, our objective is restricted to understanding and proposing protection for agents from yield losses caused by drought.

[10] Appendix D depicts the number of policy claims grouped by preponderant events in Brazil and corroborates with this information.

# 3 Theoretical Framework

Provision of insurance lies within the framework of information economics, which discusses the existence and concept of information asymmetries. The theory of markets with asymmetric information rests on the works of three laureate researches, who brought up seminal articles augmenting economic theory with the assumption that one side of the market has better information than the other. For example, why is it in the interest of insurance companies to offer a menu of policies with different mixes of premiums, coverage and deductibles? Akerlof (1970), Spence (1973), Rothschild & Stiglitz (1976) showed that it is straightforwardly because insurance clients know more about their risks than the company. As formally detailed by Mas-Colell et al. (1995), asymmetric information violates one of the implicit assumptions of the fundamental welfare theorems, namely that the characteristics of all commodities are observable for all market participants; hence, it is so relevant for the definition of market equilibria.

In one of the most important research in this framework, Akerlof (1970), demonstrated how information asymmetries give rise to adverse selection in markets, which arises because one agent does not have knowledge about complete information of the other. In the agriculture environment, crop insurances are usually contracted annually, so farmers can decide when to insure and which crop should be insured each year. This definition is conclusive by itself: farmers insure themselves according to information owned by them and not shared with the insurer. For example, if an insurance policy specify a trigger derived from a regional average yield, farmers whose yields are generally lower than average will have an incentive to insure, while farmers whose yields are better than average will have an incentive not to insure. In other words, the problem of adverse selection arises when farmers have different characteristics that affect the likelihood and size of indemnity payments, however insurance companies can not reflect it appropriately in the premium structure (QUIGGIN, 1994; JUST; CALVIN, 1994; QUIGGIN et al., 1994).

Before the consolidation of information economics by the above mentioned authors as a relevant research subject, Arrow (1963) have also explored related concepts to asymmetric information when delving into the uncertainty and welfare economics of medical care. With a different focus on the issue of hidden information, Arrow developed on the concept of moral hazard, which occurs when insurance companies do not have knowledge about the consumer's actions after purchasing the insurance rather than hidden information of the consumer before contracting a policy. An ideal insurance contract takes place when the event against which insurance is purchased is not in the control of the individual. As to moral hazard in the agricultural context, it arises in indemnity-based crop insurance as farmers can take many actions that affect their final yield. For instance, they choose whether or not to apply pesticides, which is costly; they can choose one or another seed variety that can be more or less susceptible to droughts or insect attacks, whilst more or less productive; they can be more or less careful when preparing the soil. Altogether, farmers will be acting rationally to use riskier technologies in exchange for potentially higher yields: they have higher earnings if the season is good and share the losses with the insurer if it is bad.

In order to overcome the challenges posed by traditional indemnity-based insurances, index insurance indemnifies producers based on the observation of a specified index and the realization of some predetermined value. It is designed to avoid problems from conventional insurance, such as the asymmetries of information mentioned above. Index insurance also exhibits lower transaction costs than conventional schemes, because contracts are standardized and do not require individually tailored terms of indemnification or separate verification of individual loss claims. Most index insurance products have been designed after exogenous rainfall and, or, temperature levels measured at available weather stations. Notwithstanding, the trade-off is that it offers less effective individual risk protection due to the so-called basis risk, which derives from the imperfect correlation between indemnity payments triggered by the index and actual losses experienced by the policyholder, especially in developing countries, which do not have a dense enough network of weather stations (MIRANDA; FARRIN, 2012; JENSEN; BARRETT, 2017).

## 3.1 Basis risk arising from information asymmetry

Traditional indemnity-based and index-based insurance are fundamentally different tools in risk exposure for vulnerable producers. For instance, rational demand for index insurance products differs from that for traditional insurance products due to the presence of basis risk, which has important implications for farmers' uptake of parametric insurance. This subsection builds upon the work of Clarke (2016), who proposed a demand model for index insurance building upon the idea of a weather derivative, in the sense that insurance payments decision derives from a predetermined index. His theoretical approach is relevant for this thesis as it focused on two puzzles related to weather derivatives distribution among producers, namely (i) the lower than expected demand for such products and (ii) the particularly low demand from the most risk averse.

In line with the model, suppose that there is a price-taking and risk averse coffee farmer (or cooperative, for instance) who wants to maximize the expected utility gained from the activity. Suppose that farmer's behaviour towards risk follows a decreasing absolute risk aversion (DARA) pattern, where an increase in initial wealth tends to reduce the individual's willingness to insure. In other words, private wealth accumulation and insurance are substitutes and wealthy individuals have less incentive to insure (CHAVAS, 2004). One critical aspect of the model is the imperfect correlation between index insurance's net transfer to the farmer and its crop loss. This is critical as it contemplates the problem of basis risk, where the producer might incur in a loss but receive no net income from the insurer, or incur no loss but receive positive net income. The presence of basis risk and DARA allows for upper bounds in the purchase of insurance products, as such an individual cares enough about the downside basis risk and would not buy a full insurance policy as he would do in an setting without basis risk.

Consider that the representative coffee grower holds strictly risk-averse preferences over wealth and a von Neumann-Morgenstern utility function $u$ satisfying $u' > 0$ and $u'' < 0$, which is to say that wealth increases provide utility gains to producers, but utility grows less than the wealth and eventually gains in wealth could represent virtually no utility gains. Our representative coffee farmer is endowed with a constant wealth $w$ at the beginning of the season, is exposed to uninsured zero mean risk $\tilde{z}$ and suffers a crop failure $l$ due to drought. Crop loss takes the value $L$ with probability $p$ or zero with probability $1-p$. Also, there is a weather index $i$ that emulates drought events, which is imperfectly correlated with the loss $l$ and takes the value $I$ with probability $q$ or zero with probability $1-q$. The indirect utility function $v$ is given by:

$$v(x) = \mathbb{E}u(x + \tilde{z}) \quad \text{for all} \quad x \in \mathbb{R}. \tag{1}$$

In this environment, where the index and the loss are not necessarily correlated (namely, there exists basis risk), but are jointly independent of background risk $\tilde{z}$, the insurance problem consists of four states $s \in S = \{00, 0I, L0, LI\}$ with a probability of $\pi_s$ for each state. Also, suppose that $r$ is the joint probability representing the probability that an individual will incur a loss but the index will not indicate bad weather conditions, for instance, it will not trigger the insurance payment. In this outcome, $\pi_{L0} = p(1-q) = p-pq$, therefore $r = p - pq = \pi_{L0}$ is by definition the probability of downside basis risk. The complete set of joint probabilities is given by $\{\pi_{00}, \pi_{0I}, \pi_{L0}, \pi_{LI}\} = \{1-q-r,\ q+r-p,\ r,\ p-r\}$ and is organized in Table 4 alongside with wealth outcomes associated with each state.

Table 4 – Four state framework of the index-based drought insurance

| State $s$ | $L0$ | $LI$ | $00$ | $0I$ |
|---|---|---|---|---|
| Probability $\pi_s$ | $r$ | $p-r$ | $1-q-r$ | $q+r-p$ |
| Outcome without insurance | $W-L$ | $W-L$ | $W$ | $W$ |
| Outcome with insurance | $W-P-L$ | $W-P-L+PO$ | $W-P$ | $W-P+PO$ |

*Source:* Adapted from Clarke (2016).
*Note:* $L,\ W,\ P,\ PO$ stand for (i) crop loss due to drought, (ii) end-of-season wealth, (iii) premium paid to purchase one insurance policy, (iv) insurance payout to indemnify insured crop failure, respectively.

To achieve the desirable insurance outcome, that is, to avoid downside basis risk, the observed index $I$ should signal that the incurred loss was $L$. This outcome requires the ratio of $\pi_{LI}$ and $\pi_{0I}$ to be greater than the ratio of $\pi_{L0}$ and $\pi_{00}$ as follows:

$$\frac{\pi_{LI}}{\pi_{0I}} > \frac{\pi_{L0}}{\pi_{00}} \quad \Rightarrow \quad \frac{p-r}{q+r-p} > \frac{r}{1-q-r} \quad \Rightarrow \quad p(1-q) - r > 0.$$

Assume that basis risk $r$ is strictly positive and that all $\pi_s$ are always nonnegative, then $0 < r < p(1-q)$ and $q + r - p \geq 0$. As discussed, due to basis risk, to consumer's DARA and to the fact that the actual loss is observable to the individual and not to the insurer, there is no market for full indemnity insurance and the policy will cover only a proportion $\alpha > 0$ of the potential loss $L$ when the index is $I$. To purchase this policy, the producer pays a premium $P = qm\alpha L$, where $q$ is the probability of the index being $I$ and $m > 0$ is a multiple to assess the actuarial fairness of the premium. Whenever $m = 1$, premium is said to be actuarially fair. If the index realization is $I$, the producer receives a claim payment of $\alpha L$; if the index is zero, there is no indemnization. Hence, individual's end-of-season wealth is $W - P - L + PO$, where $PO = \alpha L$. Our representative coffee farmer chooses a level of coverage $\alpha$ that maximizes his expected indirect utility as follows:

$$\begin{aligned}\mathbb{E}V = {} & (p-r)v[w - \alpha qmL - (1-\alpha)L] \\ & + (q+r-p)v(w - \alpha qmL + \alpha L) \\ & + (1-q-r)v(w - \alpha qmL) \\ & + rv(w - \alpha qmL - L).\end{aligned} \tag{2}$$

For an interior solution, the first-order condition after canceling $Lq(1-qm) > 0$ is given by

$$Av'_{LI} + (1-A)v'_{0I} - B \times [Cv'_{00} + (1-C)v'_{L0}] = 0, \tag{3}$$

where $v'$ denotes marginal indirect utility in state $s$ and $A$, $B$ and $C$ are conventional simplifications for:

$$A = \frac{p-r}{q}, \quad B = \frac{m-qm}{1-qm}, \quad C = \frac{1-q-r}{1-q}. \tag{4}$$

From the restrictions derived before, it follows that $p < A < 1$ and $1 - p < C < 1$, implicating $A + C > 1$. Also, $B > 0$ with $B \lesseqgtr 1$ corresponding to $m \lesseqgtr 1$. Clarke (2016) states that when the premium is actuarially fair, optimal coverage $\alpha^*$ is decreasing in basis risk $r$ and the individual chooses to contract positive and partial indexed coverage $0 < \alpha^* < 1$. Yet, given that advancing through the four-state probabilities model does not make immediately apparent which summary statistics are more reliable to evaluate a given correlation structure from the perspective of the coffee grower, the author provides a ratio for monitoring the welfare cost of basis risk, where careful attention is given to the value of the multiple $m$, as it translates into premium rates that are actuarially unfair, actuarially fair and actuarially favorable for $m > 1$, $m = 1$, and $m < 1$, respectively. The basis risk ratio is defined as follows:

$$\kappa(l) := \frac{\mu_i(l)}{m\mu_i} = \frac{E[\tilde{i}|\tilde{l} = l]}{mE[\tilde{i}]}, \tag{5}$$

where $\mu_i(l)$ is the expected claim payment conditional on incurring a loss, $m\mu_i$ is the commercial premium and $m$ is the multiple defined before. For any risk-averse farmer, the author demonstrates that the optimal level of coverage is zero if $\kappa(l) \leq 1$ for all $l \in [0, L]$.

This theory serves to the purpose of this thesis in significant ways. First, it depicts the importance of basis risk in the proposed demand theory and shows how careless assessment of basis risk can jeopardize index insurance design and development. In coffee production, the particular phenological cycle and the coexistence of vegetative and reproductive years in the coffee tree translates into a complex relationship between coffee yields and unexpected climate events. For this reason, the concept of indemnity-based insurance may have greater appeal among coffee growers; however, it is more expensive and is constrained by government limited budget. It has been discussed how parametric insurance overcomes traditional insurance issues, but Clarke (2016) demonstrated how the issue of basis risk has been overlooked.

Second, despite shining light on the severe issue of basis risk that arises when insurance claims are triggered by an exogenous index, Clarke (2016) does not neglect the potential of parametric insurance. Instead, the framework highlights the importance of assessing basis risk and suggests that index insurance products are likely to offer reliable protection against catastrophic shocks with the adoption of reliable indices and modelling.

# 4 Material and Methods

## 4.1 Index-based insurance framework

In any agricultural production system, climate is an important factor that impact plants' growth, development and productivity. Through its development cycle, plants respond rapidly to meteorological conditions and, in the case of tree crops like coffee, water availability accounts for one of the most relevant factors for productivity (MONTEIRO, 2009). Following Elabed et al. (2013), we assume coffee yields to be represented by $\tilde{y}$, a random variable stochastically dependent on weather conditions. Since weather conditions affect productivity through plant's health, we assume that $\tilde{y}$ is dependent on a given drought index $I$:

$$\tilde{y} = h(\tilde{I}) + \tilde{\varepsilon}$$

where $h(\cdot)$ estimates the average coffee yield in the form of $\overline{y} = \tilde{I} + \tilde{\vartheta}$. Along these lines, $\tilde{\varepsilon} = \tilde{\varphi} + \tilde{\vartheta}$, where $\tilde{\varphi}$ represents idiosyncratic and stochastic shocks uncorrelated with $\tilde{I}$ and $\tilde{\vartheta}$ are shocks associated with imperfections in the index design.

As theoretically described in Clarke (2016), the index insurance is designed as an derivative[11] and coffee growers are indemnified whenever the weather index falls below a given strike level $S$. For instance, the strike could be endogenously determined as the inverse of the fitted yields, $S = h^{-1}(\overline{y})$, or set to meet any previously determined categorization. Additionally, a marginal change $T$ in insurance payments is considered for each unit change in the underlying index. From these parameters, insurance payout is defined by

$$PO = T \times max\{0, S - I\}.$$

Finally, farmer's end-of-season wealth at each year $t$ is

$$W_{i,t} = y_{i,t} + PO_{i,t} - P_{i,t},$$

where $P_{i,t} = E(PO_{i,t})$ is the actuarially fair premium paid by the farmer to purchase the insurance policy.

## 4.2 Weather index for drought monitoring

Drought monitoring is crucial for understanding and predicting drought events, which can have significant impacts on agriculture, water resources, and ecosystems. Weather indices, such as the Standardized Precipitation Index (SPI), provide valuable tools for assessing drought conditions. The SPI is a widely used drought index that measures anomalies of

[11] More specifically, the derivative is a put option, which is a contract that gives the option buyer (the farmer) the right to sell a specified amount of an underlying security (the index-based index) at a predetermined price (the strike price) within a specified time frame (the insurance period).

accumulated precipitation during a given period and has been considered as the underlying index in studies for parametric crop insurance. It is calculated by standardizing the difference between precipitation for a specified time scale and the long-term average precipitation for that time scale. SPI values can be interpreted as follows:

Table 5 – Drought Intensity

| SPI Values | Category |
|---|---|
| 0 to -0.99 | mild drought |
| -1.00 to -1.49 | moderate drought |
| -1.50 to -1.99 | severe drought |
| $\leq$ -2.00 | extreme drought |

*Source:* McKee T.B. & Kleist (1993)

SPI has been shown to be effective in replicating agricultural drought, particularly for short-term periods of 2 to 3 months. For instance, the 3-month SPI considers the cumulative precipitation of month $t$ minus the average of the three preceding months, $t-1$ through $t-3$. This makes SPI a valuable tool for assessing drought impacts on coffee production. Moreover, SPI has been recommended by the World Meteorological Organization (WMO) as the main index to detect and characterize meteorological droughts (HAYES et al., 2011; WMO, 2016). In this study, we use SPI values to identify drought periods and evaluate their potential effects on coffee yields. By analyzing SPI values and their corresponding drought intensity categories, we can gain insights into the severity of drought events and their potential impacts on coffee production.

Calculation of the SPI for a specific time period at any location requires a long-term monthly precipitation database at least 30 years of data, a requirement met by our 59-year gridded database. The index can be calculated for different time scales of $t$ averaging periods, where $t$ normally takes the values of 3, 6, 12, 24 or 48 months, although agricultural drought has been replicated best by SPI on a scale of 2 to 3 months. For such short-term periods, SPI frequently moves above and below zero, whereas a drought event is defined when the index continuously presents negative values and ultimately marks values of -1.0 or less (MCKEE T.B.; KLEIST, 1993; HAYES et al., 1999; MISHRA; SINGH, 2010).

## 4.3 Empirical strategy

### 4.3.1 Yield-index relationship

To design a parametric solution to insure coffee growers against drought risk while aiming the reduction of basis risk, a positive and statistically significant relationship between index and yields is a necessary condition. To address this requirement, one needs to address the sources of disturbances in this relationship. As in subsection 4.1, consider $\tilde{\varphi}$ and $\tilde{\vartheta}$ as representations of such sources: whilst the portion $\tilde{\varphi}$ of the error term is idiosyncratic and represents risks caused by factors uncorrelated with the drought index, $\tilde{\vartheta}$ is related to risks derived from the insurance design, which implies that improvements in the insurance development is likely to reduce basis risk. The empirical strategy presented here aims to reduce the basis risk caused by insurance design, or $\tilde{\vartheta}$.

First, we consider the linear regression framework to describe individual impacts of droughts on coffee yields:

$$Y_{i,t} = \beta_{0_i} + \beta_{1_i} \cdot I_{i,t} + \varepsilon_{i,t}, \tag{6}$$

where $Y_{i,t}$ is the coffee yield at municipality $i$ in year $t$, $\beta_{0_i}$ and $\beta_{1_i}$ are regression's intercept and slope, $I_{i,t}$ is the drought index measured at municipality $i$ in year $t$ and $\varepsilon_{i,t}$ includes both the idiosyncratic error and the basis risk.

The approach to infer the value of parameter $\beta_{1_i}$ through a linear regression, that is, to fit a line to the observed data, derives from the Conditional Expectation Function (CEF). The CEF provides a straightforward summary of the empirical relationship between coffee yields and drought index and is written $E[Y_i|X_i]$, where $Y_i$ is a vector with coffee yields and $X_i$ is a vector with covariates $X_i$. In this case, $X_i$ is an $1 \times 1$ vector containing the drought index, therefore the CEF is given by

$$E[Y_i|I_i] = \underset{f(I_i)}{\arg\min}\ E[(Y_i - f(I_i))^2] \tag{7}$$

and provides the minimum mean square error (MMSE) predictor of $Y_i$ given $I_i$ because it minimizes the mean square error (MSE). The function $E[Y_i|I_i]$ determines how the average value of $Y_i$ change as elements of $I_i$ changes; for instance, it determines the relationship between drought events and the average value of coffee yields (WOOLDRIDGE, 2002; ANGRIST; PISCHKE, 2009).

Given the likelihood of heterogeneous effects of weather conditions across the distribution of agricultural yields, fitting a linear model such as the Ordinary Least Squares (OLS) – which is the sample equivalent of the linear MMSE – to $Y_i$ might be a source of bias to the parameter estimation and a source of basis risk to insurance design. Accordingly, Ozaki et al. (2014) compared different distributions to estimate probabilities of loss in soybeans crops in the state of Paraná and found that they were always higher in the normal case. They suggested that this resulted in overpriced risk and higher premiums, which would ultimately attract higher risk producers and give rise to adverse selection. Therefore, to provide robustness to the estimation and avoid biased coefficients, we also estimate the relationship between droughts and yields in quantiles of the distribution rather than in the mean.

To estimate the impacts of climate shocks on agriculture yields, quantile regression has been increasingly prevalent in contemporary studies of crop insurance[12,13]. Quantile regression has been introduced by Koenker & Bassett (1978) to circumvent issues with parameter estimation in linear models with non-Gaussian error, in which case conventional least squares estimator is biased. One advantage of quantile regression estimators is that they provide comparable efficiency to ordinary least squares for Gaussian linear models, whereas outperform the least-squares estimator over a wide class of non-Gaussian error distribution. Following Angrist & Pischke (2009), as in the case of CEF and OLS estimation, the starting point for quantile regression is the conditional quantile function (CQF):

$$Q_\tau(Y_i|I_i) = F_y^{-1}(\tau|I_i), \tag{8}$$

where $F_y(y|I_i)$ is the distribution function for $Y_i$ at $y$ and at quantile $\tau$ given the index vector $I_i$. For instance, $Q_\tau(\cdot)$ describes the lower decile of $Y_i$ given $I_i$ when $\tau = 0.10$, while $\tau = 0.50$ gives the conditional median. The CQF of coffee yields as a function of the drought index provides information on whether the dispersion of yields is greater or smaller with the index. Hypothetically, coffee yields could be generally lower with droughts and more dispersed with precipitation within the required range. As the CEF provided the solution to a mean-squared error prediction problem, the CQF solves the prediction problem by minimizing absolute errors:

$$Q_\tau(Y_i|I_i) = \underset{q(I)}{\arg\min}\; E[\rho_\tau(Y_i - q(I_i))], \tag{9}$$

where $\rho_\tau(u) = u(\tau - 1(u \leq 0))$ is the asymmetric loss function. The purpose of this function is to give the asymmetric penalty $\tau$ when the predicted coffee yield is smaller than the actual yield and $(1-\tau)$ for overprediction. This mechanism can be formulated for better visualization as the following case statement:

$$\rho_\tau(Y_i - q(I_i)) = \begin{cases} \tau \cdot (Y_i - q(I_i)) & \text{if } q(I_i) \leq Y_i, \\ (1-\tau) \cdot (Y_i - q(I_i)) & \text{if } q(I_i) > Y_i. \end{cases} \tag{10}$$

Moving forward from the CQF solution to the linear regression framework, the quantile regressor estimator, $\hat{\beta}_\tau$, is the sample analog of the minimization solution provided by CQF. It is given by the following equation:

$$\hat{\beta}_\tau = \underset{\beta_\tau}{\arg\min}\left( \sum_{y_i \geq x_i'\beta_\tau} \tau \cdot |y_i - x_i' \cdot \beta_\tau| + \sum_{y_i < x_i'\beta_\tau} (1-\tau) \cdot |y_i - x_i' \cdot \beta_\tau| \right), \tag{11}$$

[12] A complementary proposal as how to reduce the error term $\tilde{\vartheta}$ is to choose relevant indices and define reliable periods to index measurement, as previously presented in subsection 4.2 and subsequently discussed in subsection 4.5.

[13] See Bucheli et al. (2020), Dalhaus et al. (2018), Dalhaus & Finger (2016), Conradt et al. (2015a), Conradt et al. (2015b).

where $\tau \in (0, 1)$ is an asymmetrical weighting factor assigned to over- and underprediction. Finally, quantile regression fits a linear model to $\tilde{y}$ using an asymmetric loss function just as OLS fits a linear model to $\tilde{y}$ by minimizing expected squared error.

The majority of studies that applied quantile regression models to estimate the effect of a weather variable on yields did it by tailoring insurance products for each individual. Therefore, these studies performed one quantile regression for each farm[14] even when repeated measurements of crop yields over the years for all studied farms were available. Their results consisted of several insurance contracts derived from several regression coefficients. Although the choice for traditional quantile regression was justified by the authors, we choose to explore the longitudinal information available in our data set and perform a panel data regression.

Quantile regression for panel data was introduced by Koenker (2004) to overcome the almost exclusive focus on least squares estimators under Gaussian conditions for longitudinal data analysis. Notwithstanding, longitudinal models need to address issues with the independence assumption since new sources of variability arise and may severely bias model parameter estimates if not taken into consideration. Apart from random errors, such sources are the serial correlation between yields from the same municipality measured at different time points (between-individual variability) and the fact that all the repeated yield realizations coming from the same municipality share the same individual propensities to drought (within-individual variability). The approach proposed by the model to account for the dependence between observations is based on the inclusion of individual-specific fixed effects in the model specification to describe the sources of unobserved heterogeneity. The conditional quantile regression is now defined by

$$Q_\tau(y_{it}|\alpha_i, \beta, x_{it}) = \alpha_i + x'_{it}\beta_\tau, \tag{12}$$

where $\alpha_i$ is the individual-specific fixed effect shared by all observations from the same municipality, therefore it represents the source of dependence between them. Conditional on this parameter, repeated measures are no longer dependent. Following Koenker (2004), parameter estimates in quantile regression for longitudinal data with fixed effects are obtained by solving

$$\arg\min_{\alpha,\beta} \sum_{k=1}^{q} \sum_{i=1}^{n} \sum_{t=1}^{T_i} \omega_k \rho_{\tau_k}[y_{it} - \alpha_i - x'_{it}\beta_{\tau_k}], \tag{13}$$

where $\rho_\tau$ denotes the quantile loss function introduced in the traditional model and the weights $\omega_k$ are included to control the influence of the $q$ quantiles $\tau_1, \cdots, \tau_q$ on the estimation of individual $\alpha_i$ parameters. Although the author showed that the estimates obtained by Equation 13 are consistent and asymptotically Gaussian under some conditions,

[14] A recent exception is Miquelluti et al. (2022).

they also noted that they would become laborious and demanding when dimensions $n, T_i$ and $q$ are large. In the particular case when $n$ is large relative to $T_i$, a penalized approach is suggested for controlling the variability introduced by the large number of estimated parameters $\alpha_i$. More specifically, a $\ell_1$ penalty term is included to shrink individual-specific fixed effects towards a common value and parameter estimations in the penalized model are obtained by

$$\arg\min_{\alpha,\beta} \sum_{k=1}^{q} \sum_{i=1}^{n} \sum_{t=1}^{T_i} \omega_k \rho_{\tau_k}[y_{it} - \alpha_i - x_{it}'\beta_{\tau_k}] - \lambda \sum_{i=1}^{n} |\alpha_i|. \tag{14}$$

As to the tuning parameter of the penalty, we obtain the fixed-effects quantile estimator described above when $\lambda \to 0$. At the opposite extreme, an estimate of the model purged of the fixed effects is obtained as $\lambda \to \infty$ and $\hat{\alpha}_i \to 0$ for all $i = 1, \cdots, n$. Finally, Koenker (2004) shows that fixed parameter estimators obtained under this approach are asymptotically unbiased and Gaussian.

Lastly, interpretation of $\beta_\tau$ is straightforward and essentially the same both in the OLS and in the quantile regression models. The intercept $\beta_{0_\tau}$ is the baseline predicted yield at the quantile $\tau$, while each coefficient $\beta_{\tau_i}$ is the rate of change at the $\tau$-th quantile of coffee yields per unit change in the value of the corresponding regressor (in our case, the drought index) while maintaining all other covariates fixed.

### 4.3.2 Insurance contract specification and pricing

After identifying the drought index that statistically correlates with coffee yield, the first step to formally evaluate its efficiency in reducing climate risk is to select a particular contract structure. Among the different types of index contracts available, we follow Vedenov & Barnett (2004) and define a index-based contract that pays an indemnity conditional on the realization of contract parameters. Indemnity value paid by the insurer after a contract claim is defined by the following payout structure:

$$f(I|MCL, I^S, I^L) = MCL \times \begin{cases} 0 & \text{if } I > I^S, \\ \frac{I^S - I}{I^S - I^L} & \text{if } I^L < I \leq I^S, \\ 1 & \text{if } I \leq I^L. \end{cases} \tag{15}$$

In such contract, the payout is a function of the realized index $I$ given the maximum compensation limit $MCL$, strike $I^S$ and limit $I^L$. More specifically, payout is a proportional payment of the maximum compensation limit (or liability) and is triggered whenever the index falls below the strike. Indemnity payments range from zero before the index falls to the strike level to 100% when the index reaches the contract limit $I^L$. Intermediate payout percentages vary according to the severity of the drought given by the difference between the index and the strike.

While a proportional payout structure pays lower indemnities whenever the index is still close to the strike, it also pays more frequently, which could pose a higher risk to the insurance provider and increase the contract price. Hence, we evaluate the performance of two contracts with different strike and limit values, where the first triggers at a high frequency with higher strike and lower limit, and the second has a lower frequency of claims with lower strike and higher limit. We also evaluate the efficiency of a third contract with an all-or-nothing payout structure, which is suitable to insure against extreme events or natural catastrophes. Such contract pays 100% of the insured value whenever the index falls below the (extreme and less likely) strike.

To calculate the first contract, we follow Conradt et al. (2015a) and use the coefficients obtained from the regression to define the strike level, which can be obtained from $s = (y_{\tau=0.3} - \beta_0)/\beta_1$, where $y_{\tau=0.3}$ is the detrended yield evaluated at the 30% quantile of the distribution and $\beta_0, \beta_1$ are the intercept and slope, respectively. The contract limit is set to represent the lowest drought index value observed in the chosen time frame and phenological stage. To calculate the second and third contracts, we set the parametric insurance according to the drought categories defined by McKee T.B. & Kleist (1993).

Besides the three types of insurance policies, we consider two alternative pricing scenarios for each contract (Table 6). In the first scenario, insurance is actuarially fair, meaning that the premium is equal to expected indemnity paid by the insurer in case of claims. As the premium rate is actuarially fair, it is also integrally paid by the policy owner, meaning that there is no premium subsidy program from the government in place. In the second scenario, we allow the loading of the premium to account for operational costs, so the premium rate will be higher. However, we also consider that part of the the premium is subsidized by the government to promote the adoption of insurance, therefore the final premium due to the contractor will be lower than the commercial premium received by the insurance company. After all, we design and evaluate six combinations of insurance policies and premiums.

Table 6 – Insurance contracts and scenarios for pricing

| | Frequency of claims | Scenario 1 | Scenario 2 |
|---|---|---|---|
| Contract 1 | Higher frequency | Actuarially fair | Premium loaded |
| Contract 2 | Lower frequency | premium and | for costs and |
| Contract 3 | Catastrophes only | no subsidy | premium subsidy |

*Source:* Authors.

To calculate the premium rates, we rely on the burning cost analysis, which is an estimate of the expected losses to a policy based on an average of the claims experienced in past years. Although methodologically simple, burning cost is one of the most widespread pricing techniques both in academic studies and in the insurance market. Parodi (2015) presents pricing as a process that starts with collecting information about a particular policyholder and ends with a commercially informed rate. Through this perspective, burning cost analysis allows a reasonably linear narrative and can be though of as a sequence of steps until the premium is defined.

With the possession of contract parameters and records on yearly liability, the first step is the calculation of historical payouts from 2006 through 2020. Secondly, we obtain annual loss ratios dividing payouts in each year and municipality by their respective liabilities. The actuarially fair premium rate is obtained in the third step, where loss ratios are averaged over the years. Although Parodi (2015) provides a case study example with 11 years of public liability loss experience data, Heimfarth & Musshoff (2011) advises that a minimum of 15 years of data is required to reliably calculate the premium from burning cost. Our data set comprises information from 2006 to 2020 and therefore is in accordance with this requirement.

### 4.3.3 Evaluation of insurance efficiency

Analysis of efficiency begins with the calculation of two different final wealth trajectories. In the first case, the suggested drought insurance is contracted in all years, whereas in the alternative case the insurance is never adopted. When coffee yields are insured against droughts, final wealth per hectare consists of coffee yields (60kg bags/ha) net from the premium paid each year and incremented by the payouts in case of contract claims. In the case without insurance, final wealth per hectare consists only of coffee yields (60kg bags/ha)[15]. The inputs to the efficiency assessment is the average wealth in each case and in each of the six combinations and will be evaluated as to mean-semivariance comparison and stochastic efficiency with respect to a function (SERF). The approach to assess insurance efficiency in mitigating wealth volatility adopted henceforth follows Lavorato & Braga (2023).

#### 4.3.3.1 Mean-semivariance

Mean-semivariance analysis departs from traditional risk metrics by considering upside volatility as a result that does not cause discomfort and emphasizing the downside risk or negative deviations from the mean return. Unlike standard deviation, semivariance focuses solely on the dispersion of returns below the mean. Estrada (2004) provides considerations that support semivariance as a more plausible measure of risk than the standard deviation. Additionally, it demonstrates that semivariance is consistent with the maximisation of expected utility as well as with the maximisation of the utility of

[15] We follow Conradt et al. (2015a) and Shen & Odening (2012) and assume output prices to be constant and normalized to unity, therefore revenue and final wealth are described in terms of productivity.

expected compound return. As in Estrada (2007), semivariance is represented as a measure of dispersion calculated by averaging the squared deviations of returns that are less than or equal to the mean return:

$$SV_i = \sqrt{E\{min[(R_i - \overline{R_i}), 0]^2\}} \tag{16}$$

where $R_i$ represents individual returns (wealth either with and without insurance) and $\overline{R_i}$ denotes the mean return (mean wealth).

After obtaining mean and semivariance statistics from the final wealth with and without insurance, their comparison within the framework of dominance provides an enhanced understanding of the effectiveness of suggested insurance mechanism. The concept of dominance offers a comparative tool to evaluate risk and return distributions and provides a clearer picture of wealth volatility mitigation strategies (PORTER, 1974). In the context of this thesis, we compare the insured and non-insured wealth ($R_{ins}$ and $R_{non}$, respectivelly) and evaluate if some strategy dominates the other. If the strategy to adopt insurance is dominant over the one of no insurance, the distribution of wealth in the insurance strategy should have the following relationship with the strategy without insurance:

$$\begin{gathered} E(R_{ins}) > E(R_{non}) \text{ and } SV(R_{ins}) \leq SV(R_{non}) \\ \text{or} \\ E(R_{ins}) \geq E(R_{non}) \text{ and } SV(R_{ins}) < SV(R_{non}) \end{gathered} \tag{17}$$

In such case, insurance would dominate non-insurance strategy and be efficient in mitigating wealth volatility.

#### 4.3.3.2 Stochastic efficiency with respect to a function (SERF)

Stochastic efficiency with respect to a function (SERF) builds upon the Subject Expected Utility (SEU) framework, where individuals make decisions by maximizing expected utility. As emphasized by Hardaker et al. (2015), when addressing agricultural policy issues involving multiple recommendations for diverse groups, such as associations, cooperatives, or numerous farmers within a specific locale, eliciting the decision makers' utility function poses a formidable challenge. In instances where the precise utility function is not available, efficiency criteria have been formulated to enable comparative evaluations of risky alternatives. For instance, stochastic efficiency methodologies provide a means to confine the analysis within a predefined range of absolute risk aversion coefficients, denoted as $r_L(w) \leq r_a(w) \leq r_U(w)$, facilitating the ranking of prospective assets for decision makers whose risk aversion falls within the lower and upper bounds, $r_L(w)$ and $r_U(w)$. Furthermore, SERF differs by assessing and ranking the alternative risky assets based on their Certainty Equivalents (CE), rather than relying on expected utility values. CE values offer a more accessible and interpretable metric than direct utility values. A common application of efficiency analysis is to guide decision making between a set of risky prospects. Accordingly, we use it to simulate a farmer's (or any other agent exposed to climate risk in agriculture) decision between purchasing an insurance policy or not.

Following Hardaker et al. (2004), $U(w)$ is the utility function of a decision maker conditional on wealth, $w$. As the SEU hypothesis states that the utility of any risky alternative is its expected value, or $U(w) = EU(w)$, and as both the utility function and the exact risk aversion are unknown, SERF calculates the certainty equivalents for each asset and for each coefficient between the risk aversion coefficient bounds. In this context, the function for utility can be defined as:

$$U(w, r(w)) = \sum_{i=1}^{m} U(w_i, r(w))P(w_i), \quad r_L(w) \leq r(w) \leq r_U(w) \tag{18}$$

where $P(w_i)$ is the probability of state $i$ materializing across all the $m$ likely states for each risky alternative.

As SERF requires the choice of some particular form for the utility function, we use the constant relative risk aversion (CRRA) function. Given that our outcomes are measured in terms of terminal wealth with and without insurance adoption, CRRA is appropriate as its interpretation does not depend on the unity of measure and therefore is the same for monetary values or yields. Moreover, CRRA functions are necessarily also decreasing absolute risk aversion (DARA). Under DARA, an increase in wealth tends to reduce the individual's willingness to insure, meaning that private wealth accumulation and insurance are substitutes and wealthy individuals have less incentive to insure (HARDAKER et al., 2004; CHAVAS, 2004). Within the CRRA framework, we use the power function to define utility:

$$U = \frac{1}{1-r} w^{(1-r)}, \quad w > 0$$

where $r = r_r(w)$ and $r_a = r/w$.

The certainty equivalent (CE) of a risky asset represents the guaranteed amount that would yield the same utility as the expected utility of a risky alternative. Mathematically, CE is determined as the inverse of the utility function:

$$CE(w, r(w)) = U^{-1}(w, r(w)).$$

As a result, SERF provides a vector of CE values for each of the alternatives for several values of risk aversion and, at each $r_i(w)$, the efficient choice between purchasing an insurance policy or not will yield the highest CE. In this study, we use the classification proposed by Anderson et al. (1992) and calculate CE values for the two risky prospects for relative risk aversion values from $r_L(w) = 0.5$ for the hardly risk averse decision makers to $r_U(w) = 4$ for the very risk averse ones.

In the context of drought insurance for coffee within the SERF framework, the strategy of insuring is dominant over not insuring if, for all values of $r(w)$, it yields higher values of CE. However, preferences among the strategies can change over the range of $r(w)$ and eventually change places in the ordered rank of CEs. In such case, the exact value where the preference between a pair of efficient strategies change is called the break-even risk aversion coefficients (BRAC), meaning that no alternative is dominant over the other for the whole set of decision makers. If this outcome materializes, it indicates a preference for one alternative when the values of $r(w)$ are lower than the BRAC, while favoring the other alternative when the values exceed the BRAC.

## 4.4 Yield data

### 4.4.1 Data cleaning

We collected coffee production data from the Municipal Agricultural Production (PAM) from Brazilian Institute of Geography and Statistics (IBGE). PAM is a survey that provides information on planted area, area to be harvested, harvested area, total production, average yield and average price paid to the producer in the reference year. The survey is carried out annually since 1974, covers the whole national territory and its results are disclosed for national and many different regional aggregations. In order to reach the whole extension of Brazilian territory, especially in remote areas and frequently without internet connection, the survey uses the paper-and-pencil interviewing (PAPI) method, which consists of in-person interviews in which the interviewer reads questions aloud to respondents while holding a printed-out questionnaire and recording their responses.

Our analysis uses the most granular data available at the municipality level. We strategically selected municipalities within the South/Southwest region of Minas Gerais (MG), which contributes a significant 45% of the state's and one-quarter of Brazil's total coffee production. Notably, coffee fields in this specific region are cultivated exclusively with the arabica variety. This crucial detail is particularly advantageous for our study considering the survey methodology only distinguished between arabica and robusta species from 2012 onwards. The fact that our chosen region comprises 100% arabica coffee allows us to confidently utilize data prior to 2012, extending the time series and the number of observations for our analysis. Among the most relevant producing regions, southern Minas Gerais consists predominantly of rain-fed coffee culture, where irrigation was present in only 3% of the harvested area in 2018. Hence, coffee production in the region depends heavily on rainfall patterns. The region also accounts for nearly half of the State's policies and liabilities in the Crop Insurance Program (JUNIOR et al., 2019; MAPA, 2023).

Our target variable is the municipalities' average yield. Although operational since the 1970s, the survey only provides municipality-level information after 1990. To prepare the data set, we first filtered it according to the rule that every municipality has had positive coffee production in all years since 1995, which was the first year after the conclusion of the *Plano Real* to stabilize Brazilian economy, thus an important institutional landmark in Brazil. This resulted in 111 municipalities with yield records starting in 1995. Moving forward, given that the estimates obtained by the agents result from contacts that they maintain with agronomists and technicians from each region, with coffee growers, and also from their own knowledge about the coffee growing activities of the municipalities or region where they operate, we also analyzed the data as to quality and consistency.

In this stage, we identified issues in the first third of the time frame, particularly identical records of production and yields in two or more subsequent crops. For instance, only 15 out of 111 municipalities remained in the data set when we forced them to present unique yearly production values. We found that the survey provides more reliable data after the Census of Agriculture of 2006. Therefore, we considered the survey only from 2006 on, thus reducing the initial time frame by 11 years. After selecting only the municipalities with unique subsequent yields in the 2006-2020[16] period, we were left with a balanced panel with 42 municipalities and 15 years of unique observations. This selection includes most of the biggest coffee producers and accounts for 65% of the coffee produced in the region in this time frame.

While the data cleaning process aimed to ensure data integrity, it's important to understand how the resulting sample relates to the overall insurance landscape in the South/Southwest region of Minas Gerais. Appendix F provides a detailed breakdown of the 42 selected municipalities. It also analyzes their share of the total insured value (liability) in the region, which stood at approximately US$ 138 million in 2022. Similarly, the table showcases their contribution to the region's total coffee production, which amounted to 8.7 million bags (60 kg each) in 2022.

It's worth noting that a separate analysis from PSR's database reveals that the top 20 municipalities with the highest liabilities accounted for an 95% of the total insured value in the South/Southwest region during 2022. Significantly, our data cleaning process resulted in the inclusion of 50% of these top 20 high-liability municipalities. While this indicates that most of the region's major insurance adopters are still represented in our sample, it also reveals that some high-liability municipalities were excluded due to data quality concerns. Despite this exclusion, the 42 municipalities in our final dataset are still responsible for a substantial 69% of the total liabilities in the region over the analyzed period.

This high level of insurance uptake within the selected municipalities reinforces the demand for risk management solutions in the South/Southwest region. It also suggests that many producers in this area are already familiar with traditional insurance products. However, the fact that some municipalities targeted for parametric insurance are not among the highest current participants in traditional insurance highlights the potential

[16] Yield data from IBGE is available until 2022, but we were not able to use them given that the drought index is available only until 2020.

value proposition of parametric insurance as a feasible alternative or complementary risk management tool in this region.

South/Southwest region of Minas Gerais is showcased on Figure 2a, where selected municipalities are located in the northern part of the region and coloured according to their average productivity in the sample period. From the selected municipalities, the ones with higher average yields are located in the most relevant producing regions. These municipalities are located mainly in the microregions of São Sebastião do Paraíso, Passos, Varginha, Alfenas and Poços de Caldas. Grey region contains the municipalities that were disregard either because of repeated records on subsequent seasons or for not being coffee producers. For instance, some cities in the extreme south of the State present lower than required average temperatures along the year and/or frequent frost days in the winter season.

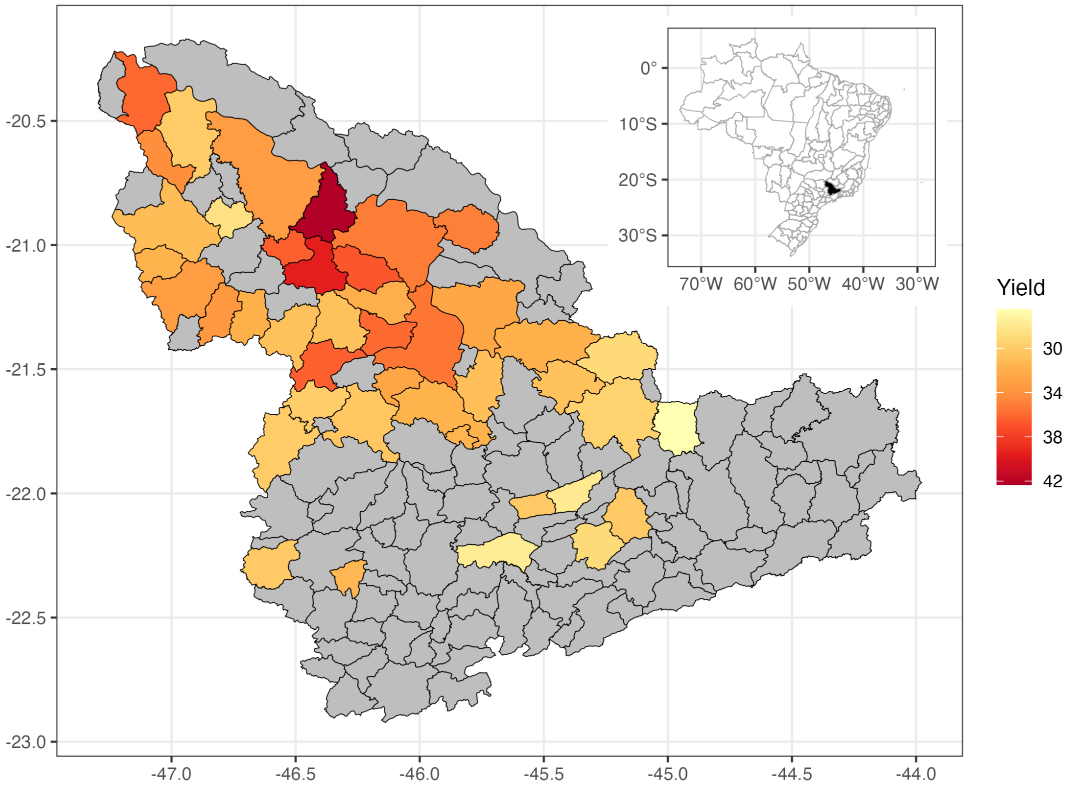
Besides the spatial distribution of yields in the region, Figure 2b displays the temporal profile of coffee productivity in the region. Yields present higher medians in even years and lower medians in odd ones, which is compatible with the biennial production pattern of coffee trees. This pattern was exceptionally not observed in the 2014 season, when the average yield was lower than that of the previous and subsequent harvests. As it will be further detailed on subsection 4.6, an extreme drought was observed in the region in the first quarter of the year, when it typically occurs the grain filling stage of coffee beans, which have impacted its potential productivity severely. In fact, according to forecasts gathered with market analysts and technicians in the South and Center-West region of the state before the drought occurred, Figure 3 shows that the expectation was for a good crop size for 2014. However, the actual crop represented a failure of more than 20% of the initial forecasts.

### 4.4.2 Data detrending

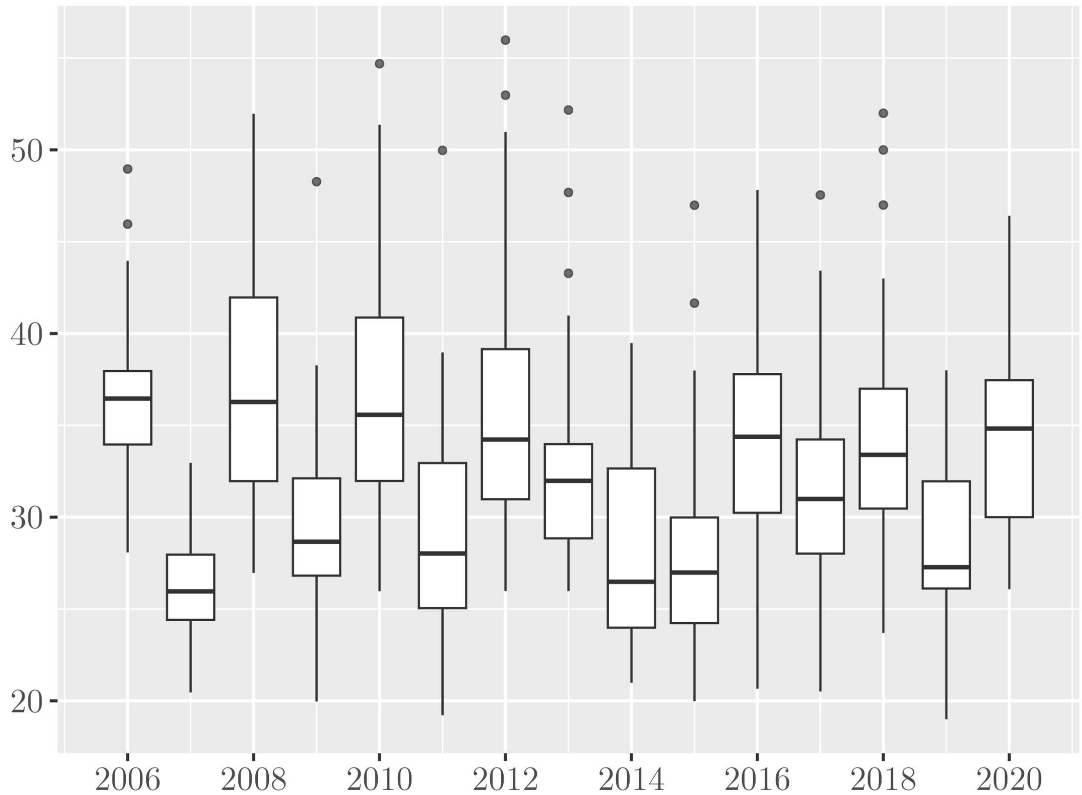
To account for technological progress in the coffee production throughout the years, we used detrended yields rather than observed yields both for exploratory data analysis and for the empirical strategy. To find a common linear time trend for all municipalities, we use yields at the South/Southwest mesoregion level, which were also provided by the Municipal Agricultural Production (PAM) (IBGE, 2022).

We applied the Mann-Kendall trend test to statistically assess if there is a monotonic upward trend of the regional yields over time (MANN, 1945; MCLEOD, 2005). It is a non-parametric test, thus no underlying assumption about the normality of the data is made. The null hypothesis states that there is no trend in the data, which is tested against the alternative hypothesis that a linear trend exists. The test statistic was 0.6 and the corresponding two-sided p-value was 0.0021535. Hence, the null hypothesis could not be accepted at the 5% significance level and we conclude that a trend is present in the yield

Figure 2 – Arabica coffee productivity (60 kg bags/ha, detrended) in selected municipalities from South/Southwest Minas Gerais between 2006-2020.



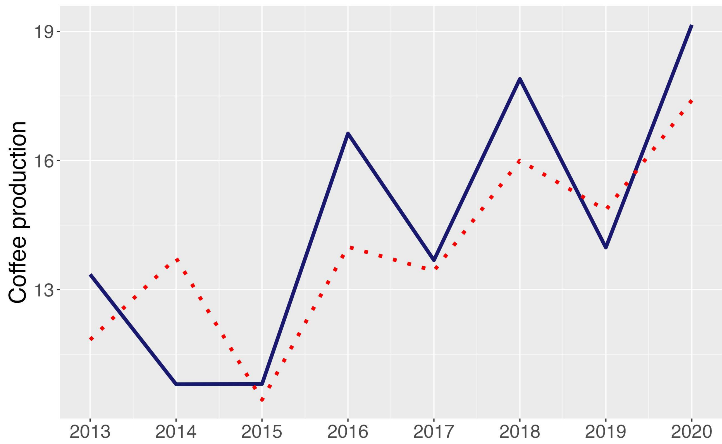

(a) Municipality coffee yields averaged across all sample years.



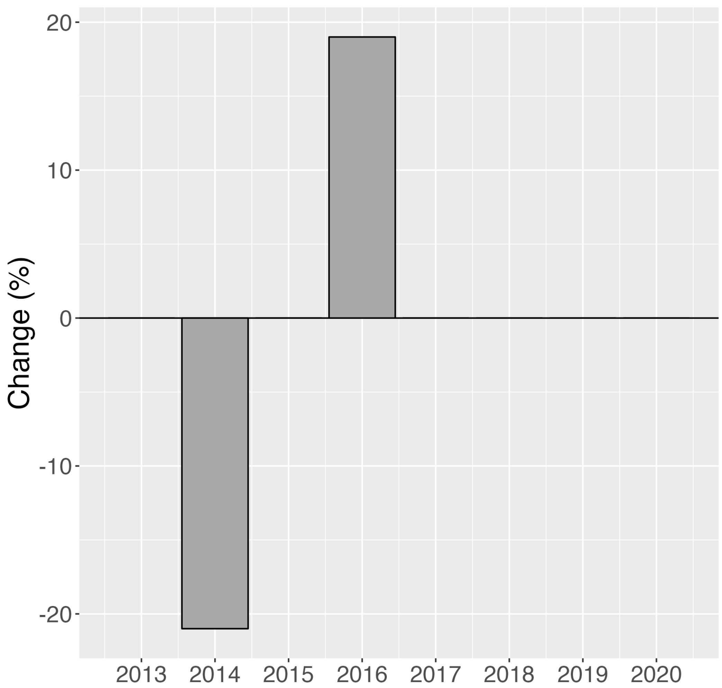

(b) Yearly coffee yields averaged across all sample municipalities.

Source: Authors with data from IBGE (2022).

Figure 3 – Coffee production in the South and Center-West of Minas Gerais: forecast vs realized.




(a) First forecast (dotted) versus actual crop size (solid).




(b) Crop failure or surprise greater than 1 standard deviation (sd = ±15%).

Source: Authors with data from Conab (2023a), Conab (2023b).

series.

Following the trend test, we employ the robust M-estimator investigated in Finger (2013) and regress regional coffee yields against (i) a simple time trend and (ii) the same time trend alongside a dummy covariate. This dummy variable takes a value of 1 in years corresponding to the high-yield phase of the biennial cycle and 0 in years corresponding to the low-yield phase. By including this dummy variable, we aim to account for the cyclical effect of biennial bearing in coffee production.

As expected by the Mann-Kendall test results, both regressions reported statistically significant trend coefficients, but the specification with a time trend and biennial bearing reported a slightly higher coefficient and slightly lower standard deviation. We use the slope from the second linear regression to derive the detrended yields in the municipalities according to the formula

$$y_{it}^{detr} = y_{it} + (t_{end} - t) \times \beta, \tag{19}$$

where $y_{it}$ is the observed yield at municipality $i$ and year $t$, $t_{end} = 2020$, $t$ is the actual observation year and $\beta = 0.9969254$ is the M-estimator of the linear trend. Detrended and actual yields are exhibited in Appendix E.

## 4.5 Insured Period

Coffee crop is permanent and thus is impacted by weather in different periods each year. As described before in subsection 2.4, the first two phenological stages in the reproductive period are especially dependent on water resources. We refer to each of them as reproductive stages 1 (R1) and 2 (R2). We investigate the effect of droughts occurred in each stage individually and on the aggregate period on coffee yields and select the insured period according to the results. The phenological stages are categorized in Table 7.

Table 7 – Phenological stages for the insured period

| Stage | Months | Milestones |
|---|---|---|
| R1 | September through December | Flowering and grain growth |
| R2 | January through March | Grain filling |
| R1R2 | September through March | Flowering, grain growth and grain filling |

*Source:* Authors.

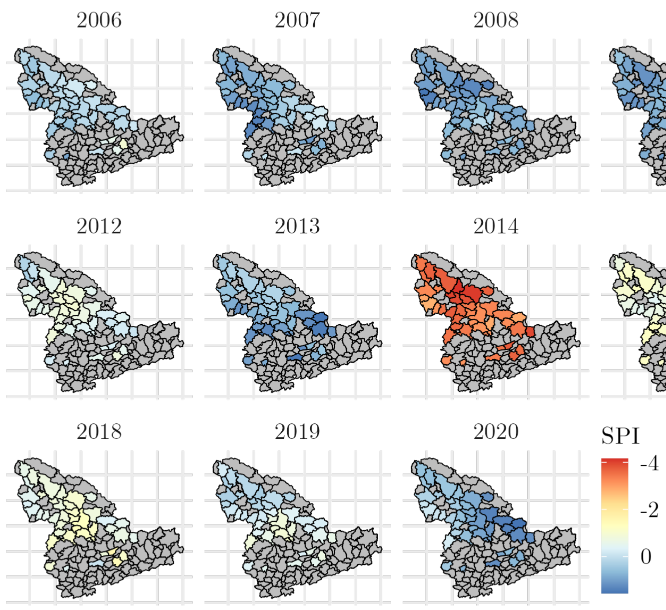
## 4.6 Weather data

We use the Brazilian Daily Weather Gridded Data (BR-DWGD) presented in Xavier et al. (2022). The BR-DWGD dataset presents daily meteorological data interpolated to a grid with $0.1^o \times 0.1^o$ of spatial resolution for the Brazilian territory, with daily data from January 1, 1961, to July 31, 2020. It used data from 1,252 weather stations and 11,473 rain gauges in its interpolation methods, cross-validated to the selection of the best method for each weather indicator. The package 'brclimr' in the statistical software environment R was used to retrieve weather indicators for Brazilian municipalities, which were created from the original gridded variables by zonal statistics (SALDANHA et al., 2023; R Core Team, 2023; Posit team, 2023). Among the weather indices available in the BR-DWGD dataset, we use precipitation (mm) to calculate the Standardized Precipitation Index (SPI).

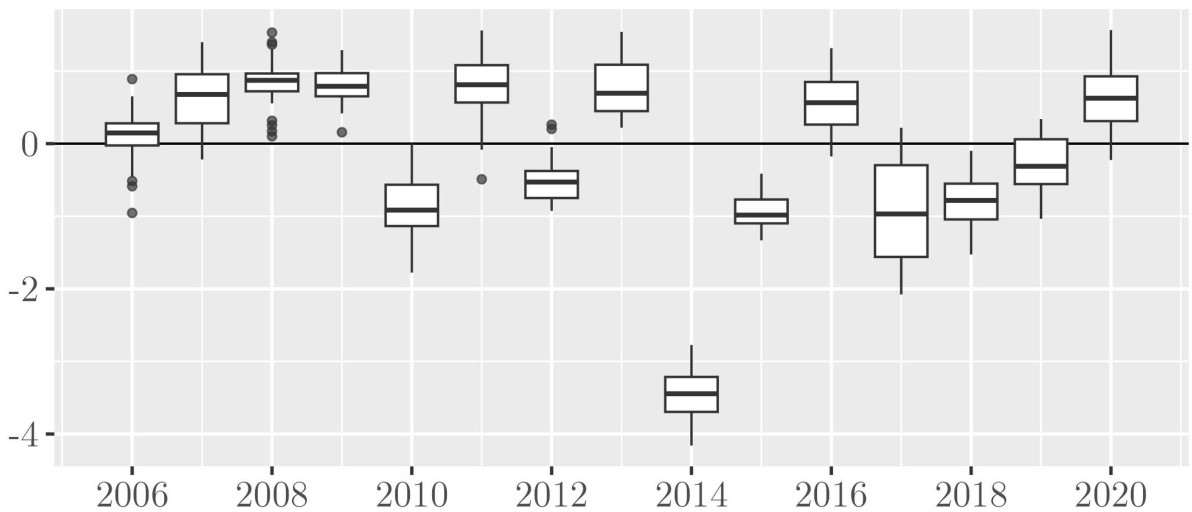
Following recommendations by McKee T.B. & Kleist (1993), we utilized our extensive 59-year precipitation database to calculate the Standardized Precipitation Index (SPI). However, coffee yield observations for the selected municipalities span only 15 years. This potential mismatch in timeframes between the weather index and yield data could affect the correlation analysis. To ensure the robustness of our results, we conducted a sensitivity analysis by calculating the SPI using different time windows for the precipitation data, ranging from 59 years (the full dataset) down to 15 years (matching the yield data). This analysis revealed minimal to no significant changes in the SPI values across these different timeframes. Therefore, based on the consistency of the SPI and the advantage of utilizing the most comprehensive data available, we opted to employ the SPI calculated with the full 59-year precipitation record for our subsequent analyses.

For short time scales, as is the case of the index calculated for the R1 (4-month SPI), R2 (3-month SPI) and R1R2 (7-month SPI), index values oscillate frequently above and below zero, thus measures between zero and -1.0 might be regarded as normal and not necessarily of great impact to coffee yield determination, holding everything else constant. From Figure 4, severe droughts (-1.5 to -2.0) in the R2 period are identified in some municipalities in crop years 2010 and 2017, although the SPI median accross all locations was slightly higher than -1.0. Nevertheless, one can affirm that some regions suffered from moderate to severe droughts in those years. However, the SPI index in the R2 period in 2014 draws more attention than any other year, as it strongly differs from the other observations. According to the index, all locations experienced extreme drought in the R2 phenological stage that year.

Figure 4 – Drought monitoring with SPI during grain filling (R2) in South/Southwest Minas Gerais ranging from extremely dry ($\leq -2.0$) to extremely wet ($\geq +2.0$).




(a) Longitudinal visualization of drought index across sample municipalities and years.




(b) Boxplot visualization of drought index averaged across sample municipalities.

Source: Authors with data from Xavier et al. (2022), Saldanha et al. (2023).

# 5 Results and Discussion

## 5.1 Yield-index dependency

We first analyze the results from the main model, which uses the pooled OLS panel model to explore how the occurrence of drought events in different phenological stages affect coffee yields. As expected, results exhibited in Table 8 indicate that coefficients associated with droughts in the first and second reproductive stages (R1 and R2, respectivelly) are statistically significant at the 5% significance level. However, we expected a positive rather than negative relationship between yields and the SPI index measured in the R1 period. Although water resources are required in the R1 period to induce flowering and allow the adequate growth of coffee beans, coffee trees that receive water very frequently at this stage have indefinite flowering. The negative effects of excessive rainfall on yields likely offset the negative effects of droughts in the model, which might explain the negative signal of the parameter.

Table 8 – Estimation results for the Pooled model, 2006-2020.

| | *Dependent variable:* | | |
|---|---|---|---|
| | Detrended yield | | |
| | (1) | (2) | (3) |
| R1 | $-0.679^{**}$ | | |
| | (0.328) | | |
| R2 | | $0.498^{**}$ | |
| | | (0.223) | |
| R1R2 | | | 0.217 |
| | | | (0.238) |
| Constant | $32.075^{***}$ | $32.317^{***}$ | $32.298^{***}$ |
| | (0.274) | (0.266) | (0.274) |
| Observations | 630 | 630 | 630 |
| $R^2$ | 0.007 | 0.008 | 0.001 |
| Adjusted $R^2$ | 0.005 | 0.006 | $-0.0003$ |
| F Statistic (df = 1; 628) | $4.298^{**}$ | $4.994^{**}$ | 0.832 |
| *Note:* | | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 |

As to the correlation between the index in the R2 period and yields, the model indicates that per hectare productivity increased nearly half (0.498) of a 60kg coffee bag for each one-point increase in the index. The positive parameter met our expectations, since water resources are required in this stage to allow coffee beans to develop internally and gain weight. The covariate in the third model is the SPI index calculated in the period that encompasses both the R1 and R2 stages. The occurrence of rainfall or drought in the aggregate period did not present statistical significance on yields.

To account for unobserved and time-invariant individual effects in the data, we further considered municipality fixed effects in the model to check the robustness of the Pooled results. A pFtest comparing the pooled OLS model with the fixed effects model resulted in a statistically significant F-statistic (F = 4.4682, p-value < 2.2e-16), indicating the presence of significant individual effects. This confirms the relevance of the fixed effects model in capturing unobserved heterogeneity across municipalities, potentially related to factors like soil quality or historical management practices.

The analysis of the results in the fixed effects model[17] did not change the interpretation in relation to the Pooled model. On the contrary, the coefficient of R2 slightly increased to 0.53 with a lower standard error. Therefore, the estimated effect of the SPI measured in the R2 period on yields improved from the 5% to the 1% significance level. This suggests that accounting for individual effects in the fixed effects model strengthens the association between drought conditions during the R2 stage and coffee yields.

We also tested the robustness of the Pooled model regarding heterogeneous effects across the coffee yield distribution. If droughts affect yields at lower quantiles differently than at the mean or at higher quantiles, then the OLS estimation is biased. In such case, parameters measured at specific quantiles should yield different results than the Pooled model. Following recent applications of quantile regression for crop insurance[18], we specified the model to estimate the effects of droughts at the 30% quantile, that is, we considered $\tau = 0.30$.

The selection of $\tau = 0.30$ in the quantile regression model balances two key considerations: adequately capturing the impact of droughts on low yield realizations and maintaining robustness to outliers. A lower $\tau$ value, although ideal for emphasizing low yields, may be overly sensitive to extreme observations. As referenced in Conradt et al. (2015a), using a very low $\tau$ (e.g., 0.1) for a 20-year time series assigns very low weights to most observations, potentially magnifying the influence of a single bad year. In contrast, a higher $\tau$ value could underrepresent the effects of drought on low-yielding farms.

We followed the literature and opted for $\tau = 0.30$ as a compromise that effectively captures the relationship between drought and yield at the lower end of the distribution while mitigating the undue influence of potential outliers. To ensure the robustness of our findings, sensitivity analyses were conducted varying $\tau$ between 0.2 and 0.4. These analyses revealed qualitatively similar results, reinforcing the validity of our choice for $\tau = 0.30$.

[17] See Appendix G.
[18] As in Conradt et al. (2015a), Bucheli et al. (2020), Vroege et al. (2021).

According to results presented in Table 9, the positive effects of the index measured during R2 on average coffee yields were corroborated in the quantile regression. In fact, the coefficient improved, since a one-point increase in the index is now related to an increase of 0.823 coffee bags per hectare at the 30% quantile and at the 1% significance level. As to R1 and R1R2, while the parameter for the former was not statistically significant, the latter was significant at the 10% significance level at the 30% quantile.

The first part of our results confirmed the expectation that rainfall patterns in the period of coffee grains filling, or the R2 stage, is positively correlated with coffee yields. This is a relevant result, since it is the first step that provides evidence that an insurance product to protect farmers against drought in the phenological stage could be feasible. This results suggests that risk basis could be likely reduced for the municipalities in the sample. We also tested the robustness of the estimation as to heterogeneous individual effects and to differences across the quantiles of the yields distribution. Our results suggested that the parameters are not biased at least for such conditions. Furthermore, Appendix H shows that the confidence intervals from Pooled and Quantile regression coefficients intersect, meaning that they are not statistically different from each other along all quantiles, corroborating with the robustness of our analysis.

Table 9 – Estimation results for the Panel Quantile Regression with Fixed Effects model, 2006-2020.

| | *Dependent variable:* | | |
|---|---|---|---|
| | Detrended yield | | |
| | (1) | (2) | (3) |
| R1 | -0.687 | | |
| | (0.450) | | |
| R2 | | 0.823*** | |
| | | (0.202) | |
| R1R2 | | | 0.558* |
| | | | (0.308) |
| Constant | 27.607*** | 28.033*** | 28.179*** |
| | (0.209) | (0.116) | (0.189) |
| Observations | 630 | 630 | 630 |
| $R^2$ | - | - | - |
| Adjusted $R^2$ | - | - | - |
| F Statistic (df = 1; 571) | - | - | - |
| *Note:* | | | *p<0.1; **p<0.05; ***p<0.01 |

## 5.2 Contract parameters and premium rate

After mapping the relationship between drought events during specific stages of coffee growing, we found that rainfall correlates mostly with yields when it is measured from January through March, when recently formed coffee beans develop internally and gains weight. Henceforth, we define the SPI index measured during the phenological stage R2 as the underlying index for the parametric drought insurance and design the three contracts accordingly. Given that all contracts are aimed to insure the same locations and individuals, they consequently have the same liability inputs. However, the remaining contract parameters (strike and limit) are different between them as each contract varies as to the frequency of payout realizations. We also consider two alternative scenarios to price the insurance policies, which resulted in the six combinations exhibited in Table 10.

To reflect the conditions outlined in scenario 2, we implemented a 40% premium rate subsidy for the insurance contracts. This subsidy aligns with the current crop insurance premium subsidy for coffee established by the Interministerial Rural Insurance Management Committee (BRASIL, 2022). By incorporating this 40% subsidy, we ensured the affordability of the insurance product within scenario 2, reflecting the real-world support offered by government initiatives to mitigate risk for agricultural producers.

As to loading costs and profit margins, while research by Bucheli et al. (2020) considered a 10-20% range for internal expenses, taxes, and profits, Parodi (2015) offers a more detailed breakdown. The author suggests a 15% loading cost for expenses, a 10% profit margin, and even recommends potential adjustments for exposure changes, risk profiles, and other unforeseen factors. To arrive at the suggested commercial rate, we opted for a prudent 40% loading on the pure rate, encompassing a 20% expense loading, a 10% brokerage commission, a 5% insurer mark-up, and a 5% buffer for potential adjustments, similar to the approach suggested. This approach balances affordability with profitability, while acknowledging potential future needs for premium adjustments.

**Contract 1** We designed the first contract with an empirical approach and used the coefficients obtained from the quantile regression to define the strike and limit. While the limit is set to represent the lowest SPI index observed in the R2 stage from 2006 to 2020, strike is obtained from $s = (y_{\tau=0.3} - \beta_0)/\beta_1$, where $y_{\tau=0.3}$ is the detrended yield evaluated at the 30% quantile of the distribution and $\beta_0, \beta_1$ are the intercept and slope, respectively. From results in Table 9 for the R2 stage, strike value is defined as $s = (27.988 - 28.034)/0.823 = -0.056$. Consequently, we rounded the strike to 0 and set contract 1 to trigger whenever the index becomes negative. As to the limit, the lowest SPI measured from January through March across all sample municipalities and years averaged $-4.081$. Therefore, this insurance contract pays the maximum payout for index measures of -4 or lower. Since this contract has the feature of triggering with a higher

Table 10 – Parameters of drought insurance contracts and premium rates

| | Liability | Strike | Limit | Average payout | Premium | Subsidized premium |
|---|---|---|---|---|---|---|
| | | | | Scenario 1 | | |
| Contract 1 | 32.23 | 0 | -4 | 4.28 | 13.29 | - |
| Contract 2 | 32.23 | -1.5 | -2 | 2.56 | 7.93 | - |
| Contract 3 | 32.23 | -2 | - | 2.25 | 6.98 | - |
| | | | | Scenario 2 | | |
| Contract 1 | 32.23 | 0 | -4 | 4.28 | 18.61 | 11.17 |
| Contract 2 | 32.23 | -1.5 | -2 | 2.56 | 11.11 | 6.66 |
| Contract 3 | 32.23 | -2 | - | 2.25 | 9.78 | 5.87 |

*Source:* Research results.
*Note:* Scenario 1 considers fair premium and no premium subsidy, scenario 2 considers the suggested commercial rate and premium subsidy. Liability and average payout are measured in yields (60kg bags/ha), strike and limit are SPI values and premiums are in percentage rates.

frequency, it turns out to be riskier to the insurance provider and the resulted premium rates were the highest among the contracts. In scenario 1, the average premium rate across all municipalities is 13,29%. In scenario 2, the suggested commercial rate increases to 18.61%, but individuals pay 11.17% of the liability to purchase the insurance policy after the premium subsidy.

**Contract 2** The second contract is designed to represent an intermediate frequency of claims, therefore it starts to pay only in case of severe droughts appointed by the underlying index. We set the strike and limit according to the categorization of drought intensity from McKee T.B. & Kleist (1993), so this contract triggers whenever the index reaches -1.5 and payout increases proportionally until 100% of liability when it measures -2. A representation of the payout structure of a proportional payout contract is shown in Appendix I with the parameters of this contract. The change of the strike value in this contract reduces the insurer risk and the average premium rate falls to 7.93% in the scenario 1. In the second scenario, the suggested commercial rate is 11.11%, but the subsidized rate decreases to 6.66%.

**Contract 3** Our final insurance contract is designed to reduce farmer's income volatility in situations of extreme drought, such as in southern Minas Gerais in 2014. Following the drought intensity categories, we define that this contract pays total liability whenever the underlying index reaches the strike level of -2. This contract presents an all-or-nothing payout structure rather than the proportional structure from contracts 1 and 2. As extreme drought events are rare, this contract offers the lowest risk to the insurer, which results in the lowest premium rates. The fair premium rate in this contract drops to 6.98% and to 9.78% when loaded to account for insurer costs, brokerage commission, profits and other adjustments. After subtracting premium subsidies, the final rate charged to contractors falls to 5.87%.

## 5.3 Evaluation of insurance effectiveness

To assess if the proposed insurance contracts are efficient in mitigating wealth volatility during dry years in the South/Soutwestern region of Minas Gerais, we first present the results for the mean-semivariance analysis between the strategy to purchase the index-based insurance policy and the strategy of not adopting it and remaining exposed to drought risks.

Table 11 shows that adopters of both strategies in scenario 1 present the same final average wealth (given that they departed from the same starting point). This result is expected as the insurance premium is actuarially fair. In the scenario with loaded and subsidized premiums, the proposed insurance was successful in guaranteeing a slightly higher wealth for the individuals who opted to insure their crops. In both scenarios and for all contracts, the difference in means corresponded to the first of the two conditions required to the dominance of insurance over risk exposure. Specifically, $E(W_i) \geq E(W_{ni})$ for all the six combinations.

Table 11 – Results for the final wealth's mean-semivariance analysis

| | Wealth$_i$ | Wealth$_{ni}$ | Difference in means | SV$_i$ | SV$_{ni}$ | Difference in SV |
|---|---|---|---|---|---|---|
| | | | Scenario 1 | | | |
| Contract 1 | 32.23 | 32.23 | 0 | 7.15 | 5.68 | 1.467 |
| Contract 2 | 32.23 | 32.23 | 0 | 6.86 | 5.68 | 1.176 |
| Contract 3 | 32.23 | 32.23 | 0 | 6.77 | 5.68 | 1.080 |
| | | | Scenario 2 | | | |
| Contract 1 | 32.92 | 32.23 | 0.685 | 7.17 | 5.68 | 1.480 |
| Contract 2 | 32.64 | 32.23 | 0.410 | 6.87 | 5.68 | 1.189 |
| Contract 3 | 32.59 | 32.23 | 0.360 | 6.77 | 5.68 | 1.090 |

*Source:* Research results.
*Note:* Scenario 1 considers fair premium and no premium subsidy, scenario 2 considers premium loaded for costs and premium subsidy. Subscript $i$ denotes the situation with insurance adoption and $ni$ otherwise. Wealth is measured in yields (60kg bags/ha) and was averaged across all municipalities. "SV" stands for semivariance, which was averaged across all municipalities.

The second step of the mean-semivariance approach is precisely to evaluate the differences in semivariance in each of the choices. Contract 1 is designed to frequently indemnify the policy holder. Even so, added to being riskier for the seller and more expensive for the buyer, it has also failed to reduce semivariance in comparison to the risk exposure situation. Although contract 1 performed worst among the others in terms of semivariance, contracts two and three were also unsuccessful to reduce wealth volatility.

The difference in semivariance between the strategy to purchase and the strategy to expose to drought risk was positive for all contracts and all scenarios, but it was slightly higher in scenario 2. From all combinations, contract 3, which has been the most affordable option for the individuals who desires to insure their coffee crop against drought, has also provided the smallest volatility from the three contracts, although higher than in the decision to remain uninsured. Finally, given that $SV(W_i) < SV(W_{ni})$ for all choices, we can not conclude that purchasing the proposed index-based insurance is dominant over the alternative prospect.

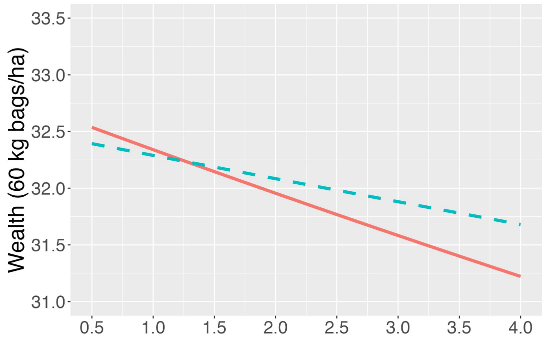
Complementing the mean-semivariance analysis, which indicated higher wealth volatility with insurance, we depict those of the stochastic efficiency analysis in Figure 5, where each contract is arranged in a row and each column represents one scenario. SERF's approach is to calculate and rank certainty equivalent values associated with the final wealth in each strategy, as well as presenting its value for different relative risk aversion coefficients ranging from low risk aversion ($r_L = 0.5$) to extreme risk aversion ($r_U = 4$). Interestingly, while mean-semivariance suggested increased risk with insurance, SERF results show that for most risk aversion levels (particularly low to moderate/high), purchasing insurance contracts can be the preferred choice.

Recall that only the choices with the highest certainty equivalents for some value in the range of $r(w)$ are utility efficient. Considering scenario 1, results show that purchasing any of our index-based insurance contracts is the efficient choice only for decision makers with low risk aversion, or for the coefficients ranging from $r(w) = 0.5$ to around $r(w) = 1.5$. In scenario 2, which considers the suggested commercial rate and government subsidy, contract 1 becomes the dominant choice for all risk aversion levels (represented by the range of coefficients $r(w)$). This means that purchasing contract 1 offers the highest certainty equivalent for all decision-makers, regardless of their risk tolerance. Contracts 2 and 3 also show significant improvement in SERF terms when analysied under scenario 2. They become the utility-efficient choice for a wider range of risk aversion coefficients, spanning from low ($r(w) = 0.5$) to moderate/high ($r(w) = 3.25$). This indicates that these contracts are attractive for most decision-makers, except for those with extremely high risk aversion.

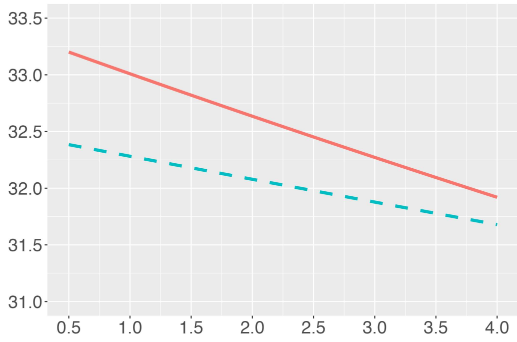
For individuals with very high risk aversion ($r(w) > 3.25$), the results of SERF converge with the mean-semivariance analysis. This suggests that these individuals might still prefer to remain exposed to drought risk (no insurance) as it aligns with their extreme risk-averse nature. Overall, the adjusted SERF results are highly encouraging. Contract 1 becomes universally appealing, while contracts 2 and 3 cater to a broad spectrum of risk preferences. This suggests that the adjusted pricing structure makes the insurance products significantly more attractive across a wider range of potential policyholders.

As a last evaluation, we calculate if the ratio proposed in Clarke (2016) suggests that the proposed contracts would have zero or positive optimal demand due to the

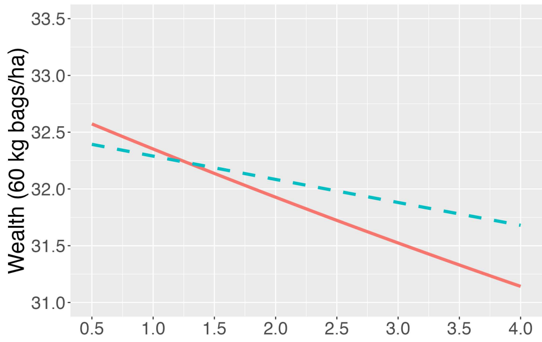
Figure 5 – Certainty equivalents calculated for wealth with insurance (solid) and without insurance (dashed).



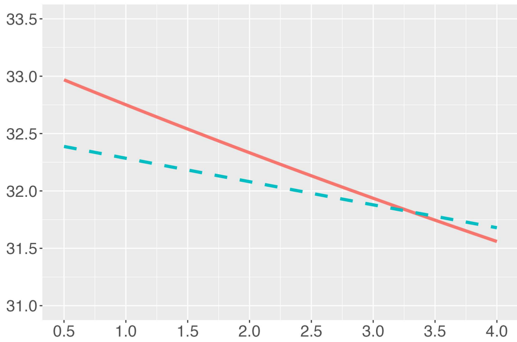

(a) Contract 1, scenario 1



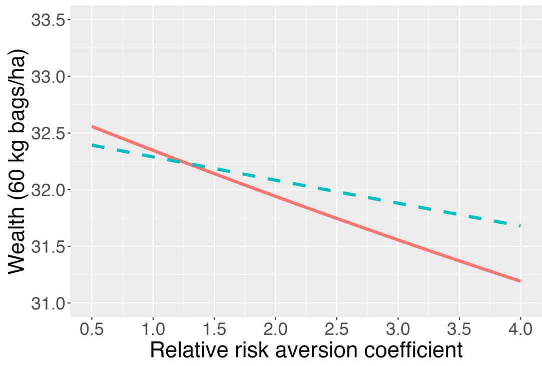

(b) Contract 1, scenario 2



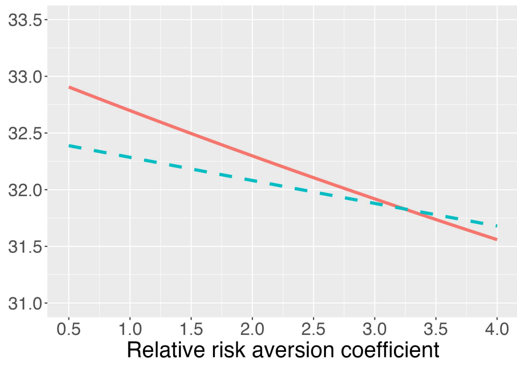

(c) Contract 2, scenario 1




(d) Contract 2, scenario 2




(e) Contract 3, scenario 1




(f) Contract 3, scenario 2

Source: Research results.

presence of basis risk. In the paper, the author demonstrate that the optimal level of coverage is zero if $\kappa(l) \leq 1$ for all $l \in [0, L]$ for any risk-averse farmer and applied the methodology developed on his paper to evaluate a set of 270 products sold across one Indian state under the Weather Based Crop Insurance Scheme. The model results that the basis risk ratio is $\kappa(l) \leq 1$ if the pricing multiple $m \geq 1.56$.

If our proposal is plagued by basis risk, then our proposed contract would not be a optimal choice for coffee growers if the multiple $m$ is greater or equal than 1.56. With the caveat that this result is dependent on the belief that the evaluated insurance program follows the same joint distribution function of yields and index-based payouts presented in the original model, we emphasize that this additional result can be more illustrative rather than definitive regarding the elimination of basis risk. However, results presented in Table 12 suggests that our contracts would not be automatically disregarded and have the potential to have positive optimal demand from drought exposed coffee farmers, especially in the contract 1 in the second scenario. In other words, results indicate that we were successful in (at least partially) addressing basis risk.

Table 12 – Premium to payouts ratio in the proposed contracts

| Fair premium | Loaded premium | Loaded and subsidized premium |
|---|---|---|
| 1.00 | 1.40 | 0.84 |

*Source:* Research results.
*Note:* As in Clarke (2016), the premium to payouts ratio is the multiple $m$ in the basis risk ratio formula.

## 5.4 Discussion

Our results demonstrate the feasibility of designing parametric drought insurance for coffee, but also highlight the complexities involved. While the chosen index positively correlates with historical yield realizations, the two-year production cycle and sensitivity to various weather events introduce challenges in establishing a perfect correlation. Consequently, the proposed insurance contracts did not necessarily reduce overall end-of-year wealth volatility compared to the scenario without insurance (as indicated by the mean-semivariance analysis).

However, a more nuanced picture emerges when we consider risk aversion through SERF analysis. Interestingly, for decision-makers with risk aversion classified as low to moderate, and even for some individuals at the lower end of the high risk aversion range, purchasing some of the proposed insurance contracts becomes the preferred choice. This suggests that for these risk profiles, the financial safety net provided by the insurance outweighs the potential increase in wealth volatility. In contrast, for individuals with very high risk aversion, the results converge with the mean-semivariance analysis, indicating they might still be better off without insurance.

These findings highlight the importance of considering both risk aversion and volatility when evaluating the effectiveness of parametric drought insurance. While our initial results based on mean-semivariance suggested limitations in overall risk reduction, the SERF analysis demonstrates the potential value proposition for risk-averse coffee growers. This reinforces the need for further research that investigates how risk perception and risk aversion can be factored into the design of parametric drought insurance products for coffee growers.

Our findings also highlight the importance of payout formulation in the success of parametric drought insurance for coffee. The premium structure, particularly the frequency of indemnities, significantly impacts the overall cost and effectiveness of the insurance product. The simulated wealth comparison in Appendix J illustrates how indemnities from the insurance could have significantly impacted the economic welfare of coffee growers during the 2014 drought. This demonstrates the potential of parametric insurance to mitigate income volatility during dry years, enabling growers to invest in recovery measures and maintain crop resilience.

Our study initially suggested the potential for parametric drought insurance to reduce the sector's reliance on Brazilian government's premium subsidies. However, the results revealed that even parametric solutions might still require subsidy to achieve widespread adoption among coffee growers. This could be because parametric insurance, with its focus on specific triggers linked to drought risk, might more accurately capture the true cost of insuring crops compared to traditional insurance models. This difference in risk assessment might necessitate continued subsidies. Therefore, further research is needed to explore alternative subsidy models that balance affordability with financial sustainability, especially from a public budget perspective.

Although limited research exists on index-based coffee insurance in Brazil, we compared our findings with recent studies proposing similar solutions for different crop types. Our premium rates align with Miquelluti et al. (2022) and Lavorato & Braga (2023), whose studies explore grain crops in Paraná and the semi-arid region, respectively. While prices are comparable (semi-arid) or exceed alternative yield insurance (Paraná), a key difference emerges in risk reduction efficiency. Our findings suggest that index-based insurance might be less effective for coffee, a perennial crop with a longer production cycle and biennial bearing, compared to seasonal grain crops. This highlights the potential influence of regional and commodity specificities on the performance of index-based insurance.

Furthermore, Branco (2023) also investigated parametric drought insurance for coffee in Minas Gerais, Brazil. However, their approach differed from ours by utilizing a probabilistic index based on the Generalized Extreme Value (GEV) distribution to predict extreme weather events, and then linked those predictions to crop losses through a logistic model. This probabilistic approach offers an alternative perspective on parametric insurance design for coffee, but further research is needed to compare the effectiveness of different index types and payout formulations in mitigating drought risk for coffee growers.

From empirical applications in countries other than Brazil, we highlight the research conducted by Vroege et al. (2021) and Bucheli et al. (2020), who investigated the effectiveness of parametric insurance for various crops using different drought indices and demonstrated that parametric insurance can effectively reduce risk exposure for farmers compared to no insurance. Their combined findings include (i) that satellite-based soil moisture index insurance outperformed insurance based on ground station measurements and (ii) that individually tailored insurances for each farm and with combinations of various drought indices provided the greatest risk reduction.

We also cite the study by Kölle et al. (2020), which is similar to ours in the sense that they assess the hedging effectiveness of parametric insurance for perennial non-irrigated olive trees in Spain. Their results showed that index insurance based on vegetation indices from satellite imagery outperformed traditional weather index insurance based on precipitation and temperature indices. Although evidence suggests that the use of satellite-based indexes for drought insurance increases its performances as it reduces basis risk, we were unable to obtain data from coffee farms with both adequate georeferencing (and planted area polygons) and sufficiently long yield history. This is a significative improvement for future research related to drought insurance for coffee.

Our study addresses important issues related to agricultural policy in Brazil, particularly regarding the implementation of parametric drought insurance for coffee growers in Minas Gerais. While our results demonstrate the feasibility of parametric drought insurance, further research is necessary to refine the product and optimize its effectiveness. The Brazilian government has recognized the potential of parametric insurance by incorporating it into its premium subsidy program since 2020. However, the development of parametric insurance for coffee has been limited. Our findings highlight the critical role of subsidies in ensuring the viability of parametric insurance products. The proposed insurance contracts did not eliminate the need for government subsidies, emphasizing the importance of adequate and mandatory funding for premium subsidies.

In terms of market implications, parametric insurance was initially anticipated to offer more affordable policies due to lower operational costs. However, our findings suggest that premiums for parametric insurance may be higher than those of existing products. This is likely due to the ability of parametric insurance to better capture and price risks accordingly. This raises concerns about the potential underpricing of current policies, which could increase risks for insurance companies and destabilize the market.

Therefore, careful consideration should be given to premium pricing strategies to ensure the long-term sustainability of both traditional and parametric insurance for coffee growers in Brazil.

This study makes significant contributions to the field of agricultural risk management, particularly in the context of parametric drought insurance for tree crops. The research is novel in Brazil, as it is the first to explore index-based drought insurance for coffee, a critical crop for the country's economy. The study addresses important gaps in the literature by providing a comprehensive analysis of different payout formalizations and considering market practices such as loading costs and premium subsidies. This in-depth examination provides valuable insights into the design and implementation of effective parametric drought insurance products for coffee growers.

This research offers valuable insights, but some limitations deserve attention. These limitations present opportunities for future research and refinement of the methods used. One limitation is the use of municipality-level yield data. This data combines information from many farms and fields, providing a general overview. However, it can mask important variations in risks and outcomes experienced by individual farmers. Similarly, averaging gridded weather data for each municipality might overlook localized weather patterns that can significantly impact crop yields. Another limitation is the data granularity. While high-quality satellite imagery enabled the creation of drought indices, the lack of georeferenced farm data with extensive yield history restricted the development of highly tailored insurance contracts. Access to more granular farm-level data would allow for risk assessments specific to individual farms.

Finally, the climate database used for constructing the drought index only extends until 2020. Although chosen for its detail and quality, the lack of ongoing updates presents a limitation for the real-world application of an insurance product based on this index. For a commercially viable product, continuous access to reliable and up-to-date data is essential. These limitations highlight promising directions for future research. Efforts to acquire farm-level yield data with geospatial references and longer historical records would enable the development of more precise risk assessments and tailored insurance contracts. Additionally, exploring alternative or complementary data sources that provide ongoing updates on climatic conditions could enhance the applicability of the proposed insurance product in the long term.

The limitations of this study highlight several promising avenues for future research. Acquiring more disaggregated data sources, such as high-resolution satellite imagery and farm-level yield records, would allow for a more nuanced understanding of the heterogeneity of risks among coffee growers. This, in turn, would enable the development of more targeted insurance products that cater to the specific needs of individual farms. Additionally, efforts to create georeferenced farm data with long-term yield records would facilitate the creation of tailored insurance contracts that consider the unique characteristics and production cycles of individual farms.

Furthermore, a comprehensive cost-benefit analysis from the supply perspective (insurers and reinsurers) would provide valuable information on the economic viability and potential impact of parametric drought insurance for coffee growers. By analyzing the costs and benefits for insurers alongside the impact on growers, this analysis would provide a more holistic understanding of the feasibility and potential of this insurance product within the coffee production system.

From the demand perspective, exploring coffee farmers' risk perception and willingness to pay for drought insurance would be valuable. Understanding farmers' risk attitudes and their economic capacity to invest in risk management tools would be crucial for designing insurance products that are both affordable and attractive to potential policyholders. Research could investigate factors influencing these aspects, such as farmers' socioeconomic status, financial literacy, and historical experiences with drought events.

# 6 Conclusion

This study investigated the feasibility and potential of parametric drought insurance as a risk management tool for non-irrigated coffee growers in South/Southwest Minas Gerais, Brazil. While the complex coffee production cycle and imperfect correlation between the chosen index and actual yield present challenges, our findings demonstrate the potential of parametric drought insurance to mitigate income volatility during dry years. The financial safety net provided by the insurance indemnity can enable coffee growers to invest in recovery measures and maintain crop resilience, particularly for those with lower risk aversion. Designing an effective parametric drought insurance product requires careful consideration of payout formulation, premium structure, and subsidy requirements. Our results suggest that parametric insurance, with its focus on specific drought triggers, might lead to higher premiums compared to traditional insurance models that may underprice risk.

This study contributes to the development of parametric drought insurance for perennial crops like coffee by addressing data gaps and providing a comprehensive analysis of different payout structures. The findings offer valuable guidance for policymakers and insurance providers seeking to enhance risk management strategies for coffee growers in Brazil. Implementing parametric drought insurance alongside existing programs could strengthen the overall risk management framework for coffee production in the region. Future research utilizing more granular data sources and exploring farmer risk perception can further refine these insurance products, ensuring their long-term effectiveness and affordability for coffee growers.

In the context of a changing climate with increasing drought frequency and intensity, developing effective risk management strategies is crucial for the sustainability of coffee production in Brazil. Parametric drought insurance, with its potential to mitigate income volatility and support grower resilience, offers a promising avenue for further exploration. By addressing the limitations identified in this study, particularly regarding data granularity, future research can pave the way for the design and implementation of efficient and affordable parametric drought insurance products for coffee growers in Brazil. This, in turn, can contribute to the economic stability and long-term sustainability of the coffee production system in the country.

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# Appendix

# APPENDIX A – Federal public budget as a determining factor for the expansion of agricultural insurance

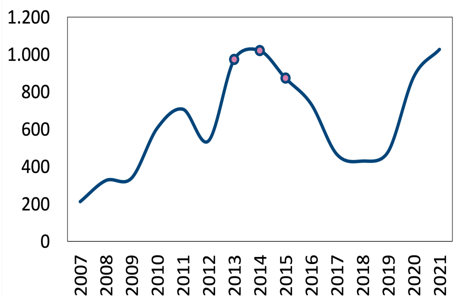
Purchase of insurance policies seems to be correlated with economic activity, which means that the use of insurance as a risk management tool tends to be higher when there is economic growth and lower when the conditions of domestic economy worsens. In Brazil, crop insurance relies on public spending through PSR, so farmers have the opportunity to insure their production at a reduced cost through financial assistance from the federal government, for instance, through insurance premium subsidies. As shown in Table 3, coffee insurance indicators performed regularly well from 2007 through 2012, when the insured area presented a compound annual growth rate (CAGR) of 161%. In 2013, insured area increased more than four and a half times over 2012 and, despite the slight decrease of 10% in 2014, insured area was still almost four times higher than the average area insured in 2007-2013.

Brazil experienced in 2015 the worst economic crisis in 20 years and was stripped of investment grade by international rating agencies. As to economic indicators from that year, consumer price index hiked to 11% from an average of 6% in the previous years, baseline interest rate SELIC increased to 13%, the R$/US$ exchange rate in 2015 depreciated by 55% in relation to 2013 and GDP contracted 3,5% (Figure 6). In fact, Figure 6a and Figure 6b show that the average premium rates applied to coffee insurance contracts hiked more than 30% in the period and that the approved budget for the concession of economic subsidy to crop insurance[1] started to plunge in 2015 after reaching record levels in 2013 and 2014. In addition, R$300 million of the approved budget for 2015 was used to settle late payments related to rural insurance for 2014. Not only that, but a new cut of R$ 51.3 million was promoted later that year, so that the contingencies corresponded to a reduction of more than 50% of the budget originally approved in the Annual Budget Law (LOYOLA; MOREIRA, 2015). Thus, the strong increase on the approved budget to subsidize PSR in 2013 and 2014 followed by Brazilian economic crisis in 2015 and the consequent budget cuts in 2015 explain the insurance performance in the period.

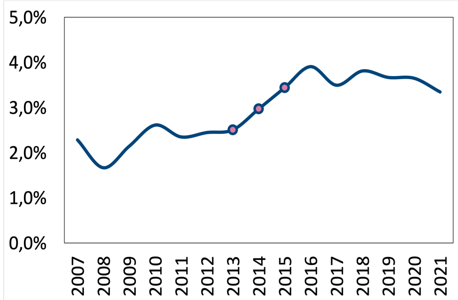
Beyond the discussed behavior of the insured area in 2013, 2014 and 2015, overall PSR performance has remained at low average levels of insured area and subsidies from the

[1] Budget line: Concession of Economic Subsidy to the Rural Insurance Premium (Law N$^o$ 10,823 of 2003).

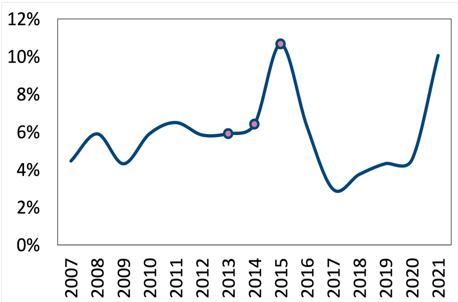
Figure 6 – Brazilian economic and crop insurance figures (2013-2015 highlighted)



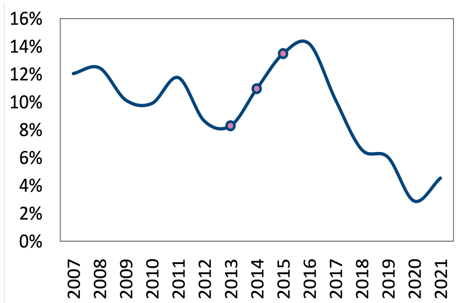

(a) Approved budget in R$ millions to subsidize PSR. Adjusted for inflation (FEDERAL SENATE, 2020).



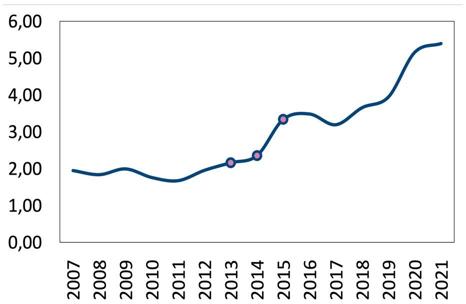

(b) Average premium rates applied to coffee insurance contracts (MAPA, 2022a).



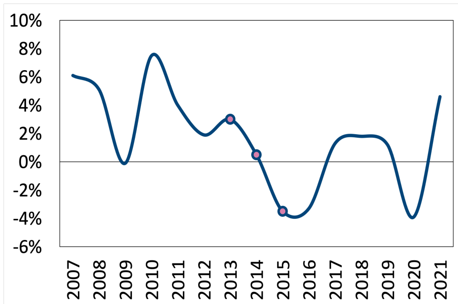

(c) Consumer Price Index – IPCA (IBGE, 2021a).




(d) Interest rate – SELIC Annual Percentage Rate (APR) (BCB, 2020b).




(e) R$/US$ exchange rate (BCB, 2020a).




(f) Gross Domestic Product (IBGE, 2021b).

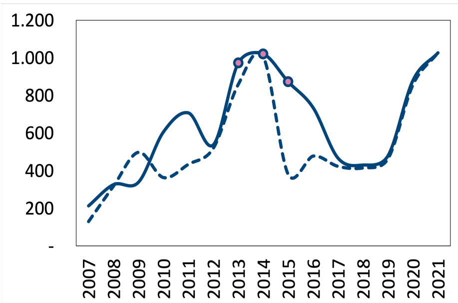
beginning of the program until 2019. As detailed elsewhere[2], indemnity-based insurance presents some significant drawbacks, especially the existence of asymmetric information between insured and insurer, which causes moral hazard and adverse selection and raises uncertainty for the insurer and costs for the insured. In crop insurance, particularly in indemnity-based schemes an in developing economies, government intervention has been paramount for the insurance industry existence. As discussed before, public spending and budget execution was determinant to the record performance in 2013/2014 as well as to the disappointing numbers seen in 2015.

Figure 7 suggests that government budget has been constraining the development of crop insurance in Brazil. Although the approved budget for 2015 was originally only

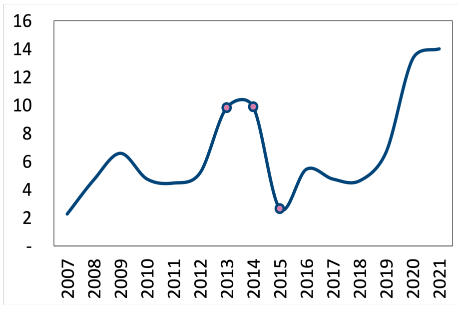
[2] See section 3 for details on indemnity-based insurance.

15% lower than in 2014, contingencies corresponded to a reduction of more than 50% of it and total subsidies dropped more than 60%. Approved budget decreased year after year until 2018 and total insured area remained low in the period. Crop insurance performance indicators seemed to regain *momentum* only after 2019, together with budget increases. Total insured area reached a record level of 14 million hectares in 2021, when the highest budget in the time series was approved to subsidize PSR premiums. For coffee, record numbers were registered for insured area, liability, quantity of policies and quantity of insured producers in 2021 (Table 3). Even so, these figures still represent only a small fraction of Brazilian agricultural production. Although other difficulties exist, such as geographical distribution and lack of information, further development of indemnity-based insurance in Brazil seems to be as uncertain as the country's fiscal policy.

Figure 7 – Budget to subsidize PSR and total insured area




(a) Approved budget (solid) and total subsidy (dashed) in R$ millions. Adjusted for inflation (FEDERAL SENATE, 2020; MAPA, 2022a).




(b) Total insured area through PSR in millions of hectares (MAPA, 2022a).

Parametric and especially satellite-based insurance figures as a potential complement to the current PSR scope because it promises to reduce basis risk in addition to mitigating asymmetric information. Thus, it is expected to increase the geographical distribution of the insurance and to reduce the premium paid by farmers, which could relieve the weight of government participation in the industry.

# APPENDIX B – The Brazilian agricultural insurance market for coffee

Brazilian market for agricultural insurance for coffee crops is composed by seven insurers, all of which offer the traditional indemnity-based insurance scheme. As detailed in Table 13, Brasilseg holds 45% of the market share and the top three players – Brasilseg, Mapfre and Sancor – accounted for 85% of the market from the beginning of 2021 through mid-2022. Among Brasilseg products, the market leader, three insurance policies (Costs, Productivity, Earnings) are dedicated to cover damages caused by climatic events to the production of the insured crop. These are multiple peril insurance policies that include hail, frost and drought. A fourth product, namely *Cobertura de recuperação do potencial produtivo das plantas*[1], aims to cover losses that require pruning management to recover the crop's productive potential.

Mapfre offers three similar products to those sold by Brasilseg. Their *Seguro Colheita Garantida*[2] is available with policies for either hail and frost or for multiple perils. Mapfre also markets an insurance to protect farmers against damages to coffee trees caused by hail, frost or fire, in the sense that it covers losses that require pruning management. All other insurance companies in the coffee growing sector work with policies to protect producers against losses caused to their production, rather than to the trees. Differently from Brasilseg and Mapfre, where multiple peril policies are more frequent, the majority of the remainder insurers (Sancor, Tokio Marine, Fairfax, Swiss Re) offer single-peril insurance policies against hail. There are no risks other than hail in single-peril policies, for example, a product specifically against drought is not available in the market. Also, all insurance policies are valid for one calendar year.

As described above, available products for Brazilian farmers to protect themselves against climate shocks lies in the indemnity-based insurance category, although parametric insurance has been officially encouraged by the government after being considered in the subsidy percentages and financial limits in 2021 (MAPA, 2022c). This is particularly relevant as theoretical discussions about benefits and drawbacks of the two insurance categories will increasingly cross the limits of universities and think tanks and reach farms through dirt roads, where index-based insurance should find both distrust and hope. On one hand, parametric insurance is expected to mitigate the problem of asymmetric information through an exogenous trigger, to reduce transaction costs and, consequently, to make the underwriting and claiming process faster and more affordable to the farmers.

[1] Coverage for recovering the productive potential of plants, in english.
[2] Guaranteed Harvest Insurance, in english.

On the other hand, index-based insurance introduces basis risk, which is specially critical in developing contexts, where weather station network is sparse and often without the necessary investments to maintain them (HEIMFARTH; MUSSHOFF, 2011; MIRANDA; FARRIN, 2012; WORLD BANK, 2011; JENSEN et al., 2016; JENSEN; BARRETT, 2017).

Table 13 – Review of the insurance products available for coffee growers in Brazil through the accredited agricultural insurers.

| Insurer | Market share | Insurance product name | Insurance coverage | Basic/mandatory named risks |
|---|---|---|---|---|
| Brasilseg | 45% | Cobertura de custeio/ produtividade | Damages caused to the production of the insured crop. | Fire, lightning, waterspout, strong winds, cold winds, hail, excessive rain, drought, frost, excessive temperature variation. |
| | | Cobertura de faturamento | Damages caused to the production of the insured crop. | All of the above plus reduction in the price of the insured crop in the reference market in relation to the base price. |
| | | Recuperação do potencial das plantas | Pruning to recover the productive potential of the crop. | Hail, frost, fire. |
| Mapfre | 28% | Seguro Cafezal | Pruning to recover the productive potential of the crop. | Hail or hail and frost. |
| | | Seguro Colheita Garantida | Damages caused to the production of the insured crop. | Hail and frost. |
| | | Seguro Colheita Garantida | Damages caused to the production of the insured crop. | Fire, lightning, waterspout, strong winds, cold winds, hail, excessive rain, drought, frost. |
| Sancor | 12% | Seguro Granizo | Damages caused to the production of the insured crop. | Hail. |
| | | Seguro Multirrisco | Damages caused to the production of the insured crop. | Fire, lightning, waterspout, strong winds, cold winds, hail, excessive rain, drought, frost, flood, excessive temperature variation. |
| Tokio Marine | 5% | Seguro Agrícola Riscos Nomeados | Damages caused to the production of the insured crop. | Hail. |
| Fairfax | 5% | Seguro Produção | Damages caused to the production of the insured crop. | Hail. |
| Swiss Re | 5% | Seguro Agrícola Granizo Cafezal | Damages caused to the production of the insured crop. | Hail. |
| Aliança do Brasil | 0.2% | Seguro Agrícola | Damages caused to the production of the insured crop. | Fire, lightning, waterspout, strong winds, cold winds, hail, excessive rain, drought, frost, excessive temperature variation. |

*Source:* Prepared by the author with research information.
*Note:* Market share consists of the participation of each insurer in the total quantity of policies sold in 2021 and in the first half of 2022. When basic/mandatory risks consists only of hail, purchase of additional risks policies may be available for some insurers/products.

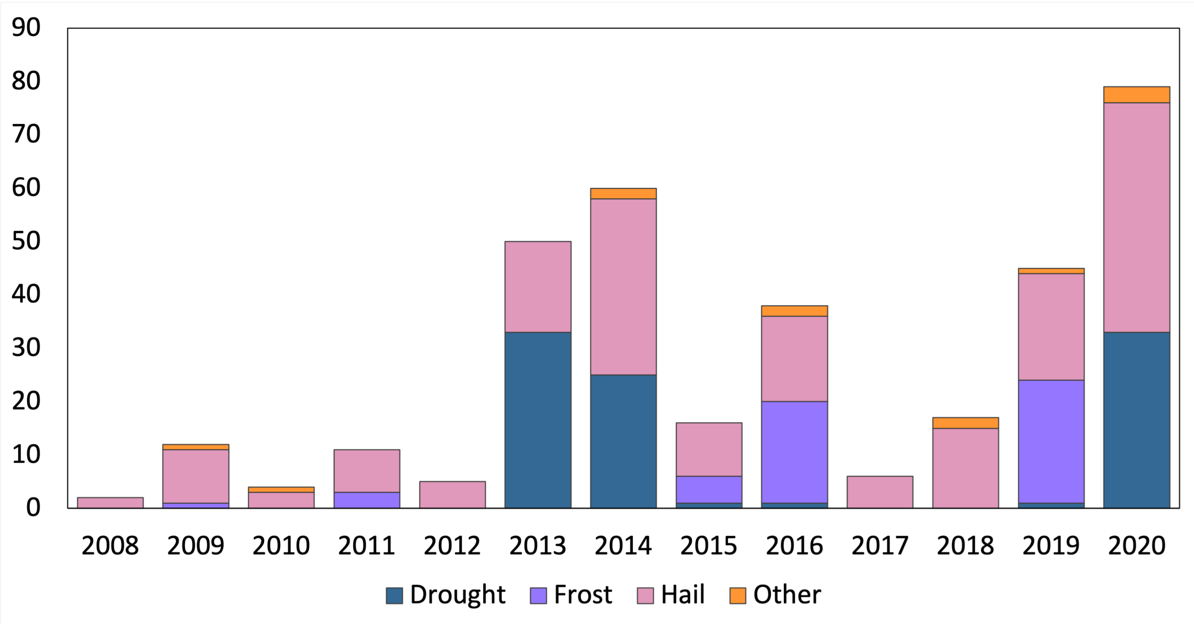
# APPENDIX C – Phenological phases of the Arabica coffee tree.

| **First phenological year**<br>Vegetative cycle | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Sep | Oct | Nov | Dec | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug |
| Coffee vegetation and formation of axillary buds | | | | | | | Induction and maturation of floral buds | | | | |

| **Second phenological year**<br>Reproductive cycle | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Sep | Oct | Nov | Dec | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug |
| Flowering, "chumbinho" and grain growth | | | | Grain filling | | | Fruit ripening | | | Self-prunning | |

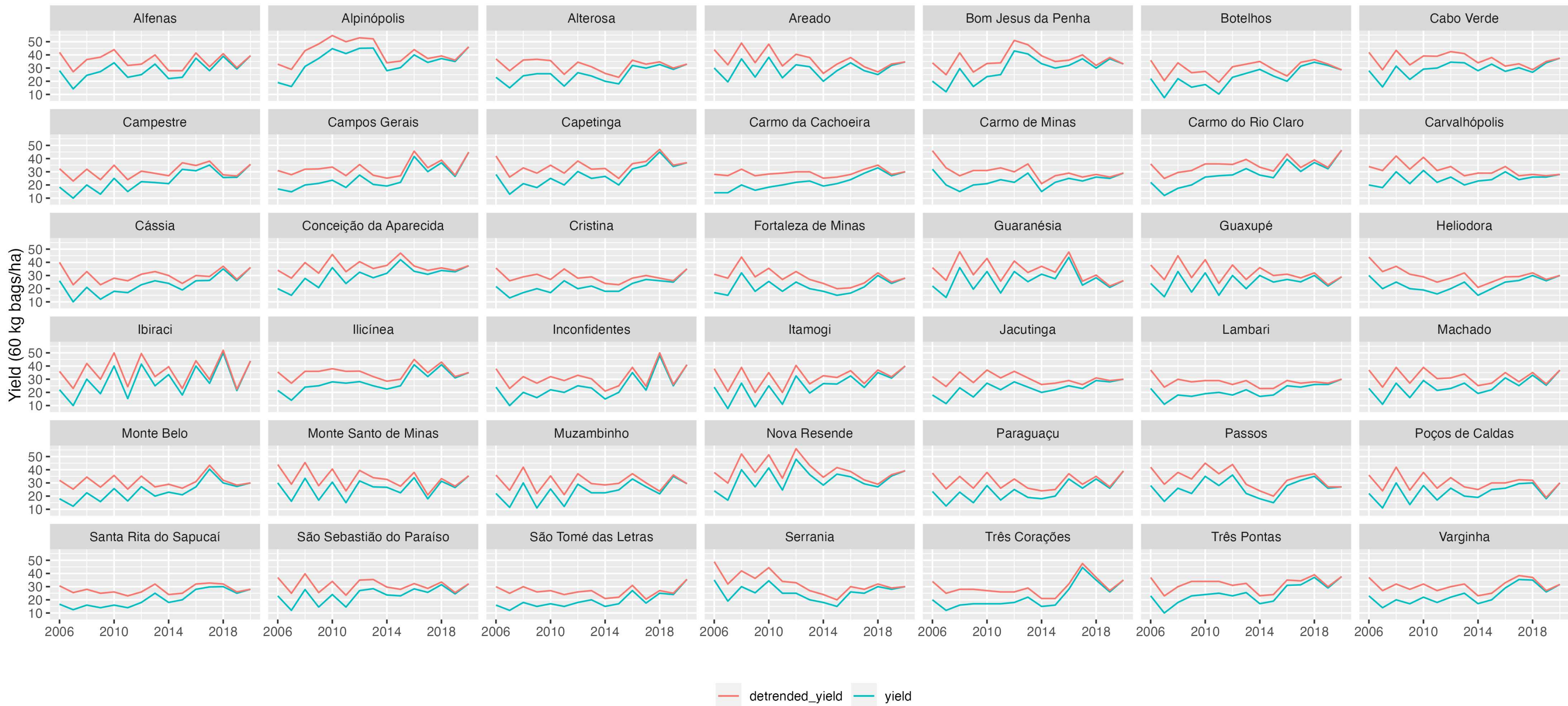
*Source:* Adapted from Camargo & Camargo (2001).
*Note:* Schematization of the six phenological phases of the Arabica coffee tree, during 24 months, in the tropical climatic conditions of Brazil. Phenological years occur concomitantly; for instance, while parts of the tree's branches form axillary buds, the parts that went through this stage the previous year have coffee beans ripening and preparing to be harvested.

# APPENDIX D – Quantity of insurance claims from coffee growers in the state of Minas Gerais.




Source: (MAPA, 2022a)

# APPENDIX E – Detrended coffee yields in the selected municipalities.



# APPENDIX F – Coffee production and liability share of selected municipalities

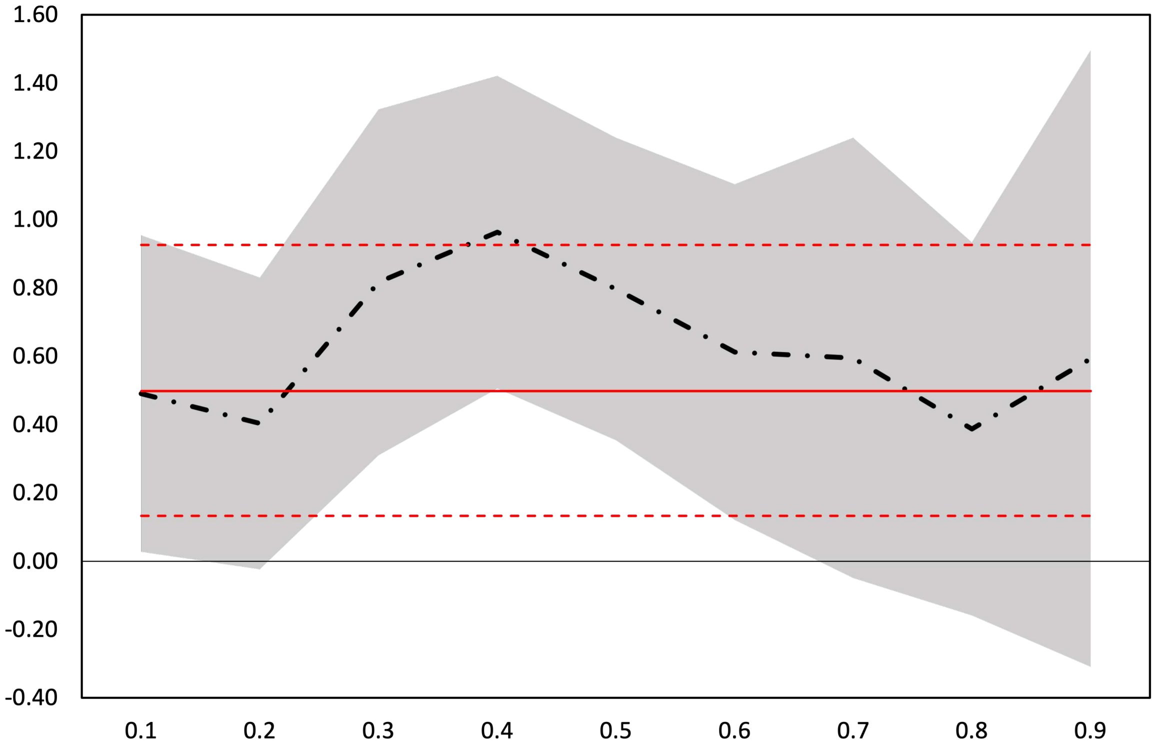
| Selected municipalities | Microregion | Liability | Total production |
|---|---|---|---|
| Campos Gerais | Varginha | 11.4% | 4.8% |
| Três Pontas | Varginha | 9.5% | 3% |
| Ibiraci | Passos | 5.4% | 3.4% |
| Carmo da Cachoeira | Varginha | 3.8% | 2% |
| Machado | Alfenas | 3.4% | 2.3% |
| Varginha | Varginha | 3.2% | 1.5% |
| São Sebastião do Paraíso | São Sebastião do Paraíso | 2.8% | 2.6% |
| Itamogi | São Sebastião do Paraíso | 2.2% | 2.1% |
| Três Corações | Varginha | 2.1% | 1.8% |
| Carmo do Rio Claro | Alfenas | 2.1% | 3.3% |
| Paraguaçu | Alfenas | 1.9% | 1.8% |
| Campestre | Poços de Caldas | 1.8% | 2.2% |
| Muzambinho | São Sebastião do Paraíso | 1.7% | 1.8% |
| Ilicínea | Varginha | 1.7% | 1.2% |
| Alpinópolis | Passos | 1.7% | 1.6% |
| Carmo de Minas | São Lourenço | 1.6% | 0.7% |
| Capetinga | Passos | 1.5% | 1.2% |
| Alfenas | Alfenas | 1.5% | 1.8% |
| Monte Santo de Minas | São Sebastião do Paraíso | 1.5% | 2.6% |
| Conceição da Aparecida | Alfenas | 1.5% | 2.3% |
| Cássia | Passos | 1.1% | 1.2% |
| Heliodora | Santa Rita do Sapucaí | 0.7% | 0.6% |
| Passos | Passos | 0.7% | 0.6% |
| Santa Rita do Sapucaí | Santa Rita do Sapucaí | 0.7% | 0.8% |
| Areado | Alfenas | 0.7% | 0.5% |
| Guaxupé | São Sebastião do Paraíso | 0.4% | 0.9% |
| Alterosa | Alfenas | 0.4% | 0.8% |
| Bom Jesus da Penha | Passos | 0.4% | 0.6% |
| Cabo Verde | São Sebastião do Paraíso | 0.3% | 2.3% |
| Botelhos | Poços de Caldas | 0.3% | 1.2% |
| Nova Resende | São Sebastião do Paraíso | 0.3% | 3.5% |
| Fortaleza de Minas | Passos | 0.2% | 0.4% |
| Serrania | Alfenas | 0.2% | 0.8% |
| Monte Belo | São Sebastião do Paraíso | 0.2% | 0.7% |
| Lambari | São Lourenço | 0.2% | 0.9% |
| Carvalhópolis | Alfenas | 0.2% | 0.5% |
| Jacutinga | Poços de Caldas | 0.1% | 0.9% |
| Guaranésia | São Sebastião do Paraíso | 0.1% | 0.8% |
| Inconfidentes | Poços de Caldas | 0.1% | 0.8% |
| Poços de Caldas | Poços de Caldas | 0.1% | 0.7% |
| Cristina | Itajubá | 0% | 0.3% |
| São Tomé das Letras | Varginha | 0% | 0.4% |

*Source:* Prepared by the author with data from MAPA (2023).
*Note:* Liability and production columns represent the share of each selected municipality within the South/Southwest mesoregion of Minas Gerais during 2022.

# APPENDIX G – Estimation results for the Fixed Effects model, 2006-2020.

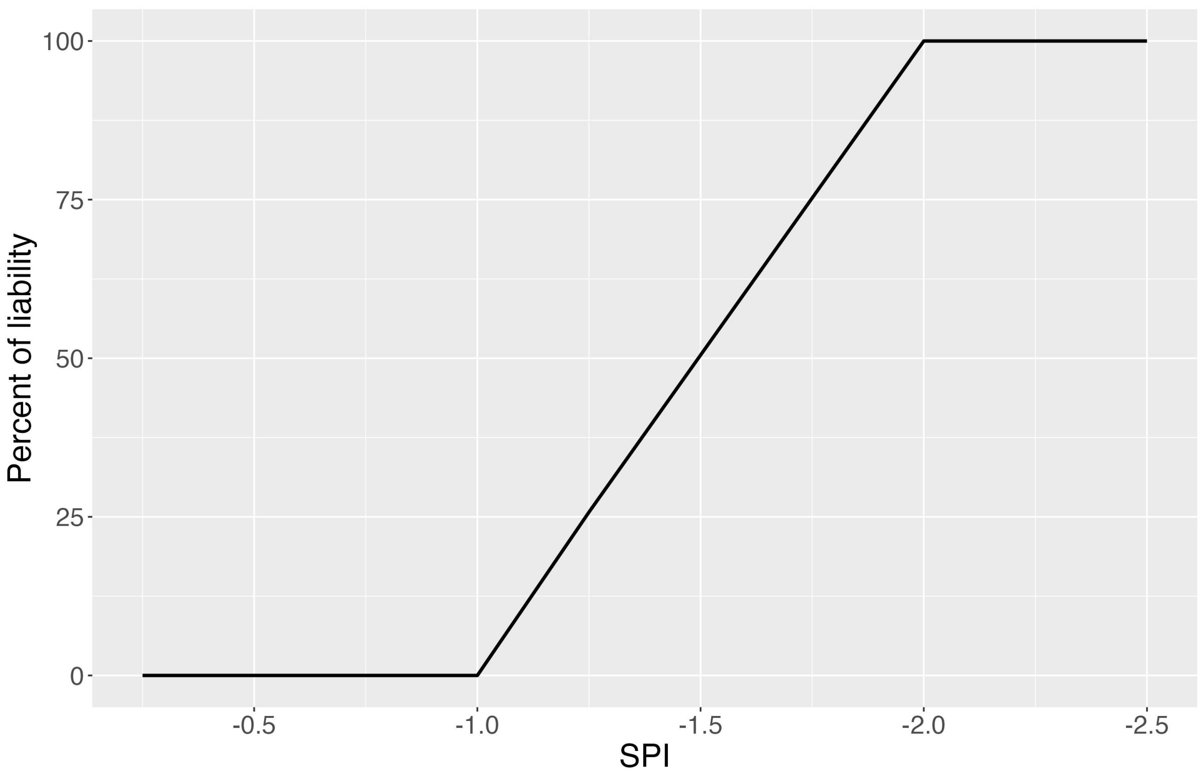
| | *Dependent variable:* | | |
|---|---|---|---|
| | Detrended yield | | |
| | (1) | (2) | (3) |
| R1 | −0.726** | | |
| | (0.299) | | |
| R2 | | 0.529*** | |
| | | (0.202) | |
| R1R2 | | | 0.225 |
| | | | (0.217) |
| Constant | 32.065*** | 32.323*** | 32.300*** |
| | (0.248) | (0.241) | (0.248) |
| Observations | 630 | 630 | 630 |
| $R^2$ | 0.010 | 0.012 | 0.002 |
| Adjusted $R^2$ | −0.061 | −0.059 | −0.070 |
| F Statistic (df = 1; 587) | 5.904** | 6.832*** | 1.069 |
| *Note:* | *p<0.1; **p<0.05; ***p<0.01 | | |

# APPENDIX H – Quantile and Pooled regression coefficients and confidence intervals.



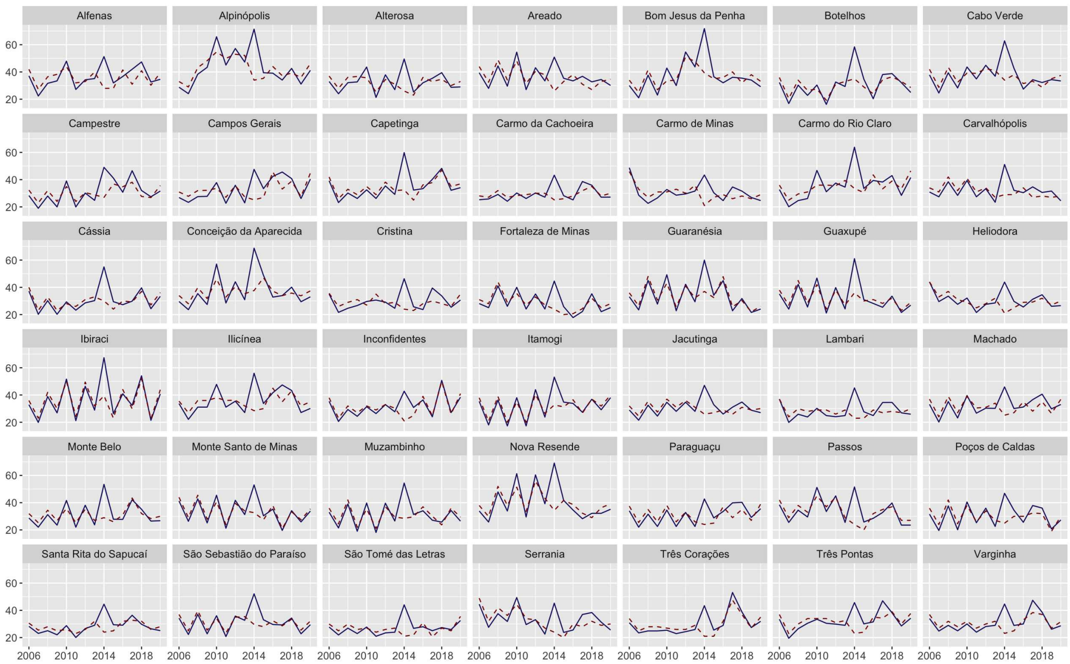

Source: Authors.

# APPENDIX I – Payout structure with parameters from Contract 2.

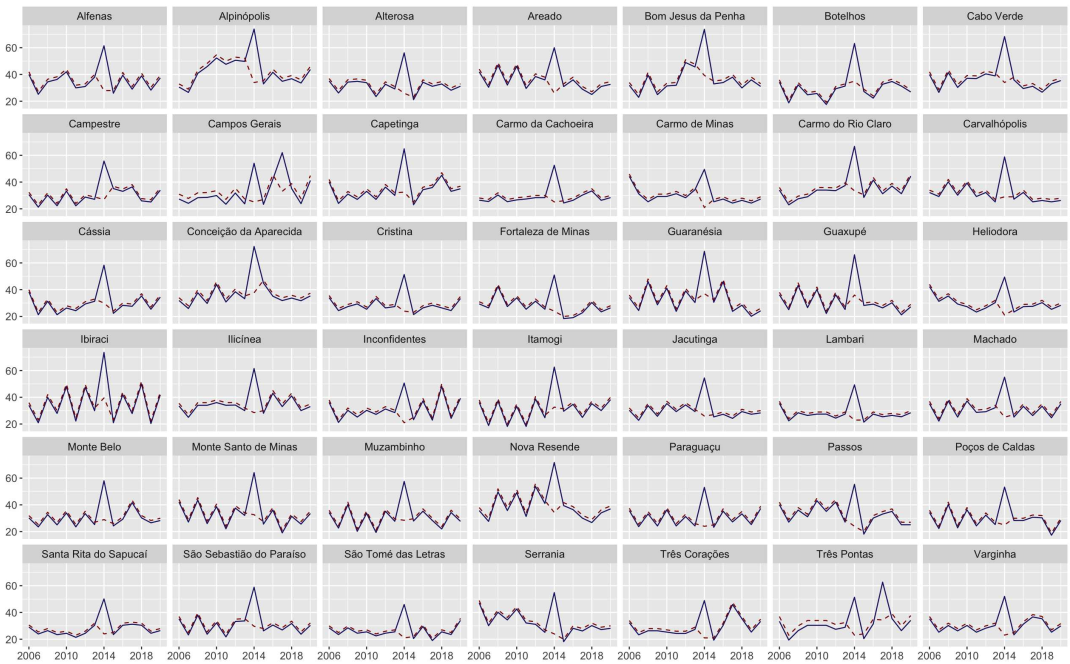



Source: Authors.

# APPENDIX J – End-of-year wealth with (solid) and without (dashed) insurance.




(a) Contract 1. Suggested commercial premium and premium subsidy.




(b) Contract 3. Suggested commercial premium and premium subsidy.

Source: Research results.