Norwegian School of Economics
Bergen, Spring Semester, 2019

Stimulating Sustainable Development in Brazil's Coffee Sector

An Empirical Analysis on Integrated Landscape Management Strategies

Nicholas Alexander Virvilis

Supervisor: Justin Valasek

Master thesis, MSc, ENE

NORWEGIAN SCHOOL OF ECONOMICS

Abstract

This report investigates the sustainable agricultural performance of coffee farms in the south-eastern states of Brazil under integrated landscape management strategies. 651 municipalities were analysed across Paraná, Sao Paulo, Minas Gerais, Rio de Janeiro and Espirito Santo between 2002 and 2016 to study the socioeconomic and environmental impacts of Nespresso's AAA Sustainable Quality Program and the 2012 Brazil Investment Plan for Sustainable Land Use and Forest Management in the Cerrado biome. Using a Difference in Difference model with fixed effects estimations, I identified that both programs have facilitated significant improvements across income, yields and crop value. The research provides insights into the strategic opportunities for value chain investors, governments, financial institutions and farmers to improve environmental practices in coffee farming with economic incentives. Ultimately, my research provides compelling insights on the efficacy of integrated landscape management approaches for meeting the growing consumption demand as well as the commitments of Brazil's ecosystem conservation and restoration initiatives.

"You cannot tackle hunger, disease, and poverty unless you can also provide people with a healthy ecosystem in which their economies can grow."

— Gro Harlem Brundtland

Acknowledgements:

I would like to thank my supervisor, Justin Valasek from the Centre for Business Economics (CBE) at the Norwegian School of Economics, for his patience, expertise and willingness to provide valuable feedback on my research into this topic.

I would also like to express my appreciation to the coffee farmers of Brazil, Kenya, India, Rwanda, Colombia and Peru for supplying me with my daily cup of excellence over the course of this study.

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1. Introduction

The past decade has seen a sharp rise in initiatives to make agricultural supply chains more sustainable. As a leading agricultural exporter and the dominant global producer of coffee (FAO, 2018), Brazil plays a critical role in meeting many of the United Nations' Sustainable Development Goals (SDGs) including zero hunger [2], clean water and sanitation [6], decent work and economic growth [8], reduced inequalities [10], responsible consumption and production [12], climate action [13] and life on land [15] (Semroc, 2018; United Nations Development Plan [UNDP], 2017). Of all agricultural commodities, coffee has made the most progress in becoming fully sustainable, with 48 per cent of all farm production being produced under a certified standard of sustainable practice (Climate Investment Funds [CIF], 2012).

Despite the widespread adoption of sustainable agriculture certifications and progressive development of environmental policy in primary economies, a multitude of sector-specific challenges are jeopardizing future of ecosystem conservation. The Brazilian government and non-governmental organizations (NGOs) operating in Brazil's forests and agricultural sectors have been effective in implementing public mandates for conservation including the Forest Code (Law 12,651/2012) and the Low Carbon Emissions Agriculture Plan (ABC Plan) (The World Bank, 2017). However, the growing economic disparities for farmers, inferior agrarian technologies and lack of access to credit has resulted in increases in illegal deforestation, soil degradation and biodiversity loss (de Souza, Miziara, & de Marco Junior, 2013). The lack of financial, technological and knowledge services is predominantly related to the meagre implementation rates of public sector initiatives in rural areas and the lack of private sector involvement for coordination between farmers and resources at the landscape level (Baudron et al., 2015; Raynolds, Murray, & Heller, 2007). Without undermining the importance of the public sector's involvement in sustainable development, an efficient and effective framework for sustainable land management should recognise that the private sector can contribute to public sector strategies and alleviate some of the demands of environmental policy while maintaining socioeconomic welfare of farming communities (Byron, Holland, & Schuele, 2001; Smyth & Dumanski, 1995a).

Integrated Landscape Management (ILM) initiatives may be the answer to reconciling environmental and socioeconomic goals in the coffee sector by combining efforts of the private and public sectors to integrate policy and sustainable development objectives at the landscape level. ILM strategies in the context of rural agriculture approach sustainable development by assessing poverty, food insecurity, deforestation, biodiversity loss, climate change and water scarcity across the ecosystem which informs necessary actions to be taken at the farm. The Brazil Investment Plan (BIP) and Nespresso AAA Sustainable Quality (AAA) Program are two different ILM investment projects in southern Brazil which simultaneously aim to support landholders and ecosystem health through implementation of public mandates, financing of low carbon emitting farm technologies, recovery of anthropically eroded landscapes, reduced production risk exposure, social standards and adoption of integrated crop-livestock-forestry systems (Alvarez, Pilbeam, & Wilding, 2010a; The World Bank, 2017).

While ILM conceptual frameworks (Sayer et al., 2013; Scherr & McNeely, 2008; Ward, Malard, & Tockner, 2002) and monitoring techniques (Botequilha Leitão & Ahern, 2002) have been frequently discussed, my research indicates that there are no available publicly available studies which empirically assess the outcomes of ILM strategies for agriculture particularly with respect to productivity and economic development. Considering the growing interest in the socioeconomic concept of 'Creating Shared Value' and its potential to improve economic performance simultaneously with value to society and the environment (Arts et al., 2017; DeFries, Sharma, & Dutta, 2016; Noss, 1983; Porter & Kramer, 2011), it is of great interest to understand the socioeconomic benefits of farms affected by these initiatives. Identifying causal relationships between ILM initiatives and agricultural performance is of great importance as it can help identify opportunities to solve macroeconomic challenges related to farmer remuneration and ecosystem management, which play an increasingly important role in the social welfare of rural communities (Bunn, Läderach, Ovalle Rivera, & Kirschke, 2015; Killeen & Harper, 2016).

In this report, I study seven sustainable performance indicators of coffee agriculture across the five southern coffee producing states in Brazil. Using two treatment groups, one consisting of municipalities within the AAA Program region and the other consisting of municipalities affected by the BIP, my study measures the impact of structurally diverse ILM initiatives on productivity and economic viability using a Difference in Difference (DiD) approach. Based on publicly available data collected from Bloomberg Weather Analytics, IBGE, FAO and the RADAM project, I was able to adjust the performance outcomes based on the time and panel-variant exogenous factors using fixed effects estimations. The DiD analysis presents strong insights that coffee farming under both the AAA Program and the BIP yield greater productivity and economic viability, however does not present tangible quantitative indications on resource intensity of improved processes. Using the qualitative analysis of both programs in Section 3, I provide motivation on the viability of the ILM programs for improving the protection of natural resources. The empirical results indicate that while ILM strategies vary greatly in their structure and motivation, their socioeconomic and environmental outcomes are largely the same, successfully reconciling many of the global challenges the coffee sector faces today.

The remainder of this paper is structured as follows. In Section 2, I provide an overview of sustainability related challenges in Brazil's coffee sector and the shortfalls of existing initiatives to promote environmental and socioeconomic development. This subsequently serves as the motivation for my analysis where I describe ILM strategies and the inherent opportunities to effectively address these issues. In Section 3, I look deeper into the variations of ILM initiatives, introducing the AAA Program and BIP as the cases which form the focal point of my study. Section 4 discusses the data used for assessing the program effects and includes the map of my analysis. Furthermore, I discuss the motivation for the chosen performance indicators used in my analysis, which are derived from the Framework for Evaluating Sustainable Landscape Management. With consideration of the data collected and the framework, I revisit my hypothesis and structure it based on resources that are publicly available in Section 5. Section 6 describes my preliminary analysis of the data, which serves as a point of departure for my methodology. In section 7, I discuss my empirical strategy including the DiD and fixed effects estimations. Further, I describe the parallel trends regression model I used to ensure my analysis is robust. In Section 8, I report on the outcomes of my model and the implications that have been drawn from the analysis, which leads to the discussion of my findings and assessment of foreseeable limitations in Section 9. Finally, Section 10 is dedicated to my concluding remarks and the pertinent areas for future research.

2. Background and Motivation of the Study

This section details the major climate and market related challenges facing coffee value chains as well as the responsive actions taken by policy makers, financial institutions and private certification agencies in Brazil related to sustainable development in coffee farming. The low adoption rates and lack of success in providing holistic strategies of these initiatives independently provides motivation for assessing ILM strategies as viable mechanisms for reconciling socioeconomic and environmental goals in coffee's agricultural industry.

2.1 Current System Challenges for Sustainable Development

Currently, the conflict related to ecological conservation and agricultural production is no greater than in Brazil. Brazil is the fifth largest exporting nation of agricultural commodities and has the highest rates of deforestation globally (55Mha of forest cover loss between 1990 and 2010) (Food and Agriculture Organization of the United Nations [FAO], 2019). With 85 per cent of Brazil's 330,000 coffee farms managed by smallholders with land coverage averaging 7.5 hectares (Arias, Hallam, Krivonos, & Morrison, 2013), coordination and strategic management of demand response is very low, contributing to one of the greatest challenges of sustainable development in coffee agriculture today (Goddard & Akiyama, 1989). The business case for sustainable land management can only become pervasive if farmers can simultaneously profit from higher yields and reduced production costs; however, the high initial investment costs for productive technologies and long-term crop and soil management techniques are frequently disregarded by farmers due to poor cash flow, lack of strategic planning and limited access to agricultural inputs.

Additionally, inelastic demands (Eakin, Winkels, & Sendzimir, 2009; Ha & Shively, 2008), variable production volumes (Haggar & Baker, 2007), and global warming (Bunn et al., 2015) have contributed to falling prices while costs for production continue to rise (Technoserve, 2013). Climate change has disrupted global production volumes by altering the geographic regions where coffee can be produced, shifting to higher elevations in which temperature and precipitation profiles are more suitable for growth. While this has presented new opportunities for nations such as Indonesia and Vietnam to develop their coffee industry, it is dramatically reducing the current arable land available for crop production, leading to increases in deforestation (Schroth, Läderach, Blackburn Cuero, Neilson, & Bunn, 2015). In fact, by 2050 the estimated global area suitable for coffee agriculture will have reduced by 50% while demands are projected to double (Technoserve, 2013).

The dramatic changes in climate profiles and low remuneration for coffee exports are alluring farmers to convert forest areas into agricultural land, leading to economic misalignment between environmental policy and economic growth. While public policy and NGO interventions have been successful in minimizing the degradational effects of coffee farming during periods when coffee prices and the Brazilian currency are strong, they have proven to be ineffective during negative fluctuations; falling short of their goals due to socioeconomic priorities (Dorward, 2013; Kilian, Jones, Pratt, & Villalobos, 2006a). The remainder of Section 2 aims to identify the current challenges facing public policy, sustainability certification and rural credit initiatives, which inherently presents the opportunity for ILM programs to meet the needs of the coffee sector.

2.1.1 The Forest Code: A Public Policy Perspective

Brazilian policy reforms from the early 2000s have had a substantial impact on environmental conservation. In 2004, advancements in satellite monitoring systems informed research on impacts of deforestation and soil degradation, leading to amendments of the 1965 Forest Code. While the modifications made to the Forest Code in 2004 were met with great success, leading to deforestation rates reducing by 80% between 2005 and 2012 (Instituto Nacional de Pesquisas Espaciais [INPE], 2014; Nepstad et al., 2009), new amendments made in 2012 have been met with inadequate results. In the Cerrado biome, the 2012 Forest Code assigned legal reserves (LRs) for 35 per cent of crop land for biodiversity conservation and permanent preservation areas (APPs) which are restricted areas for ecosystem preservation (Soterroni et al., 2018). In view of the conflicting interests with the environmental outcomes of the Forest Code and economic interests of farmers, the adoption rates of LRs have been very low (Moutinho, Guerra, & Azevedo-Ramos, 2016; Sparovek et al., 2011; Vieira et al., 2018). In addition to the Forest Code’s overly-stringent mandate, the frequent changes in legal requirements of the Forest Code, lack of government enforcement and apparently high opportunity cost of conservation have resulted in the widespread policy infringement by farmers (Sparovek et al., 2011; Vieira et al., 2018).

According to the 2010 Brazil National Communication to the UN on Climate Change, over three quarters of the CO_2 emissions in Brazil have been attributed to the Land Use Change and

Forestry (LUCF) sector, which is largely pressured by urbanization and agricultural development. The conflicting viewpoints of farmers and policy-makers makes full enforcement of the 2012 Forest Code an impossibility. From an environmental policy perspective, the 2012 Forest Code has the potential to restore 12.9Mha of forest area in Brazil by 2050 (Moutinho et al., 2016), however the high costs of investment in sustainable development, limited access to rural credit initiatives and a lack of inter-farm coordination present conflicting interests from the farmers' perspectives.

2.1.2 Sustainability Certification Programmes: An NGO Perspective

Sustainability certification programmes (SCPs) are defined as a third-party agency's set of criteria which are adhered to voluntarily by farmers. The SCPs are renewed consistently by members of the certification agency following successful audits of the farms for an annual service and inspection fee (Bray & Neilson, 2017). Of all sustainable farming initiatives, SCPs are the most widely adopted due to an increasing demand for sourcing sustainably produced resources across value chains with approximately 2 billion pounds of coffee certified in 2007 alone (Specialty Coffee Association of America [SCAA], 2009). In particular, third-party organizations such as UTZ and Rainforest Alliance have grown to prominence over the past two decades for their holistic approaches to assessing environmental, social and economic standards. In practice, impacts of SCPs have shown mixed results, largely depending on the presence of existing municipal and value chain support systems (Bray & Neilson, 2017). Though SCPs provide the necessary framework for sustainable land use planning and effective coordination of multiple objectives, without the involvement of value chain investors, there remains an insufficient access to smallholder capital, technical training, investment planning, gender training and resource management for effective alignment of economic, environmental and social development (Kilian, Jones, Pratt, & Villalobos, 2006b; Kilian, Pratt, Jones, & Villalobos, 2004).

2.1.3 Rural Credit Policies

To improve the socioeconomic and environmental impact of farming standards, rural credit policies such as the National Rural Credit System (SNCR, Portuguese acronym) in Brazil have focused on providing farmers access to credit, primarily for operating lines and agricultural inputs (Lopes et al., 2015). The SNCR's introduction of three credit programs; Moderagro (2003), the ABC program (2010) and Inovagro (2014) have been active facilitators of financing Brazilian farms to employ low-carbon emission practices and enhance productive investments (The Brazilian Development Bank [BNDES], 2015), however adoption rates have been insignificant.

Current challenges facing the SNCR are related to ensuring widespread adoption of sustainable agriculture credit facilities. Lack of adoption is due to information gaps between financial institutions and farmers, higher restrictions on what the credit can be used for, unappealing interest rates and impediments related to the access of credit in rural areas. As a result, SNCR data from 2014 reported that all credit funds had administered less than 35% of total lending capacities. In fact, FUNCAFÉ, the public credit fund specifically targeted at sustainable coffee production across Brazil distributed less than 2% of its total allocative capacity in 2012 (Lopes et al., 2015). It is to be expected that farmers are competitively incentivised to apply for credit programs that promote sustainable practice.

Higher start-up costs or transition costs associated with sustainable farming practices will only be met by farmers when it is proven to be more profitable, technology becomes largely available in rural areas, and information becomes widespread regarding sustainability loans (Pretty, 1997; Schaller, 1993). Thus, there is a need for third-party involvement in rural agriculture value chains to introduce practices for sustainable development on farms and communicate the importance of credit for long term strategies. Shared value systems with multinational enterprises and public investment plans for sustainable land management are targeted approaches to aid smallholders in accessing sustainability-related subsidized credit facilities, specifically structured to address financial barriers pertinent to farming communities (Kramer & Pfitzer, 2016; Porter & Kramer, 2011).

2.2 Integrated Landscape Management Initiatives

An ILM program – alternatively referred to as sustainable landscape planning (Botequilha Leitão & Ahern, 2002), integrated landscape initiative (Milder, Hart, Dobie, Minai, & Zaleski, 2014), landscape management approach (McCarter, Wilson, Baker, Moffett, & Oliver, 1998) or integrated natural resource management (Saxena, Rao, Sen, Maikhuri, & Semwal, 2003) – is defined as a “project, program, platform, initiative, or set of activities that: (1) explicitly seeks to improve food production, biodiversity or ecosystem conservation, and rural livelihoods; (2) works at a landscape scale and includes deliberate planning, policy, management, or support activities at this scale; (3) involves inter-sectoral coordination or alignment of activities, policies, or investments at the level of ministries, local government entities, farmer and community organizations, NGOs, donors, and/or the private sector; and (4) is highly participatory, supporting adaptive, collaborative management within a social learning framework" (Instituto Brasileiro de Geografia e Estatística [IBGE], 2016). As such, ILM programs do not operate independently; they require the presence and collaboration of governments, NGOs and value chain investors to collectively improve the environmental and socioeconomic state of affairs in the coffee sector.

Research related to ILM strategies were published as early as 1983, with the seminal publication by Noss on biodiversity management (Noss, 1983); however, ILIs have not seen effective participation in the agricultural sector by policy makers and corporations until the past decade with the outset of low-cost landscape monitoring technologies and implementation frameworks (Milder et al., 2014). For successful implementation of sustainable landscape projects in the agricultural sector, public-private-civic partnerships are paramount. The process of integrating landscape management captures a holistic view of the risks and prospects of agricultural processes by addressing overexploitation of resources, degradation of ecosystems, inter-farm competition, social welfare, efforts to reduce deforestation, management of water systems, and natural capital accounting (Shames, Gross, Ana Borges, Bos, & Brasser, 2017). Considering its relatively new presence in public policy and business models, this report aims to understand the socioeconomic and environmental capabilities related to sustainable land management in the coffee sector (Stern, 2004).

In the current environment of rising costs and falling market prices, coffee producers see little business case to comply with rigorous environmental policies, invest in SCPs or apply for sustainable credit programs with above-prime interest rates (Ceña, 1999; Lopes et al., 2015). Thus, there is a need for an invested stakeholder to manage and assess farms on a landscape level to ultimately ensure goals related to agricultural productivity as well as the biodiversity, natural resources stocks and social welfare are achieved.

3. Integrated Landscape Management Strategies

The previous section's discussion on multiple definitions and structural varieties raises an inherent challenge of measuring ILM strategies. As such, this section aims to describe the two stakeholder approaches for ILM which meet the four definitive criteria which are mentioned in Section 2.2. Using two architecturally different approaches, my aim is to illustrate how ILM frameworks can have strategic differences from the investor's perspective, but nonetheless achieve the same sustainable development goals for farmers. The description of the Brazil Investment Plan and Nespresso's AAA Sustainable Quality Program will provide a point of departure for my analysis on evaluating the performance outcomes of these strategies.

3.1 Brazil Investment Plan: An Environmental Policy Framework

Brazil's efforts to enforce REDD+[1] has been supported by the 2012 Brazil Investment Plan for Sustainable Land Use and Forest Management in the Cerrado biome (BIP), a USD 127 million initiative to coordinate the mandates set out by Brazil's Environment, Science, Technology & Innovation, Agriculture & Livestock, and Food Supply ministries. The BIP is a target program under the World Bank's Forest Investment Program (FIP), which aims to finance development in climate change response activities (Climate Investment Funds [CIF], 2012). Under direction of FIP, investments are deployed to facilitate transformation and development of policies related to forest management. Since May 2012, the BIP has been active in the promotion of, "(i) improving food production, biodiversity or ecosystem conservation, and rural livelihoods; (ii) working at a landscape scale and include planning, policy and management, or supporting activities at this scale; (iii) involving intersectoral coordination or alignment of activities, policies or investments at the level of ministries, local government entities, farmer and community organizations, nongovernmental organizations (NGOs), donors, and/or the private sector; and (iv) participation and support adaptive collaborative management within a social learning framework." (The World Bank, 2017)

[1] Initiatives set out by nations for reducing emissions related to deforestation and forest degradation, and for supporting conservation, sustainable management of forests, and enhancement of forest sequestration (World Bank, 2017).

The underpinning strategy of the BIP is to improve environmental management using an ILM approach to support the Forest Code's Rural Environmental Cadaster[2] (CAR), the Low Carbon Agriculture (ABC) Plan[3], and the Native Vegetation Protection Law (NVPL)[4] (Climate Investment Funds [CIF], 2012). Following the criteria of these policies, the scope of the BIP seeks to promote sustainable land management in the Cerrado biome – a tropical savanna, which spans across the states of Goiás, Mato Grosso do Sul, Mato Grosso, Tocantins and Minas Gerais, and smaller regions in Sao Paulo and Paraná (see Figure 1). The BIP is an important investment vehicle for ensuring implementation of policy and sustainable land management, working directly in relation to the environmental policy of the region. As stated by the World Wildlife Foundation (WWF), "Without the effective participation of decision-makers and supply chain actors, it is unlikely that the new Forest Code will be fully and effectively implemented" (WWF, 2016).

The BIP works to achieve the financial and regulatory challenges that rural credit initiatives and agricultural policy makers face related to information, compliance and technology gaps. Investments from the BIP are focused on initiatives *outside* of the forest sector, but directly contribute to the conservation of forests, such as management of deforestation in the agricultural sector (The World Bank, 2017). In line with this strategy, the BIP aims to successfully integrate the mandates of the 2012 Forest Code, allocating LRs on farms in the Cerrado while simultaneously supporting farm productivity. With an ILM strategy as the framework for investment decision-making of the BIP, regional agronomists will be able to manage farmers more holistically, incorporating forest conservation as a point of emphasis (Climate Investment Funds [CIF], 2012).

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[2] Brazil's national database for controlling deforestation in Brazil.

[3] A low-interest rural credit initiative which aims to target sustainable practices and investments in agriculture under the National Plan on Climate Change

[4] Law under the Forest Code which stipulates that rural property owners must allocate a portion of their land for legal reserves and permanent preservation areas.

3.2 Nespresso's AAA Sustainable Quality Program: A Value Chain Investment Framework

ILM approaches in the private sector provide a context to mitigate a company's climate change externalities through more effective measurement practices of the greater region while upholding higher social standards by integrating policy and practice. It is a framework to purposely integrate food production, ecosystem conservation, and rural livelihoods across at a landscape level to manage for the effects which cannot be measured at the farm level (Alvarez, Pilbeam, & Wilding, 2010b). From the business perspective, ILM allows investors to avoid cost considerations of environmental externalities, mitigate community and reputation risk, manage resource scarcity and lack of substitutes, strategically differentiate between competitors of the same resource, and recognize of the value of ecosystem services to business performance (Kissinger, Brasser, Buchanan, & Millard, 2013).

Nespresso's AAA Sustainable Quality (AAA) Program is one such value chain investor (VCI) strategy which focuses on improving quality, sustainability and productivity at the farm cluster level through long term partnerships and ILM (Alvarez et al., 2010a; Amado, 2019). Through effective partnership with traders, exporters, cooperatives and NGOs, the AAA Program can provide effective training, certification, quality control, traceability and human rights training to improve socioeconomic welfare for farmers and conservation of ecosystems (Nestlé Nespresso SA, 2018). All organizations within the value chain work together to create shared value by integrating all five capitals into the collective strategy (human, social, natural, physical and financial) (Porter & Kramer, 2011). In fact, the AAA Program was developed in alignment with Porter and Kramer's seminal work on "Creating Shared Value" (2011), which highlights a critical shift in the strategic considerations of corporate social performance and financial performance. This model helps strategically solve social and environmental issues while maintaining a dominant value creation model, viewing society and competitors as collaborators with shared resources. As Nespresso CEO, Jean-Marc Duvoisin stated in the company's 2018 'Creating Shared Value Report', "Sustainability is a business imperative for Nespresso, and a core part of our strategy" (Nestlé Nespresso SA, 2018).

The AAA Program presents a very compelling ILM approach in the private sector to achieve economic, social and environmental sustainability across its supply chain by explicitly convening multiple stakeholders, including SCPs, traders, exporters, cooperatives and other NGOs (Alvarez et al., 2010a; Amado, 2019; Nestlé Nespresso SA, 2017, 2018). The program has been under development in Brazil since 2005 and currently consists of 1200 farms with 15 agronomists in the field (Amado, 2019). Brazil remains the largest coffee supplying nation for Nespresso, and under partnership with the Dutch SCP, Rainforest Alliance, Nespresso has managed to ensure 90 per cent of its coffee production is sustainably certified (Nestlé Nespresso SA, 2017). Ultimately, the AAA Program stands to benefit Nespresso and its farmers in three key ways:

First, credit facilities from VCIs have helped sustain operations for smallholders. This is particularly important for coffee farming because coffee trees are perennial crops, which cannot be easily substituted for more economically viable crops during periods of low market prices. Calculated investment decisions for farmers are introduced by the agronomists, which informs investors on necessary funding, capacity building, training and agricultural inputs. This differs from rural credit policies because the VCI is involved with the strategic management of investments, adding a component of expertise to the provision of funding. Furthermore, the fixed, long-term nature of the contracts mitigate selling and purchase volatility for both counterparties, ensuring fair living wages for farmers and effectively ‘decommodifying’ coffee production (Nestlé Nespresso SA, 2018). Ultimately, this leads to better long-term investment planning at the landscape level and more effective price risk mitigation for the VCI.

Second, ILIs employ cluster structure management, which requires investment on the regional level and encompasses several to hundreds of farms within a region of interconnected climatological systems (Amado, 2019). Through the investment of farms at the landscape level, farms can receive more holistic strategies for management of soil, hydrology, biodiversity, socioeconomic development and vegetation that are immeasurable at the farm level. Nespresso’s AAA Program involves the assessment of social infrastructure in the region of investment including health care, education, gender equality and farm management training, and reliable access to utilities, which in turn improves the livelihoods of rural communities as well as crop quality and yields (Nestlé Nespresso SA, 2016).

Finally, the scalable infrastructure of a multinational institution provides greater data collection practices and stronger insights, particularly with the proliferation of mobile technologies in rural markets. Data insights provide Nespresso with the capability of monitoring food security and rural development, optimal crop management, legal compliance, resource needs and productivity at a farm level with respect to the surrounding environment.

Furthermore, data insights ensure transparency in the value chain, which informs investment decisions strengthen the social welfare of farming communities and ensures that all stakeholders remain accountable for their actions (Alvarez et al., 2010a).

4. Data Description and Detailing of Hypothesis

Based on the compelling stakeholder approaches with ILM, it is of great interest to empirically analyse their impacts on farmers and the value chain. In this section, I describe my approach for data collection, process for data management, and framework for evaluation of sustainable land management. Prior to discussing my empirical strategy, I revisit my hypothesis and provide a more detailed overview based on the understanding of both ILM models and the available data.

4.1 Data Collection

To effectively identify the causal relationship of increased farm performance for the AAA and BIP in Brazil, a DiD approach using a fixed effects model is necessary to isolate the impact of endogenous variables related to crop productivity, resource intensity and remuneration. As such, my initial step to creating a comprehensive model was to collect data on coffee production, which would form the foundation of my dependent variables. Using the Brazilian Institute of Geography and Statistics' (IBGE) database, I developed a dataset of municipal performance metrics in coffee production for the years 2002 to 2016 across 2,217 unique municipalities.

Elevations, soil profiles, annual rainfall and mean temperatures make this region a climatologically ideal location for coffee production. With this consideration, environmental variables such as precipitation, soil chemistry, elevation and temperature were measured across all municipalities with available weather stations in the respective region. Time-variant climate data such as annual rainfall and mean annual temperatures were collected between 2002 and 2016 to include variance over time, providing a more robust analysis. The collection process gathered 723 municipalities across south eastern Brazil, including states Minas Gerais, Espirito Santo, Rio de Janeiro, Paraná and Sao Paulo.

After eliminating all gaps in the data across the time horizon, the scope of study was narrowed to 651 municipalities, maintaining validity in the analysis. Finally, regional data was collected from the Rainforest Alliance website and IBGE to segment the analysis between Nespresso-certified regions and natural biome borders, allowing for accurate identification of focus and control groups.

With the following resources, a dataset was developed and incorporates all independent and dependent variables between 2002 and 2016, represented in Appendix 1. For my analysis, time-specific dummy variables were assigned to each municipality, identifying pre and post treatment of Nespresso’s AAA Program and the BIP. Based on the reported implementation dates, the AAA Program and BIP treatments begin 2006 and 2013, respectively (Amado, 2019; The World Bank, 2017).

4.2 Description of the Area Studied

To categorise the treatment and control groups, mapping of the region was necessary to understand which municipalities fit within the geographic boundaries of the projects. Using the natural biome borders map from IBGE, I was able to identify municipalities within the Cerrado biome, ultimately specifying the impact region of the BIP (Rainforest Alliance, 2019). Similarly, Rainforest Alliance’s website provides the geographic coordinates of farms and regions certified under the AAA Program project region, including the Nespresso AAA Program project region (Joffre, Poortvliet, & Klerkx, 2019), which allowed me to capture the majority, if not all municipalities under effect. The treatment areas span across Minas Gerais and Sao Paulo, consisting of 124 municipalities under the BIP, 107 municipalities within Nespresso’s AAA Program region, and 23 municipalities under both ILM programs. The remaining the 443 municipalities, which form the control group, are present across the five south-eastern states, including Sao Paulo, Espirito Santo, Paraná, Minas Gerais and Rio de Janeiro.

To illustrate, I developed a map of the study regions using the geographic information system QGIS, and is presented in Figure 1 below:

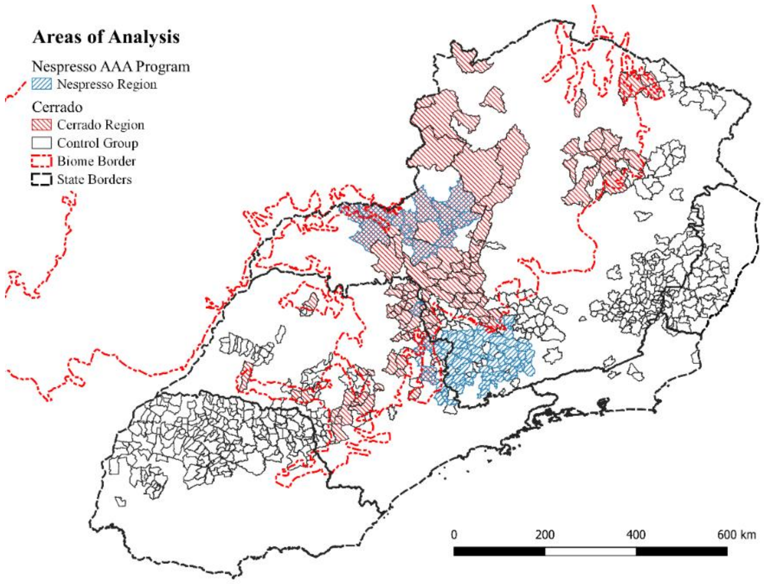

Figure 1: Five Southeastern States of Brazil and Natural Biome Border Between the Cerrado and Atlantic Forest, (Source: own, rendered using QGIS)

While the specifications related to the geographic boundaries of analysis with the BIP rely on whether the municipality is within the Cerrado biome, the boundaries for the AAA Program are not as simple. Nespresso's prominent investment footprint in Brazil's coffee sector, in conjunction with its cluster structure strategy provides assurance that we can reasonably measure the improvement of farm performance on the municipal level (Amado, 2019). This implies that the majority of coffee production in the AAA Program's treated municipalities is under management or associated with the Program, however the degree of investment in a municipality is not necessarily 100 per cent. Still, spill-over effects from resource and knowledge sharing under sustainably certified farms is prominent and empirically validated (Brasier et al., 2007; Rueda & Lambin, 2013; Takahashi & Todo, 2017), which are prominent in the presence of clustered agricultural investments (Brundtland, 1987; Terry & Dumanski, 1998) and support the validity of my results. Thus, I conclude that despite a presence of unobserved heterogeneity which I cannot account for at the municipal level for the AAA Program regions, the treatment effects maintain their validity.

4.3 Sustainability Performance Indicators

To identify the appropriate metrics of analysis for sustainable agricultural performance, a working definition of sustainable agriculture is needed. In line with the Brundtland definition of sustainable development[5], sustainable agriculture aims to benefit both present and future generations by simultaneously increasing biophysical and economic welfare (Terry & Dumanski, 1998). Sustainable development of agricultural systems implies increases in farm productivity and management of resources while eliminating the degradational impacts of land transformation for pasture or crop production (Smyth & Dumanski, 1995b). Considering that ecosystem conservation is a slow and gradual process and often requires considerable initial investment, sustainable development can be viewed as a long-term investment opportunity, whereby resources and structural systems are sufficiently available in the future based on the decisions made in the short term (Raynolds et al., 2007). From an agricultural perspective, Smyth and Dumanski (1995) define sustainable development for land management as the combination of improved technologies, policies and practices to reconcile socioeconomic and environmental development objectives such as "[1] *improvement in productivity*, [2] *reduction of risk in production*, [3] *protection of natural resources and prevention of degrading soil and water quality*, [4] *improvement of economic viability* and [5] *social acceptability"*. Simultaneously, these five goals form the foundation of the international 'Framework for Evaluation of Sustainable Land Management' (FESLM) and provide a point of departure for my analysis on sustainable performance (Amado, 2019; Smyth & Dumanski, 1995a).

Considering that the data collected for my analysis were acquired from publicly accessible databases, measurement of *risk in production* and *social acceptability* in a quantitative capacity is thus not possible as it relies on internal farm reporting (Dumanski, Gameda, Pieri, World Bank., & Canada. Agriculture and Agri-Food Canada., 1998). Furthermore, Alvarez & Pilbeam conducted an empirical research study in 2010 regarding the risks related to the environmental, social and governance factors with the AAA Program, stating that the introduction of the program was enforced as a risk management mechanism to secure supply chain actors over long term engagements while promoting environmental sustainability as an opportunity to mitigate future risks from the farmer to the consumer (Alvarez et al., 2010b).

[5] Sustainable development: meeting the needs of the present without compromising the ability of future generations to meet their own needs. (Brundtland, 1987)

Given that the strategies for ILM is centred on ecosystem conservation and the lack of publicly available resources and existing literature on risk mitigation, natural resource protection and social acceptability across the value chain, a continuation on the analysis under an economic lens will help identify the business case of ILM programs for farmers and relevant stakeholders.

For the remaining two objectives, which form the central focus of this study, *improvement in productivity* is measured by average yield and income per hectare and *improvement of economic viability* is measured by municipal income, income per farmer, and income per kilogram of green coffee produced. These sustainability performance indicators (SPIs) (defined in Appendix 6) address the efficacy of the ILM programs in meeting socioeconomic development goals for coffee producers. In the remainder of this section, I review the two FESLM objectives and their respective SPIs as a point of departure for my analysis.

4.3.1 Economic Viability Indicators

Considering the growing challenge of remuneration for coffee farms presented in Section 1 and 2, economic performance represents the most important component of my empirical study. Income is a highly valuable measurement because it can indicate improvements in quality of production (income per kilogram produced) as well as socioeconomic viability (income per farmer and municipal income), which provides a multidimensional assessment of sustainable development.

Furthermore, economic viability may also be a clear indicator of environmental preservation (Bravo-Ureta et al., 2006; Ashby et al., 1996; Lyngbaek & Muschler, 2001). The Environmental Kuznets Curve (EKC) hypothesis aligns with this phenomenon, proposing that environmental degradation – in the form of CO_2 emissions or deforestation – is a function of income per capita whereby greater incomes leads to better resource management and efficient processes, ultimately reducing the intensity of environmental degradation (Shafik and Bandyopadhyay, 1992; Panayotou, 1993; Grossman and Kreuger, 1993; Selden and Song, 1994). Though it has not held true to all empirical cases, studies in the Brazilian context have largely validated the hypothesis (Eggleston et al., 2006; Alam et al., 2016; Choumert et al. 2013). While this study is limited to the economic considerations of ILM programs ultimately, if economic viability indicators present positive outcomes for ILM treatment areas, this study can serve as a motivating business case for farmers and VCIs to feasibly employ holistic sustainable development in their business model. As a result, I use annual municipal income is used as the primary variable of assessment for this study and is supported by the other SPIs.

4.3.2 Productivity Indicators

Definitively, productivity in sustainable agricultural systems refers to minimizing inputs while increasing or maintaining output levels related to production (Byerlee & Murgai, 2001). ILM can be a successful approach for determining productivity because it exhaustively measures environmental and socioeconomic indicators in an ecosystem and addresses technical or infrastructural opportunities to optimize farming processes. The cluster structure approach that the AAA Program employs aims to improve the sharing of local resources (input minimization) while capitalizing on the sharing of technical expertise (output maximization). This aligns with the concept of Total Social Factor Productivity (TSFP), which is a holistic assessment of outputs and inputs, including all market and non-market resources as well as their associated externalities (Dumanski et al., 1998). Though this model is theoretically robust, TSFP has been rarely used in practice due to informational constraints related to resource quality and environmental degradation (Arraut et al., 2012; Carreiras, Jones, Lucas, & Gabriel, 2014). Ultimately, successful assessment of TSFP would need to be measured using farm-level data to access data regarding inputs.

Using the data available, productivity is measured by measurable market resources at the municipal level, namely coffee production, farmer populations (see Appendix 5), land used for harvest and income per hectare. While the incorporation of non-market inputs and outputs such as resource quality, erosional effects and pollution statistics would present a more holistic assessment of productivity, a lack of publicly available information at the municipal level makes this impossible. Based on the conservational strategy outlined in ILM programs (Kissinger et al., 2013; Shames et al., 2017), I assume that agricultural inputs remain constant over time relative to the use of land for harvest. As a result, this study measures productivity in the more economic sense, using land and farmers as the inputs and coffee as the output. Still, the improvement in coffee production per hectare and production per farmer identifies very important insights related to the programs' effectiveness in improving farm efficiency and socioeconomic development.

5. Detailed Hypothesis

As a continuation of the hypothesis outlined in Section 1, Sections 2, 3 and 4 provide greater context to the case and the framework for measuring sustainability, which demands a more detailed explanation of this study's premise. Based on the holistic approaches employed by ILM strategies at a landscape-level, I propose the following hypotheses:

Hypothesis 1 (H1): The treatment effects of ILM programs will lead to greater productivity and economic performance than the untreated municipalities (control group).

Hypothesis 2 (H2): The AAA Program's integrated value chain approach, guaranteed quality premiums to farmers and long-term partnerships with farmers (Amado, 2019) will indicate the strongest improvements in income-related performance indicators.

Hypothesis 3 (H3): The BIP's strategy to align with environmental policy plans will help enforce better environmental management and result in greater productivity rates.

Hypothesis 4 (H4): Under the scenario where H1 is validated, regions where both ILM programs are present will produce a program effect that is relatively the same as the highest performer, which rests on the notion that there remains a high degree of overlapping strategies, and ultimately negligible synergies in sustainable socioeconomic development.

Using the defined SPIs, I can effectively measure the validity of these hypotheses with an econometric approach. As such, the remainder of this paper focuses on my empirical analysis to validate my hypotheses.

6. Preliminary Study of the Dataset

Prior to engaging in an econometric analysis of the ILM programs, my first step was to conduct a preliminary analysis of the dataset to assess whether there is a reasonable case for further investigation into this study. This preliminary investigation focused on understanding the unadjusted effects on treatment and the validity of municipality-variant factors.

6.1 Treatment Effects

Using the SPIs, my preliminary test revisits the literature on sustainable performance metrics to ensure the feasibility of the study and reasonable validity of the collected data variables (Terry & Dumanski, 1998). By segmenting the mean annual performance of treated and untreated municipalities, I was able to assess the average performances of municipalities after the implementation dates of ILM programs. Table 1 provides an overview of my panel dataset using mean values of the reported data. The values match the periods pre and post treatment and indicate stark improvements in performance across all regions in the dataset.

Mean Performance Data Pre and Post Treatment

	Nespresso		Cerrado		Both		Control	
	2002-2005	2006-2016	2002-2012	2013-2016	2002-2005	2006-2016	2002-2005	2006-2016
Output per farmer (kg)	2,679.12	3,365.48	9,728.07	11,344.01	6,314.41	8,249.37	2,726.78	3,302.77
Average yield (kg/ha)	1,028.67	1,357.32	1,411.51	1,687.81	1,189.96	1,683.47	944.67	1,197.83
Annual income (1000 R$)	10,969.04	29,891.27	15,566.96	32,373.77	12,626.78	35,599.70	4,267.49	11,212.46
Income per kg (R$)	2.76	5.47	4.00	6.25	2.90	5.40	2.37	4.81
Income per ha (R$)	2,840.27	7,548.54	5,858.37	10,639.79	3,480.66	9,272.05	2,217.54	5,873.34
Annual farmer income (R$)	7,745.89	18,943.38	40,437.00	73,399.48	19,194.54	45,774.50	6,472.87	16,317.18
# Obs	428	1177	1383	504	92	253	1772	4872

Table 1: Mean SPI Data of Municipalities Pre and Post Treatment

The preliminary results indicate that across all productivity and economic SPIs, improvements are observed during the post-treatment years irrespective of whether the municipality is treated For a breakdown of performance on a municipal level, see Appendix 7. Though some of this improvement could be explained by the treatment of the ILM projects, a net increase in performance from the control group indicates that improvements are likely as a result of a multitude of unobserved homogeneous factors such as national GDP growth, national policy implementation, inflation, and technological development.

I continued my preliminary study by visualizing the income performance of groups across the time horizon to understand the year-specific variances between groups. Figure 2 illustrates the mean annual income from coffee farming across the time horizon where *N-Start* and *C-Start* refer to the respective implementation years for the AAA Program and BIP.

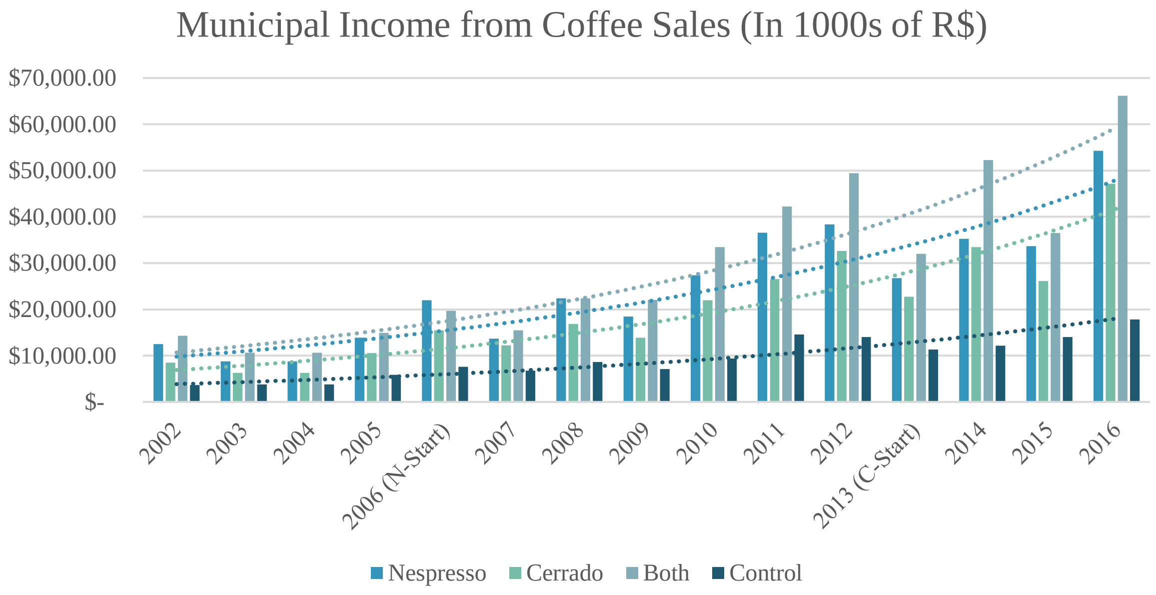

Figure 2: Mean Income of Treated and Untreated Groups: 2002-2016

In alignment with H1 and H2, the performance data illustrates that the treated municipalities outperform the control group with the AAA Program outperforming the BIP. However, there also appears to be the greatest treatment effect for municipalities affected by both programs, which contests H4 and possibly indicates high rates of synergy. However, the validity of these interpretations remain unclear as performances for all treated groups were stronger pre-treatment, subject to selection bias and the municipalities with both treatment effects may be simply impacted by the small sample size (Saunders, Lewis, & Thornhill, 2009).

Though there is an evident increase in incomes of treated groups, the treated regions also indicate higher incomes prior to program implementation dates. With respect to the AAA Program, it is likely that investment in this area was strategic to capitalize on the existing superior performance in coffee production. Moreover, there may be network effects of farm clusters in the regions, which can be conducive for greater resource and knowledge sharing (Brasier et al., 2007; FAO, 2010; Joffre et al., 2019).(Meyer, 1995)Similarly, the northern region of Minas Gerais is a climatologically optimal area for coffee production (Lopes et al., 2015), which drives coffee related production and income for the region (See Appendix 2). Nonetheless, the exponential trendlines which are interpolated in Figure 2 identify a continuous growth pattern in income for treated municipalities relative to the control. This observation motivates the continual investigation of this study.

6.2 Climate Testing

The final introductory assessment I conducted was on the viability of the unobserved heterogeneous climate variables in impacting productivity. Using the literature review on coffee ecophysiology presented in Appendix 3, I confined my dataset according to municipalities where mean rainfall, temperature elevation and soil composition profiles (see Appendix 4 for methodology) fit within the optimal range (See Table 2).

Climate Data Testing on Farm Performance

	Total	**Elevation (900-2800m)**	**Temperature (18-23˚C)**	**Rainfall (1200-1800mm)**	**Soil Acidity (pH 5-6.5)**	**Combined**
Quantity Produced (t)	2,848	4,292	3,434	2,788	2,725	4,586
Average Yield (kg/ha)	1,207	1,317	1,228	1,205	1,213	1,290
Income (1000 R$)	13,251.25	21,925.04	16,501.61	13,183.45	13,010.94	23,507.91
Farmer Income (R$)	20,033.67	33,617.55	19,176.59	17,765.37	19,505.03	30,240.19
Income per kg (R$)	4.32	4.70	4.47	4.35	4.38	4.74
Income per Ha (R$)	5,458.40	6,484.66	5,719.05	5,470.22	5,547.76	6,405.67
# Municipalities	652	88	408	560	382	49

Table 2: Climate Data Testing on Coffee Farm Performance in Brazilian Municipalities (2002-2016)

Across the entire dataset, climate-related factors were measured independently and collectively to validate the respective impacts on productivity. Based on my analysis, I found that mean productivity metrics are correlated with the optimal climate conditions. The following study indicates that the literature on coffee ecophysiology is consistent with the data collected thus, they serve as effective exogenous variables to use in the fixed effects estimator in the empirical strategy section of this study.

7. Empirical Strategy

This section reviews my multi-method empirical strategy for analysing sustainable development of ILM programs. I provide a detailed description of my methodology for my DiD model and the fixed effects calculations using several estimation approaches. Finally, I describe my parallel trends analysis to address the validity of my results.

7.1 Difference in Difference Model

To analyze the causal effects between the observed ILM models and sustainable agricultural performance against the untreated municipalities, an effective quasi-experimental design is needed. One of the main challenges of conducting a quasi-experiment is that internal validity is questioned when unobserved heterogeneous factors are not randomized (Meyer, 1995; Wooldridge, 2012). In the preliminary testing of the study, I discussed the conflict of analysing performance of dependent variables without adjustments for exogeneity. It is apparent that average incomes in the treatment groups were considerably higher before the ILM treatments, and therefore an assessment of performance without differencing out the potential omitted variables bias would raise concern on the empirical validity of this study (Wooldridge, 2012). With this consideration, a Difference in Difference (DiD) method of analysis can measure the outcome variable by measuring the within group differential between groups for both treatment groups and the control (Meyer, 1995).

The seminal work of Ashenfelter and Card popularized the use of DiD analyses as a methodological approach for assessing outcomes of an observed treatment group by comparing outcomes of a group not exposed to the treatment during the same period (1985). In other words, a DiD method differences the permanent confounders between focus and control groups measuring the average outcome of pre and post treatment periods (Ashenfelter & Card, 1985; Chabé-Ferret, 2014). The change within groups are compared between groups to analyse the average change following treatment. Effectively, the DiD eliminates bias from the second difference (between groups), which could be because of differences prior to treatment. A generic formula for a DiD approach can be written as follows (Wooldridge, 2012):

$$\hat{\delta} = \left(\bar{y}_{A,Post} - \bar{y}_{A,Pre}\right) - \left(\bar{y}_{B,Post} - \bar{y}_{B,Pre}\right) \tag{1}$$

Where $\hat{\delta}$ signifies the difference between the average change in the treatment group A and the average change in the control group B for the desired outcome $\bar{y}$ over time. *Pre* and *Post* represent the period before and after treatment of the program, respectively. In the context of this study, the DiD will assign ILM programs to variable A, untreated municipalities to variable B and SPIs to variable $\bar{y}$.

In this study, I aim to look at the DiD for municipal performance in coffee agriculture using the seven SPIs defined in Section 4. The DiD is particularly important for the study of sustainable agricultural performance because differing landscapes impose a variety of different physical and biological advantages or disadvantages. Municipalities which are endowed with stronger resource bases often have abundant access to robust agricultural services and ultimately more investment from private and public institutions. This presents an uneven arena for the measurement of agricultural performance between farms or municipalities (DaMatta, Ronchi, Maestri, & Barros, 2007). While the DiD manages for inherent differences between groups, there are three assumptions which the model cannot manage for independently.

First, the DiD assumes that pre and post treatment of the focus group already account for panel-variant exogenous factors (Wooldridge, 2012). For example, considering the extensive body of literature on coffee ecophysiology (DaMatta et al., 2007), it is apparent that the climatological differences between municipalities can vary greatly, and inherently can alter the SPI outcomes. For validity purposes, it is vital that I measure the isolated treatment impact of the ILM programs by accounting for climatological and other unobserved panel-variant factors, particularly because the measurements of treatment areas are not randomized and thus, are subject to high probabilities of selection bias (Chabé-Ferret, 2014).

Second, the DiD assumes that treatment status of a municipality does not gradually vary over time (Wooldridge, 2012). For the AAA Program, this consideration is more relevant because while the treatment from the program began in 2005 (Amado, 2019), the reality is that the treatment group likely did not consist of the current investment region (Rainforest Alliance, 2019). Ultimately, the lack of disclosable information regarding investment timelines of the AAA Program make this limitation impossible to account for. However, the DiD results for the AAA Program, can provide reasonable assumptions that most performance data between

2006 and 2016 (after the treatment date) are related to the AAA Program, and not to the untreated municipalities. This does question the validity of the SPI coefficients, but still maintains the validity of the relative impact.

Third, the DiD model assumes that the studied groups within the panel data are non-overlapping, which conforms with the nature of quasi-experimental designs (Meyer, 1995). With consideration that this study measures two mutually unexclusive treatment groups across different treatment years, the treatment programs would be partially impacted by the effects of the other treatment. As a result, the DiD requires fixed effects estimations to effectively account for unobserved heterogeneity and measure the *true* impact of the ILM programs (Angrist & Pischke, 2014).

In the next section I discuss the fixed effects model to measure the treatment effect; however, I use the term DiD to refer to the conceptual method of identification.

7.2 Fixed Effects Estimator

As mentioned in the previous subsection, to causally measure the relationship of ILM programs and sustainable performance, one first needs to control for all unobserved heterogeneity at the municipal level. The panel data collected allowed me to observe the same entities over time, and therefore provides cluster-robust statistics which account for within-panel correlation. Furthermore, the panel data made it possible to produce a fixed effects estimation with municipal-level unobserved heterogeneity (Wooldridge, 2015). As a result, the fixed effects estimation controls for unobserved time-variant factors such as climate, population growth, pane-wide environmental policy implementation, inflation and foreign exchange variation. As discussed in Section 4, this analysis is multidimensional, focusing on dependent variables such as yield, productivity per farmer, municipal income, income per hectare, income per kilogram and income per farmer. Considering the multi-dimensionality of my analysis and the illustrative capacities of the indicators, my initial analysis focuses more broadly, measuring the net effect of the AAA Program and the BIP on municipal income before addressing on the other six indicators (Wooldridge, 2012).

First, I wanted to control for the unobserved heterogeneity across the panel data by analysing municipality (Equation (2)) and time (Equation (3)) fixed effects independently to identify whether they return statistically significant coefficients. Once there is an understanding that both regressors are statistically valid variables, I incorporate the time and municipality variables into a third regression model represented in Equation (4). Finally, using the climate data and time dummy variables as a fourth model, I measure the impact of climate against the dependent variable to assess the explanatory power of environmental factor in Equation (5). The treatment-specific dummy variables allow for the integration of differences between treatment and non-treatment groups for Nespresso and the BIP over the time horizon, which are necessary for the DiD analysis. Ultimately, using the fixed effects estimation, we can calculate the endogenous results of income pre and post-treatment by removes unobserved effects. The regression equations for identifying statistical significance in exogenous factors are provided below:

Municipality Fixed Effects

$$Y_{it} = \beta_0 + \beta_1^N d_{it} + \beta_2^C d_{it} + I_i + e_{it} \tag{2}$$

Time Fixed Effects

$$Y_{it} = \beta_0 + \beta_1 N d_{it} + \beta_2 C d_{it} + I_t + e_{it} \tag{3}$$

Time and Municipality Fixed Effects

$$Y_{it} = \beta_0 + \beta_1 N d_{it} + \beta_2 C d_{it} + I_t + I_i + e_{it} \tag{4}$$

Time and Climate Fixed Effects

$$Y_{it} = \beta_0 + \beta_{1,it}^N d_{it} + \beta_{2,it}^C d_{it} + \beta_3 {T_{it}}^2 + \beta_4 {P_{it}}^2 + \beta_5 E_i + \beta_6 {S_i}^2 + \beta_7 I_t + e_{it} \tag{5}$$

Where *Y* is the dependent variable (in this case, municipal income from coffee sales), *i* refers to the municipalities, and *t* represents the years from 2002 to 2016. *N* and *C* refer to AAA Program and BIP regions, respectively; and *d* refers to the respective ILM program dummy variable over time (*d* = 0 or 1 to represent the control and treated groups, with consideration that the treated group only receives treatment when t > 2005 or t > 2012 for the *N* and *C*, respectively). S^2 is the coefficient for the regressor related to soil pH which does not vary over time, T^2 is the coefficient for mean temperature varying over location and time, and P^2 is the coefficient for annual rainfall in the respective year for each municipality. Because these climatological variables have concave relationships with the dependent variable, they must be measured quadratically (Wooldridge, 2015). Conversely, since the elevation profiles of the studied municipalities do not lie above the inflection point for elevation on coffee growth (DaMatta et al., 2008), we may view this relationship as a positive monotonic slope. I_i and I_t

describe the independent variables for all other unobserved municipal and time variant factors which impact the dependent variable. Finally, e is the error term which captures time-varying, idiosyncratic error (Wooldridge, 2015).

While the climatological variables included in Equation (3) have correlative capacities on performance (See Table 2), I also accept that the variables may not be entirely reflective of the unobserved heterogeneity, which can result in an omitted variable bias. As a result, fixed effects may be able to explain more of the exogeneity using the municipality as the panel-variant indicator (Mummolo & Peterson, 2018).

7.3 Parallel Trend Analysis

The final component of my empirical strategy ensures that the fixed effects coefficient from the DiD is validated by the calculated regressand trends before and after implementation of ILM treatment. The outcomes of the methodology are thus to identify the causal differential in pre and post treatment of the ILM programs. The parallel trend (or parallel paths) assumption ensures validity of the DiD model by assessing whether absence of treatment would result in the outcome variable remaining constant over time (Cerulli & Ventura, 2017). The fundamental problem with the DiD model is that the counterfactual[6] is not observed, making it impossible to address the relative differential between the pre and post treatment dates had the treatment not occurred. Without an analysis of the regression's trendline, the assessment of the DiD over-states the treatment effect because it assumes that pre and post-treatment would have remained parallel under the hypothetical scenario that the treatment programs had not been implemented. While a visual analysis of pre and post trends would provide observable changes in trends, a formal approach of testing this is more compelling. We can measure the difference of the pre-treatment slopes between the control and the treatment group, which can identify whether a different trend was observed prior to the treatment period. This can be modelled in Equation (5) below (Wooldridge, 2012):

$$Y_{it} = \beta_0 + \beta_{1t} + \beta_2(Treatment_i * Trend) + \beta_3 Treatment_i + \varepsilon_{it} \qquad (6)$$

[6] The anticipated outcome of a dependent variable if the treatment effect had not been implemented (Wooldridge, 2012)

Where the treatment dummy (*Treatment*) of the ILM program is measured for all municipalities in years before treatment. The *Trend* variable captures the change in the defined regressand during the pre-treatment period and is measured independently for the two ILM programs to eliminate the contamination effects that are not captured in the model. This is particularly vital for the validity of the later treatment program (BIP) regression because measurement of the pre-treatment effects would fail to account for the impact of the earlier treatment program (AAA Program) which would be captured in the control group (Cerulli & Ventura, 2017).

It is also important to note that the time dummy variable used for this regression differs from the fixed effects model because it must identify regions assigned to treatment even before the implementation of the ILM program. This provides the ability to compare the trajectory of the municipalities during pre-treatment years that eventually become treated against the control group (Wooldridge, 2012). Using this calculation, I was able to independently assess the BIP and AAA Program pre-treatment trends, which identify an observed impact only if the coefficient is substantially smaller than the post treatment coefficient. Furthermore, if the coefficient in the pre-treatment equation is less than or equal to zero, it can be deduced that the parallel trends assumption is not violated (Cerulli & Ventura, 2017).

8. Empirical Results

This section presents the results of the empirical strategy. First, I report the DiD results without the presence of a fixed effects estimation to illustrate the actualized change in performance post-treatment. Next, I present the outputs for four different fixed effects models to address which is most statistically valid for the remainder of my analysis. I then use this model and present the findings of the regressions assessing the SPIs across treatment groups and provide a validity check using my results from the parallel trends measurement.

8.1 Preliminary Difference in Difference Model

Based on the methodology outlined in Equation (1), a preliminary testing of the DiD allowed me to observe the following unadjusted results:

	(1) AAA Program (2006-2016)	(2) BIP (2012-2016)	(3) Both (2006-2016)
Output per Farmer	949	1,096	1,591
Average Yield	76	23	240
Municipal Income	11,977.25	9,861.84	16,027.94
Farmer Income	1,353.18	23,118.18	16,735.65
Income per kg	0.27	-0.19	0.06
Income per Hectare	1052.47	1125.62	2135.58
Number of Municipalities	107	126	23

Table 3: Preliminary DiD Testing

As discussed in Section 7, the results represent the within-group change in performance following ILM treatment relative to the control region. These post-treatment outcomes address that the impact of ILM programs correlate with greater productivity metrics since the productivity and economic viability SPIs remain positive (with the exception of income per kilogram in Column (2)). Additionally, incomes at the municipal level and per kilogram of coffee provide insights that the AAA Program is successful in increasing quality of output. While these results align with H1 and H2, H3 cannot be validated by this assessment because changes in yields remain higher the AAA Program, rejecting the notion that policy enforcement has a greater effect on intensification. Ultimately, the results remain unclear and are likely subject to omitted variable bias (Wooldridge, 2012). Thus, an effective fixed effects model is necessary to provide causal insights on the treatment impacts of ILM initiatives.

8.2 Fixed Effects Model Decision

In Table 4, I present the regression output for four different fixed effects models outlined in Section 7. To reduce complexity of the fixed effects analysis, I needed to outline one estimation model which would return the most descriptive results for my analysis. Furthermore, I needed to measure the significance of my outputs to identify whether the impact observed in the preliminary assessments matched statistically. Using Equations (2), (3), (4) and (5) on the regressand municipal income, I conducted a comparative study to arrive at the appropriate model for the remainder of my analysis. The interaction terms for the AAA Program and BIP all yield high statistical significance, with positive coefficients at the 1 percent significance level.

DiD Fixed Effects Estimators – Municipal Income (in 1000s of $R)

	Model Equation			
	(2)	(3)	(4)	(5)
	Year Fixed Effects	Municipality Fixed Effects	M&Y Fixed Effects	Y&Cl Fixed Effects
AAA Program	16,426***	17,584***	9,983***	17,139***
	(808.1)	(847.6)	(863.7)	(891.2)
BIP	14,597***	15,242***	8,238***	12,803***
	(1,318)	(851.9)	(869.5)	(1,291)
Both	1,126	1,885	4,644**	1,297
	(2,923)	(2,017)	(1,884)	(2,874)
Constant	10,515***	10,335***	5,637***	-435,550***
	(271.5)	(183.7)	(539.9)	(31,860)
Observations	9,791	9,791	9,791	9,791
R-squared	0.059	0.092	0.212	0.111
Year FE	YES	-	YES	YES
Municipality FE	-	YES	YES	-
Climate FE	-	-	-	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Fixed Effects Estimations on Municipal Income

Equation (2) represented in the first output column represents the simplest fixed effects model, capturing the adjustments to yearly income variances across treatment regions. The interaction term makes it apparent that municipalities treated by ILM programs have dramatically higher incomes, aligning with H1. Furthermore, adjustment of time-variant factors indicates that the BIP treatment municipalities experience the highest fixed effects adjustments on the interaction term, likely as a result of treatment occurring later, during years with low market prices. Despite the high adjustments to the BIP, different fixed effects equations still support H2, representing higher relative improvements in economic viability (Wooldridge, 2012).

Similarly, the fixed effects estimator in the second output column uses municipalities as the panel-variance indicator (Equation (3)) and presents an even more pronounced positive adjustment in the coefficients (Mummolo & Peterson, 2018). Since the treatment regions are not randomized and predominantly clustered in the same geographic region, they are subject to high degrees of selection bias, such as climate or other geographically-specific factors impacting the production and income of these regions. With the municipality fixed effects, the between-unit variation is eliminated (Wooldridge, 2012), and identifies that municipalities in the treatment group are negatively impacted by municipality-specific shocks after the treatment had occurred, relative to the same change in the control group. Similarly, this estimator supports H1 and H2, but remains statistically insignificant to understand the effects on municipalities treated by both programs.

Equation (4) in the third output column presents the most compelling fixed effects estimation for two reasons. First, Equation (4) indicates that the independent variables, year and municipality are the most explanatory, with the highest R^2 value. This indicates that 21 per cent of the total variation in income can be explained in this model (Wooldridge, 2012). Second, it is the only model which returns statistical significance with a 95% confidence interval for all three treatment groups. This allowed me to further validate H1 and H2, while rejecting. Ultimately, this model regresses the treatment on the dummy variables which comprise the best estimators for fixed effects and accurately represents the variation in time and municipalities to estimate the income resulting from ILM treatment.

While Equation (5) presents statistically significant insights on how climate and time-relevant factors impact coffee income, the model is less explanatory than Equation (4), illustrating that a multitude of other unobserved factors at the municipal level contribute to the output. Thus, the fixed effects model used for the remainder of the analysis is justifiably Equation (4).

8.3 Fixed Effects Results

In continuation of the previous subsection, outcomes for the seven SPIs have been assessed across both ILM programs using Equation (4) and have been presented in Table 5. This section will discuss the interpretation of the fixed effects estimations across all chosen SPIs for individual treatment groups and assess the validity of H1, H2 and H3. Due to the small sample size of municipalities with both treatment effects, municipal income and income per hectare were the only statistically viable interaction terms and have thus been omitted from the table. I revisit the viability and constraints of H4 in the discussion and limitations section.

DiD Fixed Effects Equation (4) – SPI Results

	Productivity SPIs			Economic Viability SPIs		
	(1) Kg per Farmer	(2) Yield	(3) Income per Hectare	(4) Municipal Income	(5) Farmer Income	(6) Income per Kilogram
AAA Program	-74.70	56.58***	761.7***	10,338***	-3,638**	0.248***
	(299.7)	(21.92)	(125.0)	(851.9)	(1,690)	(0.0463)
BIP	1,304***	103.5***	1,509***	9,083***	25,233***	0.0862**
	(215.5)	(20.57)	(117.3)	(799.2)	(1,586)	(0.0434)
Constant	4,214***	1,153***	2,060***	5,637***	7,953***	1.751***
	(145.6)	(13.90)	(79.26)	(540.0)	(1,071)	(0.0293)
# Observations	9,791	9,791	9,791	9,791	9,791	9,791
R-squared	0.023	0.195	0.628	0.212	0.125	0.827
# Municipalities	649	649	649	649	649	649
Year FE	YES	YES	YES	YES	YES	YES
Municipality FE	YES	YES	YES	YES	YES	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Municipality and Year Fixed Effects Estimations

SPIs (1), (2) and (3) assess the treatment effects on productivity and intensification of coffee production. While SPI (1) did not return a statistically significant interaction term for the AAA Program, the BIP indicates stronger improvements in SPI (2) and (3) by nearly double following implementation of the treatment programs.

SPIs (4), (5) and (6) relate to the economic component of sustainable development. The interaction terms indicate that while outputs and income are greater for the BIP on a per-hectare basis, the AAA Program produces coffee with greater value, represented in SPI (6). In Nespresso's mandate for the AAA Program, they promise quality and sustainability premiums of 20 to 30 per cent paid directly to farmers and are supported by technical assistance to improve quality, sustainability and productivity at farm level (Amado, 2019). Though farmer income decreased in relative performance, the methodological approach for measuring farmer income is largely based on the rural density assumptions, and thus could result in a considerably different outcome if the assumption variables are changed (see Appendix 6 for the discussion on methodology).

Using the productivity and economic viability regressions, I have interpreted that H2 and H3 are empirically validated. This interpretation is supported by the stronger intensification changes (SPI (2) and SPI (3)) for municipalities under treatment of the BIP, while production quality and income improvements (SPI (4) and SPI (6)) are more prominent in the AAA Program regions. The R^2 values for SPIs (3) and (6) indicate that the independent variables are highly explanatory, providing a high degree of confidence that the model is robust in capturing exogeneity. Furthermore, the regressions using Equation (4) indicate that economic validity and productivity metrics are almost unanimously positive for both programs, which confirms H1.

Ultimately, the results of this test indicate that both the AAA Program and the BIP are economically viable models for improving productivity and income at the farm level; however, to ensure validity in this statement, I present the parallel trends assessment in the following subsection.

8.4 Parallel Trends Analysis: Robustness Check

As mentioned in Section 7, while H1, H2 and H3 hold true based on the results of the fixed effects regressions, if the parallel trends assumption is violated, the results from the DiD cannot be validated. Included in this section are the parallel trends regressions on income and yield using Equation (6) and are presented in Tables 6 and 7. While the assessments of parallel trends are measured for the other indicators, the tables have been omitted, but will be discussed below.

8.4.1 AAA Program Trend Analysis

Table 6 below includes the regression analysis for assessing whether the AAA Program validates the parallel trends assumption.

Nespresso AAA Sustainable Quality Program:
Parallel Trends Regression on Municipal Income (in 1000s of $R)

	Treatment Periods	
	(1)	(2)
	Pre Treatment	Post Treatment
AAA Program Trend	-268.7*	1590.8***
	(422.9)	(284.1)
Control	683.1***	1208.9***
	(171.2)	(115.0)
Constant	3732.9***	2359.6**
	(540.0)	(1097.4)
# Observations	2,612	7,179
R-squared	0.068	0.074

Standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Table 6: AAA Program Parallel Trends Regression

For the AAA Program, there is no evidence that the parallel trends assumption is violated. Despite an improvement in the trend for the control variable, the trend is more pronounced in the AAA Program, which indicates that the fixed effects regressions are validated. Measurements of average yields, income per hectare and income per kilogram were also measured, presenting similarly indicative results of post-treatment improvements. For robustness purposes, the trend lines are plotted for yield and income as linear slopes in Figures 3 and 4 below.

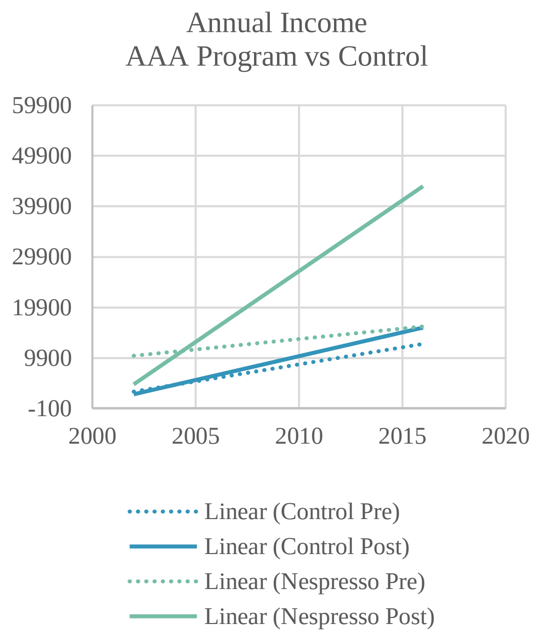

Figure 3: AAA Program Trend Analysis on Income

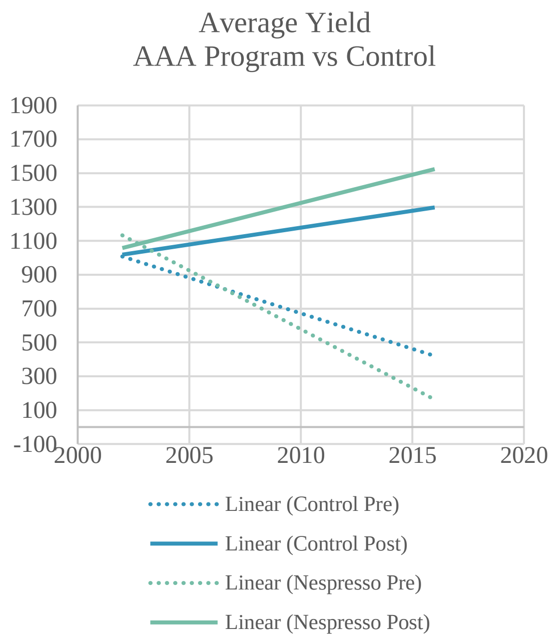

Figure 4: AAA Program Trend Analysis on Yield

The analysis of the slopes indicates that while improvements are made after the treatment of the AAA program for both treatment and control, the improvements are far more pronounced in the Nespresso Program. Thus, it can be deduced that H1 and H2 are validated hypotheses (Wooldridge, 2012).

8.4.2 BIP Trend Analysis

Similarly, Table 7 conducts the same regression from Equation (6) to assess the outcome of the parallel trends test.

Brazil Investment Plan:
Parallel Trends Regression on Municipal Income (in 1000s of $R)

	Treatment Periods	
	(1)	(2)
	Pre-Treatment	Post-Treatment
BIP Trend	1021.8***	3,985.9**
	(173.3)	(1579.5)
Control	1048.2***	2142.5***
	(75.2)	(686.0)
Constant	2498.0***	-12,962.5
	(445.0)	(8,609.7)
# Observations	6,002	2,184
R-squared	0.0762	0.0455

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 7: BIP Parallel Trends Regression

Looking at Table 7, there is evidence that the municipalities within the BIP treatment region were growing faster than the control municipalities prior to the treatment. However, before treatment, the BIP municipalities were growing at roughly twice the rate of the control municipalities, but after the treatment the BIP treatment municipalities were growing at roughly three times the rate of the control municipalities. Therefore, while the parallel trends analysis shows that some of the average treatment effects may be due to a higher rate of growth pre-treatment, the evidence suggests that the treatment resulted in an even higher rate of growth in the treated municipalities. To illustrate this measurement, see Figures 5 and 6 below:

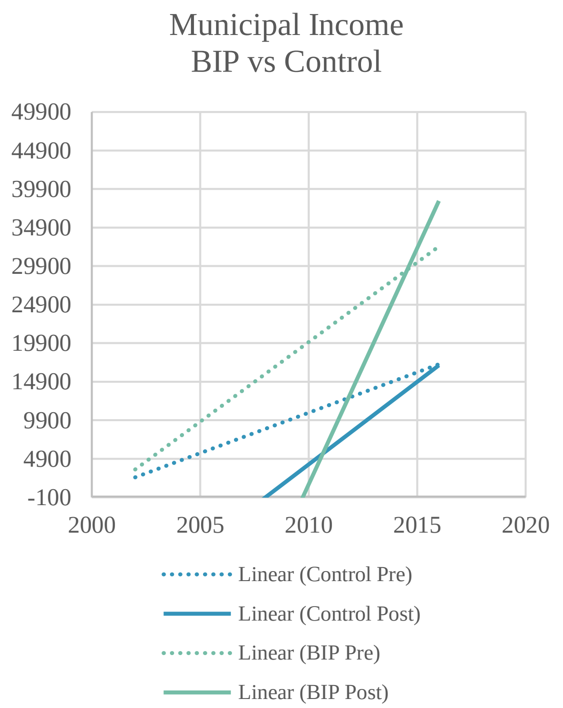

Figure 5: BIP Trend Analysis on Income

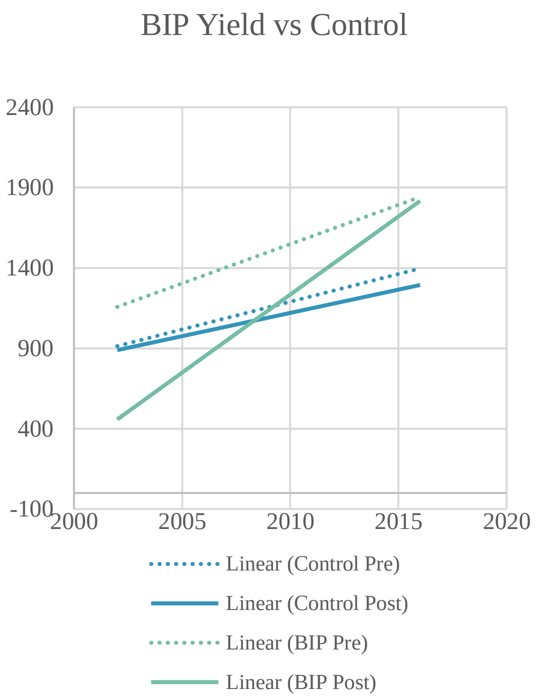

Figure 6: BIP Trend Analysis on Yield

Similar to the AAA Program, the analysis of slopes between the BIP and the control indicates that while improvements were stronger following the implementation of the ILM initiative for BIP as well as the control, the slopes of the trend lines are significantly greater than in the control. Thus, it can be deduced that H1, H2 and H3 are valid hypotheses.

9. Summary of Results and Limitations

In this section I discuss the key results of this study in relation to my hypotheses and highlight the limitations of the analysis.

9.1 Summary of Results

The results of this study indicate that economic and productivity rates of the AAA Program and BIP were considerably improved following the implementation of the programs. More specifically, the increases in process intensification (namely yields and income per hectare) of coffee farming were most impacted by the implementation of the BIP, likely as a result of the program's strategy to enforce environmental policy changes. Moreover, the AAA Program recorded the strongest improvements in economic viability (namely annual municipal income and income per kilogram produced) which was likely prompted by the quality training and investment efforts set out in Nespresso's shared value strategy. In relation to the four hypotheses outlined in Section 6, the study draws the following conclusions:

1. *The BIP and AAA Program are effective strategies for increasing productivity and income at on an aggregate and unit basis. The results indicate that the implementation of ILM programs are causally linked with increases in municipal income, yields, income per hectare and income per kilogram of green coffee produced.*
2. *The BIP's targeted focus on enforcement of environmental policy, namely the Forest Code, ABC Program and CAR, has been most effective in intensifying coffee production on a per hectare basis.*
3. *The AAA Program's emphasis on creating shared value and socioeconomic welfare of farmers has been most effective in creating higher value crops and aggregate income.*
4. *The data presents no conclusive evidence on the combined impacts of value chain investment and public policy ILM approaches in improving productivity or economic viability indicators.*

9.2 Summary of Limitations

In this section, I discuss the limitations of this study in relation to data constraints, methodology, and interpretations of outcomes.

9.2.1 Limitations of SPIs

As discussed in Section 4, data restrictions serve as the greatest limitation in assessing the productivity and economic viability indicators for sustainable development of coffee farming in Brazil. With respect to productivity, restrictions to data with regards to agricultural inputs and land redevelopment would allow for a more robust analysis of productivity indicators as my analysis would capture the total factor productivity of the farms. As a result, this study assumes that input quality and consumption remain constant across harvested area and coffee production. If for example, input demand for coffee production was higher in municipalities treated by the ILM programs relative to the control, this would indicate that increased output and value related to coffee was as a result of more intensive use of natural resources such as water, fertilizers and non-renewable energy, the SPIs would have a more subdued effect relative to the control. As a result, the outcomes of this study must assume that increases in farm intensification and economic development remain unchanged in relation to the quantity and quality of coffee production.

9.2.2 Limitations of Combined ILM Strategies

While the regression analysis using Equation (4) presents statistically significant interaction terms for SPI (4) and SPI (6), indicating positive improvements post-treatment, the sample size is small, which causes uncertainty in understanding how multiple ILM programs impact performance. Nonetheless, this consideration lies beyond the scope of the study and remains of least important to the nature of this study.

9.2.3 Causal Identification of the BIP's Impact

In Section 3, I discussed the framework to which the BIP operates. Considering that the investment plan is targeted at improving the adoption of environmental policy, the plan was enacted in the same year as the 2012 Forest Code. Though the Forest Code addresses farms across all municipalities in the study, the policy is more stringent in the context of the Cerrado biome. The varying directives for each biome represent unobserved exogenous impacts which cannot be isolated from the impact as they affect all municipalities in the BIP over the same time period. While this presents an unobserved heterogeneous factor, which is remains unaccounted for, the stricter policy mandates enforce greater restrictions on agricultural development, which suggests that farmers are still benefitting from the BIP irrespective of the stricter mandates. Furthermore, in Section 3 I discuss the need for ILM strategies to work collectively with public policy to enforce the strategic plan for ecosystem conservation initiatives. Thus, there is no validity in measuring the independent impact of the BIP without the presence of policy implementation.

9.2.4 Causal Identification of the AAA Program's Impact

While the BIP impacts all coffee production in the Cerrado biome, the farm penetration rate for the AAA Program remains unclear. Literature on the AAA Program provides great certainty that Nespresso's investments in the treated municipalities is large and concentrated (Amado, 2019; Nestlé Nespresso SA, 2016, 2018), however it is illogical to assume that 100 per cent of the production in the AAA Program region is impacted by ILM approaches. Still, the high statistical significance of the treatment regions and my review of the empirical research on spill-over effects in sustainable agriculture has justified my hypothesis.

10. Conclusion

In this report, my aim was to assess the efficacy of ILM approaches in reconciling environmental strategies with social and economic sustainable development goals in the coffee sector. By studying the agricultural performance of municipalities affected by two strategically different plans between 2002 and 2016 in south-eastern Brazil, I identified that ILM programs driven by environmental or economic development both succeed in improving agricultural productivity, income and crop quality. Using a DiD model with fixed effects regressions, I identified a causal relationship between project implementation and superior agricultural performance. On average, yields improved for the BIP and AAA Program by 104kg/ha and 57kg/ha, respectively as well as improvements in municipal annual coffee revenue by R$9,100,000 and R$10,400,000, respectively. This supports my hypotheses that both plans achieve the same productivity goals, however the AAA Program is more effective at improving remunerative goals while the BIP offered greater improvements in the intensification of crop production.

While there remain considerable limitations of this study regarding the data available and the generalizability of the ILM models, the implications are substantial and present a strong business case for using sustainable landscape strategies as vehicles for improving agricultural and economic performance. The research serves as a point of departure for future research into the strategic opportunities for value chain investors, governments, financial institutions and farmers to improve environmental practices in agricultural value chains while aligning with economic development goals.

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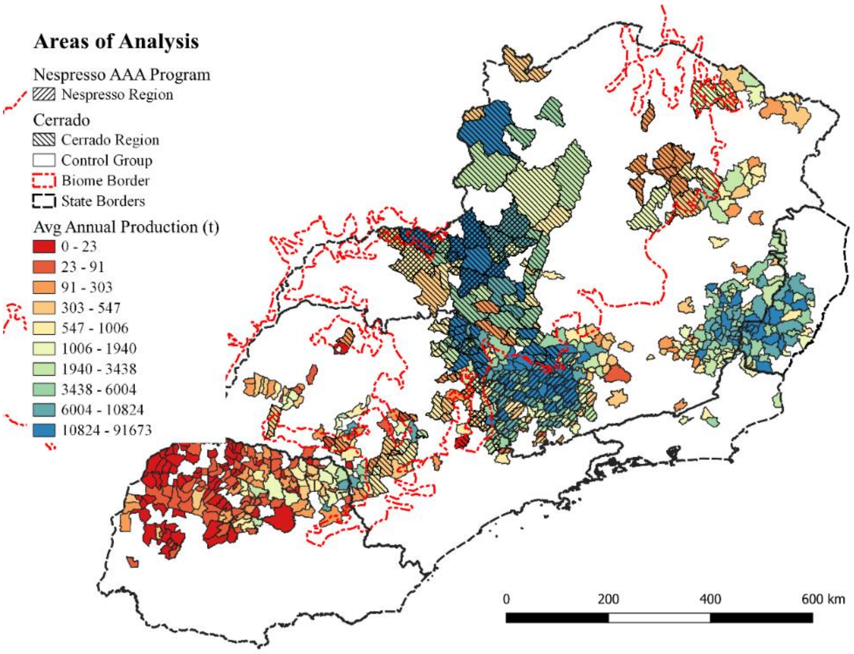
12. Appendix

Appendix 1: Data Collection List

SOURCE	*DATA*	*LEVEL*	*UNIT*	*DATE(S)*
BLOOMBERG	Annual accumulated precipitation	Municipal	mm	2006-2012
	Annual mean temperature	Municipal	˚C	2006-2012
IBGE:	Elevation (measured from the municipality centroid)	Municipal	m (a.s.l)	2010
	Annual production quantity of coffee	Municipal	Mt	2002-2016
	Annual coffee revenue	Municipal	1000 R$	2002-2016
	Annual average coffee yield	Municipal	kg/ha	2002-2016
	Harvested area in respective year	Municipal	ha	2002-2016
	Annual population estimate	Municipal	people	2002-2016
	Municipal rural population distribution	Municipal	%	2016
	Size of municipality	Municipal	km^2	2016
	Coordinates of municipality	Municipal	˚	2016
	Geographic borders	Municipal	shapefile	2016
	Rurality scale	Municipal	nominal	2004
	Natural biome borders	Regional	shapefile	2007
	Consumer price index (IPCA)	National	R$	2002-2016
OECD	Annual mean exchange rate	National	USD/BRL	2002-2016
RADAM PROJECT	Soil composition	Locational	pH	1985
	Soil sample coordinates	Locational	˚	1985
RAINFOREST ALLIANCE	Nespresso Coffee Project region	Regional	polygon	2018

Appendix 2: Mean Coffee Production (t): 2002-2016



Appendix 3: Description of Coffee Ecophysiology

Though there are over 100 recorded species of the *Coffea* genus worldwide, 99% of world production consists of *Coffea arabica* (arabica) and *Coffea canephora* (robusta) (Milder et al., 2014). Of the two, 74 per cent of production in Brazil is of the arabica variety, which produces a higher quality cup, but is less resilient to climate variations than robusta (Velmourougane, 2013). Though arabica and robusta species have been found to grow in a variety of climate profiles (Guardia & Gonzálvez, 2013), optimal growth requires natural climatic factors such as elevations of 900-2800m (DaMatta et al., 2007), mean annual temperatures between 18 and 23˚C, annual precipitation from 1200mm to 1800mm (DaMatta et al., 2007; Lima Filho & Malavolta, 2003; Malavolta, 1989; Velmourougane, 2013), and soil acidity profiles between 5.2 and 6.5 pH. Other climatological factors impacting coffee production which remain unobserved include wind stress, atmospheric humidity, cloud cover, presence of frost growth, cation exchange capacities and soil saturation levels.

Until 2012, the federal statistics collection agency for agricultural production in Brazil known as Municipal Agricultural Production (PAM, Portuguese acronym) collected non-segmented production data on coffee varieties. As a result, the scope of my research focuses on both the total production statistics of arabica and robusta varieties. Forming the foundation of my analysis, my methodology – outlined in Section 4 – examines the five southern states of Brazil, including Minas Gerais, Espirito Santo, Rio de Janeiro, Paraná and Sao Paulo, which produce 93.4 per cent of total national arabica yield (Bloomberg, 2019).

Appendix 4: Soil pH Integration Methodology

For optimal growth in coffee production, soil acidity must be within a specified range. As such, productivity of coffee farming largely depends on the soil profile. Though soil composition is largely a factor of farming practices such as tillage, use of fertilizers and anti-erosional management, natural soil composition has a significant impact the productivity of coffee yields. Thus, profiling municipalities based on natural soil composition is a necessary component for developing a robust fixed-effects estimator (Meyer, 1995).

In 2005, a comprehensive database of Brazil's soil profiles was developed by Cooper et al. using survey data published from the Radam Project (Projeto Radambrasil, 1973-1986). The project collected 4600 soil profiles to analyse the chemical and mineralogical compositions and tracked the geographic coordinates of each. Using the following database, I was able to cross-reference the closest soil profile with each municipality centroid by developing a Visual Basic program. The program identified the closest soil sample and its relative distance using the easting northing formula:

$$d_i = \sqrt{\frac{2\pi R \Delta \varphi_i}{360}^2 + \frac{2\pi R \Delta \lambda_i}{360}^2} \tag{7}$$

Where d is the distance between the soil and municipality centroid coordinates and i is the individual direct link between closest nodes. R represents the radius of the earth in kilometres, or 6,371km. ϕ and λ represent longitudinal and latitudinal coordinates, respectively. Though the haversine formula may be more accurate, reflecting the great circle distance between two nodes, the relatively small focus area would only reflect a rounding error difference.

Distances between soil samples and municipality centroids ranged from 240m to 137km with a mean of 27km. To maintain relevance of soil data, the 14 municipalities with distances greater than 100km from the municipality centroid were omitted from the analysis.

Appendix 5: Farmer Income Estimate Methodology

IBGE's municipal-level population estimates also provide information on the rural/urban typology of the region on a 5-point scale. To compare individual farmer incomes, annual farmer population in each municipality was necessary to calculate. As a result, the following formula was derived:

$$Fpop_{it} = H_{it} * \left(\frac{P_{it}}{A_i} * d_i\right) \tag{8}$$

Where *Fpop* represents the farmer population, *i* represents the municipality and *t* represents the time-relevant factor. *H* is the reported area available for harvest for coffee farming in hectares, as reported by the annual IBGE survey data. *P* represents the municipal population, *A* is the total area of the municipality in hectares and *d* is the assumed rural density discount ratio based on municipal typologies.

In this calculation it is assumed that there is rural density discount based on the municipality's typological description. The five categories are urban, intermediate-adjacent, intermediate-remote, rural-adjacent and rural-remote with respective density discounts of 0.80, 0.85, 0.90, 0.95 and 1.00 respectively. The discounts were made on the underlying assumption that in urban areas, the density variation is greater in urban areas relative to the rural areas. Alternatively, in rural-remote regions, no urban area exists, and thus the population density remains the same as the municipality total. Based on the new density metric, the area available for harvest assumes that farm regions take on the same density ratio as other rural areas within the municipality, thus arriving at a population estimate for farmers which varies across years and municipalities.

From here, the calculation for income per farmer is simply:

$$Frev_{it} = \frac{Crev_{it}}{Fpop_{it}} \tag{9}$$

Where *Frev* is farmer revenue and *Crev* is cumulative revenue reported by IBGE. Since this calculation rests on the underlying assumption that density factors are accurate, a sensitivity analysis is conducted in Section 5.2.

Appendix 6: Data Summary for SPIs

	Observation Group	*#Obs*	*#Municip*	*Population*	*Rural Population*	*Harvested Area (ha)*	*Quantity Produced (t)*	*Average Yield (Kg/ha)*	*Value (1000 R$)*	*R$/farmer*	*R$/kg*	*R$/Ha*	*Kg/Farmer*
Pre-Treatment	Control	1772	443	18071.43	4964.25	2124.49	1886.44	944.69	4267.48	6472.87	2.37	2217.54	2726.78
	Both	92	23	54829.72	6025.16	3554.30	4238.03	1189.96	12626.78	19194.54	2.89	3480.66	6314.41
	AAA Program	428	107	27661.76	4894.61	3991.24	3939.30	1028.67	10969.04	7745.89	2.77	2840.27	2679.12
	BIP	1383	125	35159.47	4987.10	2633.75	3549.35	1411.51	15566.96	40437.00	4.00	5858.37	9728.07
Post-Treatment	Control	4872	442	19286.82	5214.67	1889.52	2287.15	1197.83	11212.46	16317.18	4.81	5873.34	3302.77
	Both	253	23	59686.03	6428.12	3428.65	6229.36	1683.47	35599.70	45774.50	5.39	9272.05	8149.37
	AAA Program	1177	107	29505.95	5134.25	3830.93	5288.63	1357.32	29891.27	18943.38	5.47	7548.54	3365.48
	BIP	504	126	38044.59	5363.30	2897.32	5046.26	1687.81	32373.77	73399.48	6.25	10639.79	11344.91
First Differences	Control	4872	442	1215.40	250.42	-234.96	400.70	253.14	6944.97	9844.31	2.44	3655.81	575.99
	Both	253	23	4856.31	402.96	-125.66	1991.33	493.51	22972.92	26579.96	2.50	5791.38	1834.96
	AAA Program	1177	107	1844.19	239.63	-160.31	1349.33	328.65	18922.23	11197.49	2.71	4708.27	686.37
	BIP	504	126	2885.12	376.19	263.58	1496.90	276.29	16806.81	32962.49	2.25	4781.42	1616.84
DiD	Both	253	23	3640.91	152.53	109.31	1590.63	240.37	16027.94	16735.65	0.06	2135.58	1258.97
	AAA Program	1177	107	628.79	-10.79	74.66	948.63	75.51	11977.25	1353.18	0.27	1052.47	110.38
	BIP	504	126	1669.73	125.77	498.54	1096.20	23.15	9861.84	23118.18	-0.19	1125.62	1040.86

Appendix 7: Post-Treatment Municipal Performance Differentials