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IMPACTS OF THE FUNDÃO TAILING DAM COLLAPSE ON FAMILIES' ALLOCATIVE DECISIONS AND OWN-USE PRODUCTION

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Dissertação apresentada à Escola de Economia de São Paulo como requisito à obtenção de título de mestre em Economia de Empresas.

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Resumo

Esta dissertação investiga os efeitos do rompimento da barragem de Fundão sobre as atividades de autoprodução realizadas pela população afetada. Ocorrido em 2015, no município de Mariana, Minas Gerais, o desastre é considerado a mais grave catástrofe ambiental da história do Brasil. O rompimento liberou grandes volumes de rejeitos de mineração, contaminando corpos d'água, degradando o solo, entre outros impactos ambientais. Este estudo tem como objetivo avaliar se, e em que medida, o desastre afetou as atividades de autoprodução da população que reside próximo ao Rio Doce. Para estimar a magnitude desse impacto, é utilizada uma estratégia econométrica de diferenças-em-diferenças adaptada para dados em *cross section*. Adicionalmente, a pesquisa analisa se o desastre influenciou outras decisões de alocação do tempo das famílias, como oferta de trabalho e frequência escolar. Por fim, busca-se identificar quais características individuais e fatores externos estão associados à participação em atividades de autoprodução.

Palavras-chave: Autoprodução, teoria da produção doméstica, avaliação de impacto de desastres ambientais, rompimento da barragem de Fundão.

Abstract

This dissertation investigates the effects of the Fundão tailing dam collapse on own-use production activities among the affected population. Occurring in 2015 in Mariana, Minas Gerais, the disaster is regarded as the most severe environmental catastrophe in Brazilian history. The rupture released vast amounts of mining waste, contaminating water sources, degrading soil quality, and causing extensive riverbank siltation, among other environmental damages. This study aims to assess whether and to what extent the disaster disrupted own-use production activities. To estimate the magnitude of this impact, a difference-in-differences econometric strategy adapted for cross-sectional data is employed. Additionally, the research explores how the disaster may have influenced other time allocation decisions, such as labor supply and school attendance. Finally, it seeks to identify the individual characteristics and external factors that are associated with participation in own-use production activities.

Keywords: Own-use production, household production theory, impact evaluation of environmental disasters, collapse of the Fundão tailing dam

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1 Introduction

The collapse of the Fundão tailing dam in Mariana, Minas Gerais, marked the most severe environmental disaster in Brazilian history[1]. The environmental damage caused by the collapse was extensive, severely compromising both soil and water quality, particularly throughout the Rio Doce basin. More than five districts near Mariana were completely devastated by the tailing. This large-scale ecological disruption had a profound impact on the livelihoods of communities residing along the river. Among the affected populations are traditional groups, including Indigenous peoples, Quilombola communities, and riverside dwellers. Own-use production activities — particularly those dependent on natural resources, such as subsistence farming, fishing, and extractivism — were significantly affected. These shifts in household production patterns reflect not only a disruption of traditional productive practices but also a broader transformation in the ways of life and time allocation decisions of local communities.

Given the environmental damage caused by the disaster, it is expected that own-use production activities undertaken by populations living along the river were adversely impacted. Own-use production refers to non-commercial activities carried out to produce goods intended for household consumption. In both Brazilian household surveys (IBGE, 2024) and international studies (Durazo et al., 2021), these activities are typically classified into four categories: *(i) Own-Consumption activities*, which include agricultural production, fishing, animal husbandry, and hunting; *(ii) Home-Production activities*, involving the manufacturing of household goods such as furniture, textiles, and pottery; *(iii) Home-Construction activities*, encompassing the construction or major repair of dwellings or farm structures; and *(iv) Extraction activities*, referring to the collection of natural materials such as charcoal, firewood, water, sand, clay, and seeds. The Participatory Household Survey conducted as part of the Rio Doce Project — the primary data source for this dissertation — adopts this same classification framework.

Household production activities dedicated to own-use remain highly relevant in Brazil. Approximately 6.8% of the Brazilian population aged 14 and over (1.8 million individuals) engage in at least one of the four categories of own-use activities. This form of

[1] Ministério Público de Minas Gerais (2020); Ministério Público Federal (2020)

production is particularly significant in rural areas, where 30.3% of the population report undertaking such activities. Geographically, own-use production is more prevalent in the North and Northeast regions, where it reaches approximately 9.5% of the population in each region. Among individuals involved in self-production, 75.4% engage specifically in Own-Consumption activities, highlighting the continued importance of these practices in shaping food consumption habits among Brazilian households (IBGE, 2024).

The first contribution of this dissertation is to advance the literature on the effects of exogenous shocks on family allocative choices and household production. In the Brazilian context, there is limited evidence regarding the impact of extreme events, such as climatic and environmental disasters, on household time allocation decisions, particularly those related to household production and own-use activities (Costa and Ravena, 2024; Silva and Garavello, 2015; Mueller and Osgood, 2009). Existing research on household production and its relationship to welfare outcomes and time allocation decisions is largely concentrated in low-income countries, especially in Sub-Saharan Africa (Jones et al., 2014). This study contributes to the literature by providing evidence on the dynamics of household production and own-use activities in a middle-income country context. To the best of our knowledge, this is the first study to examine a broader set of own-use activities — including fishing, extraction, construction, and manufacturing — beyond the traditionally analyzed domain of food production.

The second contribution of this dissertation is to improve the understanding of of the impacts of the Fundão tailing dam collapse on previously unexplored dimensions. A growing body of research has examined the disaster's effects on various outcomes, including population health (Carrillo et al., 2020; Firmiano and Irffi, 2020; Freitas et al., 2019), educational achievements (Firmiano and Irffi, 2020), and local economic conditions (Simonato et al., 2018; Castro and Almeida, 2019; Niquito et al., 2021). However, none of these studies investigates the impacts on household production activities for own-use, nor their relationship with broader time allocation decisions.

In addition to the immediate possible effects of reduced or discontinued own-use activities — such as decreased food variety — these disruptions also reflect broader changes in the consumption and production behaviors of affected families. Activities such as small-scale farming, fishing, and the use of shared natural resources have long been part of local traditions. Therefore, analyzing the impact on own-use production helps to shed light on how the environmental disaster altered the daily lives, routines, and practices of these

communities. This discussion also engages with the broader literature on environmental injustice.

Environmentally harmful activities such as monoculture plantations, grazing, road construction, and mining operations often generate negative externalities that disproportionately affect local populations (Lillywhite et al., 2015; Margulis, 2004; Martin et al., 2018). These groups are frequently composed of low-income households and marginalized ethnic communities that rely on food gathering, small-scale production, and artisanal practices, and tend to be less integrated into formal market systems (Acselrad et al., 2009). The environmental damage imposed on such groups can be interpreted as a form of environmental injustice. As defined by Acselrad et al. (2009), environmental injustice refers to the "disproportionate imposition of environmental risks on populations with fewer financial, political, and informational resources". Within this framework, the unequal impacts of the tailing dam collapse — particularly on riverside communities — can contribute to a deepening of pre-existing social vulnerabilities.

The remainder of this dissertation is organized as follows. Chapter 2 provides a review of the literature on household production. The first section discusses the theoretical foundations of household production and its relevance for understanding the core focus of this study. The second section summarizes the empirical evidence, with particular emphasis on own-use production activities. Chapter 3 describes the collapse of the Fundão tailing dam and introduces the dataset from the Rio Doce Project. Chapter 4 presents descriptive analyses and examines the factors associated with engagement in own-use activities. Chapter 5 outlines the econometric methodology employed, and Chapter 6 presents the main results. The final chapter offers the concluding remarks of the dissertation.

2 Household Production: Literature Review

The objective of this chapter is to provide a synthesis of the literature on household production, with a focus on its relevance to the research question addressed in this dissertation. The first section outlines the theoretical foundations of household production models, highlighting their core assumptions and the key insights they offer into household decision-making processes. The second section presents a review of the empirical literature, with particular emphasis on own-use production activities. It also explores how these activities are linked to other time allocation decisions within households, such as labor market participation and educational engagement.

2.1 Household Production Theory

The first economic model dedicated to the understanding and interpretation of domestic production was proposed in the seminal work of Becker (1965), which was the first to systematically address household production as an object of economic analysis. This section aims to present the main foundations of Household Production Theory. Although the objective of this dissertation is not to develop a structural model, this theoretical framework offers a valuable basis for understanding the phenomenon of domestic production and for interpreting the shock that the tailing dam collapse represented for the affected families.

The central idea of Becker's Household Production Theory is that households function as small production units, utilizing their time, resources, and labor to generate goods and services for their own consumption in addition to acquiring them from the market. Becker (1965) expands the neoclassical theory of consumer choice by acknowledging that households are not merely consumers but also producers of valuable outputs, including meals, childcare, and cleaning. He introduces the concept of a household production function, in which time and purchased goods are combined to generate household commodities. This theoretical framework emphasizes that household members must decide how to allocate their time between market work and home production. A key insight of this theory is that the opportunity cost of home production is the wage one could earn in the labor market. Consequently, this perspective highlights the economic significance of

unpaid work.

We begin by providing an overview of the unitary model of household decision-making. This model conceptualizes the household as a single decision-making entity that seeks to maximize a joint utility function. More complex models, which account for the cooperative behavior of family members, were developed later, with the most prominent contributions being the cooperative models (Chiappori, 1992, 1997, 1988). These frameworks incorporate intra-household bargaining processes and assume the existence of a stable decision-making mechanism that leads to Pareto-efficient outcomes. For the purposes of this study, however, the basic unitary model provides an adequate framework to analyze the disruption caused by the tailing dam collapse and its implications for domestic production and time allocation decisions of affected households.

Becker (1965) defines three key components of time allocation: L = leisure time; T_x = time spent producing good x (household production); T_w = time spent on market work.

Consequently, the household time constraint is:

$$T = L + \sum T_x + T_w,$$

where T is the total household available time.

Each commodity x is produced using time (T_x) and market-purchased goods (Z_x), forming a household production function:

$$X = f_x(T_x, Z_x),$$

where, X is the amount of the commodity x produced, T_x is the household time spent producing x and Z_x are the purchased inputs used to produce x.

The household budget constraint is given by:

$$I = wT_w + V = \sum p_x Z_x,$$

where w is the market wage and the total income (I) comes from labor income (wT_w) and from non-labor income (V). The total earnings should equal, at most, the total expenditure, which is represented by the sum of all market goods (Z_x) at prices (p_x).

The household problem is, then, defined as the maximization of the utility function:

$$U = U(X_1, X_2, ..., X_n, L),$$

subject to: i) the time constraint; ii) the budget constraint and iii) the household production function.

The first-order conditions of this program imply that the household optimally chooses T_x, Z_x and T_w such that:

$$MU_x/MU_L = w/MP_{T_x},$$

where MU_x is the marginal utility of x; MU_L is the marginal utility of leisure and MP_{T_x} is the marginal productivity of time in producing x.

This condition summarizes the household's optimal time allocation behavior. Households allocate time to household production up to the point where the marginal value of time equals the market wage. In this framework, households optimize their time allocation by equalizing the marginal value of time across all possible uses. If wages increase, for example, the opportunity cost of household production also rises, potentially leading individuals to substitute market work for home production, provided that the substitution effect outweighs the income effect. Conversely, when the substitution effect dominates, higher wages are likely to result in a reduction in household production activities.

The marginal value of time represents the utility an individual derives from allocating an additional unit of time to a specific activity. In the context of household production, it corresponds to the marginal utility obtained from spending more time on home production tasks. This value is ultimately determined by the marginal productivity of time in household production: the more productive an additional unit of time is in generating household goods or services, the greater its marginal value is.

The environmental disaster caused by the collapse of the Fundão tailing dam represents an exogenous shock that directly impacted the marginal productivity of household production. The degradation of natural resources—particularly soil and water—compromised the viability of activities that depend on these inputs, such as fishing and farming. In the aftermath of the disaster, it is expected that the same amount of time devoted to these activities would result in lower returns, both in terms of the quantity and quality of food

produced for household consumption. This disruption introduces a negative productivity shock to domestic production technologies.

Such a decline in the marginal productivity of household production alters the equilibrium conditions underlying time allocation decisions. In this context, the theoretical framework of household production proves useful in illustrating how changes in the relative productivity of any activity—be it domestic production or market work—can lead to reallocation of time across competing uses. It also emphasizes the interconnectedness of various household decisions, where a shock to one domain, such as own-use production, may generate indirect effects on labor market participation, school attendance, and other key aspects of household behavior. This integrated perspective is essential for understanding the broader consequences of the disaster on affected populations.

2.2 Empirical Evidence: Household Production and Time Allocation

Beyond the theoretical frameworks developed to describe the phenomenon of household production, the economic literature also includes a substantial body of empirical research on the topic. Drawing on household-level data that capture both household production and other dimensions of family life, these studies aim to analyze several closely related aspects of household behavior. First, they examine how decisions related to household production interact with other allocative choices made within the household, including how these interconnections are influenced by exogenous shocks. Second, the literature investigates the implications of household production for welfare outcomes, particularly those related to health and nutrition, which are often used as proxies for overall household well-being.

A first strand of the literature—within which the present study is situated—focuses on assessing the effects of exogenous shocks on patterns of household production and, by extension, on broader allocative decisions. As predicted by household production theory, shifts in household production activities lead to reconfigurations in how families allocate their time and resources across various domains. In particular, environmental and climate-related disasters—such as floods, cyclones, and droughts—have been shown to directly disrupt household food production activities.

Changes in the marginal productivity of household production—whether directed toward own-consumption or market-oriented—have a direct impact on household labor

allocation decisions. When faced with productivity losses, households often respond by shifting their labor resources and identifying new income-generating opportunities. The empirical literature consistently points to two prominent adaptive strategies: increased participation in off-household labor (Mathenge and Tschirley, 2015; Mottaleb et al., 2015) and migration (Gröger and Zylberberg, 2016; Mueller and Osgood, 2009). Mathenge and Tschirley (2015) analyzes how rural households in Kenya respond to weather-related agricultural shocks. They show that families not only expand their engagement in off-farm work in reaction to weather shocks but also adjust their labor strategies in anticipation of deteriorating farming conditions.

Beyond shaping labor allocation, some studies investigate how shocks to household production influence educational outcomes (Maccini and Yang, 2009; Mottaleb et al., 2015). Since school attendance is itself a component of household time allocation, it can be affected by disruptions in the productivity of domestic activities. Mottaleb et al. (2015) explores this dynamic in the context of a cyclonic disaster in coastal districts of Bangladesh, focusing on its impact on educational expenditures. Their findings reveal a decline in spending on boys' education, driven by a reduction in agricultural income and an increased demand for labor — particularly in male-intensive tasks such as farm reconstruction. In response, many households withdrew boys from school to involve them in income-generating or repair activities. In contrast, educational expenditures for girls remained largely unaffected across both farm and non-farm households, underscoring the gendered nature of these coping mechanisms.

Exogenous shocks that disrupt household production patterns often have significant implications for family welfare. A strand of the literature focuses on short-term impacts, particularly those affecting consumption decisions (Salem and Jabari, 2022; Amare et al., 2018; Duflo and Udry, 2004). Salem and Jabari (2022) analyze the effects of flooding on farming households in Iran and find that flood-affected families markedly reduced their food consumption and increased expenditures on essential services such as energy, transportation, and healthcare. Similarly, Amare et al. (2018), using a nonseparable farm household model that captures the interconnected nature of production and consumption decisions, demonstrate that negative rainfall shocks in rural Nigeria led to reductions in food consumption.

Evidence from Brazil further highlights the adverse effects of disruptions in own-use production. Costa and Ravena (2024) investigate the unregulated expansion of the global

palm oil value chain in northeastern Pará, that provoked environmental degradation, biodiversity loss and lower productivity of activities for own-consumption and extraction. They documented its detrimental consequences for the food sovereignty of Quilombola and Indigenous communities in Tailândia and Tomé-Açu. Likewise, Silva and Garavello (2015) examine dietary changes among the Xavante Indigenous people in Mato Grosso and observe a marked decline in the consumption of traditionally gathered wild foods, replaced by increased intake of processed products—a shift associated with a high prevalence of anemia (56.3%) in the surveyed population.

Duflo and Udry (2004) investigate the impact of rainfall shocks in Côte d'Ivoire, focusing on how these climate variations affect crops managed either by men or women within the same household. Their study finds that when rainfall positively affects crops traditionally cultivated by women, households tend to increase spending on goods such as food and education. These findings add to the existing literature that highlights gender-differentiated effects in household responses, challenging the foundational assumptions of the unitary household model which posits a single utility function and pooled resources across all members (Attanasio and Lechene, 2002; Chiappori, 1988; Hotchkiss, 2005).Instead, they emphasize that resource allocation within households is the result of bargaining processes, shaped by each member's relative contributions, fallback options, and the broader social and institutional context — including gender norms and cultural expectations.

There is evidence that the effects of shocks on household production extend well beyond the short term, with lasting consequences for human capital, asset accumulation, and anthropometric outcomes (Azibo Balgah and Buchenrieder, 2013; Maccini and Yang, 2009; Mueller and Osgood, 2009). Maccini and Yang (2009), using data from the Indonesia Family Life Survey linked to historical rainfall patterns, show that positive rainfall shocks at birth significantly improve long-term outcomes for women — including height, years of schooling, and household asset ownership — while having no comparable effect on men. In the Brazilian context, Mueller and Osgood (2009) combine PNAD survey data with municipal precipitation records to estimate the long-term wage impacts of droughts. They find that workers exposed to droughts in rural areas take, on average, up to five years to catch up to the earnings of their unaffected peers, a pattern partially explained by migration to urban labor markets in response to agricultural shocks.

A second strand of the literature that underscores the importance of household production focuses on its relationship with broader individual and family outcomes,

particularly those related to food security, nutritional status, and anthropometric indicators. A substantial body of evidence from low-income countries shows that both the diversity and quantity of food produced for own-use are positively associated with reduced food insecurity across various settings. Most of these studies center on subsistence-based smallholder farmers in developing regions such as South Africa, Uganda, and the Philippines (Rogan, 2018; Whitney et al., 2018; Duong et al., 2023) — contexts where household production plays a vital role in daily sustenance (Hawkes, 2007). Wahdat et al. (2021), analyzing farming households across 18 African countries, finds that greater agricultural diversity improves a household's ability to meet consumption needs, although the benefits tend to diminish beyond a moderate threshold of crop diversity per hectare. Moreover, the positive impact is more consistent when families can supplement their diet through off-farm income or by selling farm produce, indicating that the interaction between own-production and market access is critical for ensuring food security. In the context of an upper-middle-income country, Konstantinidis (2024), using data from the recession period in Greece, finds that self-provisioning is associated with a two-percentage-point reduction in the probability of experiencing food insecurity.

Household production is not only linked to food security — often measured through caloric adequacy — but also to dietary and nutritional quality. A growing body of research investigates the relationship between production diversity and nutritional outcomes, using indicators such as crop and animal species count, Household Dietary Diversity Score (HDDS), Women's Dietary Diversity Score (WDDS) and Food Variety Score (FVS). These studies, typically focused on smallholder farming communities in low-income countries, consistently find a positive association between agricultural diversification and dietary diversity (Kabunga et al., 2014; Bisht et al., 2018; Ecker, 2018). Kabunga et al. (2014), studying rural Ugandan households, explores the causal relationship between fruit and vegetable (F&V) production and various food and nutrition outcomes. The findings suggest that F&V production reduces food insecurity and improves anemia outcomes among women of childbearing age, with hemoglobin levels increasing by 0.14–0.15 grams per deciliter in F&V-producing households. Similarly, Gaillard et al. (2022), analyzing smallholder households in central Tunisia, identifies a weak but consistent positive association between multiple measures of on-farm production diversity and women's dietary diversity. Interestingly, neither market diversity nor proximity significantly influenced dietary outcomes, while on-farm availability of specific products such as dairy was associated with higher consumption.

Studies based on nationally representative panel data present more mixed evidence on the relationship between household production and dietary diversity. Using data from Nigeria, Olabisi et al. (2021) find that households relying heavily on own-production tend to have lower dietary diversity scores than those that purchase all their food; their estimates suggest a 27% lower dietary diversity score for fully self-producing households. However, once the share of other income sources are accounted for, the diversity of food items produced at home is positively associated with dietary diversity in both rural and urban settings, suggesting that production diversity, rather than production reliance, may be the key determinant. In Bangladesh, Islam et al. (2018) shows that adding one additional crop, vegetable, or fruit species to household production increases the dietary diversity score by 1.9%. He points that, while both farm commercialization and off-farm income contribute positively to household dietary diversity, their influence is found to be less substantial than that of household production diversification.

The relationship between household production and dietary diversity is complex and shaped by a range of contextual factors (Jones, 2017). The literature highlights several key sources of heterogeneity. First, household characteristics such as gender dynamics, wealth levels, and decision-making power significantly influence how production diversity translates into dietary outcomes (Kabunga et al., 2014; Gaillard et al., 2022; Jones et al., 2014; Waha et al., 2018). Second, access to markets plays a critical role, as households are often constrained in the variety of foods they can produce themselves (Hawkes, 2007; Qaim, 2014). Households are more successful in meeting their consumption needs when they can complement own-production with food purchases financed by off-household income or farm sales (Waha et al., 2018; Jones et al., 2014). Third, the rural-urban division introduces additional variation: in rural areas, limited access to diverse food markets and fewer non-agricultural employment opportunities may restrict dietary options (Olabisi et al., 2021; Waha et al., 2018). Evidence from Rahman and Mishra (2019) and Waha et al. (2018) indicates that non-farm income sources significantly enhance dietary diversity in rural settings. Finally, the availability of land resources also mediates the impact of production diversity, with land-constrained households facing greater challenges in achieving a varied diet (Waha et al., 2018).

Until now, this discussion has not explicitly distinguished between household production and own-use production. While household production refers broadly to goods and services produced within the household, own-use production specifically denotes

production intended for direct family consumption, as opposed to market sale. This distinction is crucial when examining the relationship between farm diversity and dietary diversity. Recent agriculture-to-nutrition conceptual frameworks outline multiple pathways through which agricultural diversity may affect nutrition outcomes (Jones et al., 2014; Sibhatu et al., 2015). The most direct pathway involves subsistence consumption of a diverse range of foods produced on the farm. A second, more indirect, pathway depends on market access: smallholder farmers may sell part of their harvest and use the resulting income to purchase a wider variety of foods (Qaim, 2014). Better market access can also encourage specialization, thereby boosting income and enabling dietary improvements (Hawkes, 2007). Additional channels include lowered food prices and women's empowerment (Islam et al., 2018). In rural Uganda, Sekabira et al. (2022) finds that animal and crop species diversity are significantly associated with improved nutritional outcomes, particularly when food is sourced from the household's own production, rather than markets. Similarly, Zanello et al. (2019), studying smallholders in Afghanistan, shows that crop diversity is positively associated with dietary diversity during the regular season, whereas livestock diversity plays a more critical role during the lean season—when market access becomes increasingly important.

3 Fundão Tailing Dam Collapse and Rio Doce Project Database

3.1 Fundão Tailing Dam Collapse

The collapse of the Fundão tailing dam occurred in the city of Mariana in the state of Minas Gerais, November 5th 2015. The Fundão tailing dam was controlled by Samarco, a mining company jointly owned by Vale S.A. and BHP Billiton. This was the largest environmental disaster in Brazilian history. The localities of Bento Rodrigues, Paracatu de Baixo, Gesteira, Barra Longa, and five other villages in the Camargo district of Mariana were completely destroyed. The disaster resulted in 19 fatalities and left 1,200 people homeless (Carmo and et al., 2017).

Millions of cubic meters of tailing flowed 670 km through the Doce River, devastating approximately 1,500 hectares of land, including Permanent Preservation Areas (PPA) and Conservation Units (Rio Doce State Park, Sete Salões State Park, Goytacazes National Forest, and the Sete Salões-Aymoré Biodiversity Corridor). The tailing crossed 40 municipalities and two states (Minas Gerais and Espirito Santo) until reaching the Atlantic Ocean (Zonta and Trocate, 2016).

The environmental damage caused by the tailing dam collapse was extensive, severely affecting both soil and river quality. A thick layer of mud with low nutrient content covered the soil surface, while contamination by heavy metals further compromised soil health (Teixeira et al., 2020). In addition, the physicochemical properties of the waste material contributed to a decline in soil fertility. For example, sodium hydroxide — commonly used in ore processing — has a highly basic nature that disrupts the natural pH balance of the soil. The small particle size of the tailing also impedes water infiltration, exacerbating soil degradation (Silva et al., 2006). Another direct consequence of the disaster was the silting of the river, as sediment deposition made the riverbed shallower. This process is expected to increase the frequency of flooding events — a phenomenon already observed in areas adjacent to the river (Zonta and Trocate, 2016).

The collapse of the Fundão tailing dam had far-reaching consequences, with impacts measurable across a wide range of outcomes, from macroeconomic indicators to micro-level

dimensions, such as health and education. The valuation of damages has been approached using different methodological frameworks (Scarpelin et al., 2022; Czajkowski et al., 2023). Czajkowski et al. (2023) uses stated preference methods to estimate the average lower-bound willingness to pay to avoid a similar disaster, yielding an aggregate value between USD 8 and 13 billion. From a macroeconomic perspective, several studies have assessed the impact on regional income and economic activity (Simonato et al., 2018; Castro and Almeida, 2019; Niquito et al., 2021; Oliveira et al., 2016). Oliveira et al. (2016) estimates that aggregate income losses for the states of Minas Gerais and Espírito Santo summed R$ 136.28 billion between 2015 and 2017.

At the microeconomic level, a growing body of literature has documented the adverse health and educational consequences of the disaster. Carrillo et al. (2020), examining in utero exposure, find significant reductions in birth weight and increases in infant mortality, with more pronounced effects among children born to single or less-educated mothers. Similarly, Mrejen et al. (2020) report that direct exposure during gestation led to a 1.86-day reduction in average gestational age and a 2.6 percentage point increase in the incidence of preterm births. In the educational domain, Firmiano and Irffi (2020) show that, in the short term, municipalities located near the disaster zone experienced negative impacts on school flow indicators, including grade promotion and repetition rates.

3.2 Rio Doce Project Database

This study relies on data from the Participatory Household Survey (*Pesquisa Domiciliar Participativa – PDP*), conducted as part of the Rio Doce Project. The Rio Doce Project was an initiative led by researchers from Fundação Getúlio Vargas (FGV) aimed at identifying and measuring the socioeconomic damages caused by the collapse of the Fundão tailing dam. The PDP is a household sample survey designed to provide inputs for diagnosing and assessing the impacts of the disaster on work, income, health, and own-use production among populations residing in the municipalities affected by the collapse.

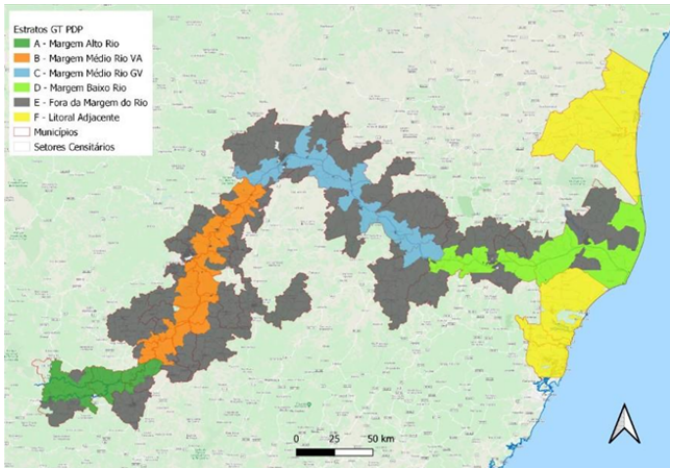

Figure 1 – Natural Strata

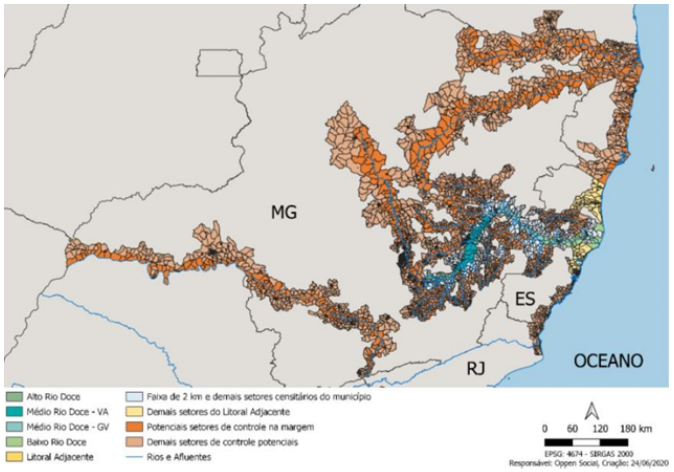

Figure 2 – Potential Comparison Area

Figure 3 – Comparison Area

The PDP was designed to assess the impact of the disaster across multiple dimensions of the lives of affected populations. To achieve this, in addition to collecting data from residents of the directly impacted areas along the Rio Doce, the study included a constructed comparison group. The survey was conducted in both affected and comparison areas. The potential comparison area is illustrated in Figure 2, while the actual comparison area selected through the matching process is shown in Figure 3.

To ensure comparability between areas, a matching of census tracts was carried out using data from the pre-disaster period. This process used information from various sources — such as the 2010 Population Census Aggregated Sector File, the 2014 Land Use and Cover Monitoring Project (IBGE), the 2014 Unified Registry (CadÚnico), the 2010 Population Census sample, the School Census (2013–2015), the 2006 Agricultural Census, and indicators from the UNDP Development Atlas (2013). Matching considered both sector-level and municipality-level characteristics. The first step was to classify tracts from the affected and comparison areas according to their location and setting. Next, matching was performed using the Mahalanobis Distance, which measures similarity based on socioeconomic and geographic indicators. The final matched pairs were selected to maximize similarity while ensuring a one-to-one match, meaning each comparison tract was paired with only one affected tract.

The Rio Doce Project considered as affected population all families living in private homes in the 45 municipalities in Minas Gerais and Espírito Santo (3,381 census tracts) included in the *Termo de Transação e Ajustamento de Conduta (TTAC)*. The potential comparison area included 257 municipalities in 4 states (Minas Gerais, Rio de Janeiro, Espirito Santo and Bahia) , covering 14,880 census tracts.

In order to ensure comprehensive representation of the entire affected area in the survey, a two-stage sampling procedure was proposed [1]. Initially, the affected area was stratified into 14 natural strata, represented in Figure 1. Subsequently, census tracts were selected in those 14 strata using probability proportional to size (PPS) sampling, with the measure of size being the number of permanent private households (PPH) in the census tract, according to the 2010 Demographic Census. Each of the selected census tracts in the affected area was matched with a similar tract in the comparison area, based on a stratified and clustered probabilistic sample. Finally, households were selected for the

[1] The information on the survey's weighting methods is detailed in the report prepared by SCIENCE Silva (2022). The report outlines the objectives, methodologies employed, and sample characteristics of the PDP.

survey through simple inverse sampling (SIS) within each selected tract, in order to reach a specified number K of households. This sampling and matching processes selected 3,381 paired census tracts and 9,904 households, 4,952 in the affected group and 4,952 in the comparison group.

The sample size for PDP was determined based on the minimum number of observations required to achieve a specified level of precision for key inference targets. The parameters of interest were: (a) D1 — the difference in the proportion of households with per capita income (PCI) 1/2 minimum wage in the affected area compared to the matched comparison area; and (b) D2 — the difference in the average monthly nominal income of heads of permanent private households (with income) between the affected and comparison areas. A bottom-up approach was adopted, in which the sample size was calculated separately for each of the six natural strata to estimate both parameters with specified margins of error. The total sample size corresponds to the sum of the strata, and the precision of estimates for the overall research area depends on this total.

In the present study, which focuses on understanding the impact of the dam collapse mainly through the environmental degradation of the Rio Doce, households located in the coastal region were excluded. This decision reflects the fact that the effects of river degradation reach these areas in a distinct manner. Accordingly, the affected (treated) group in our analysis comprises households situated along the Rio Doce within the following strata: Upper River, Middle River (Vale do Aço), Middle River (Governador Valadares), and Lower River.

Aiming to estimate the impact of the disaster on household time allocation and engagement in own-use production activities, this study uses data on whether household members participated in one of the following four categories of own-use activities: Own-Consumption, Home-Production, Home-Construction, and Extraction. In addition, we incorporate information on the occupational status of household members—including whether they are employed and whether they hold formal employment—as well as school attendance among children and adolescents. The analysis also incorporates detailed socioeconomic characteristics of residents and household composition.

To the PDP data, we added information on the distance between households and nearby rivers. For households affected by the disaster, we used data on the distance from the census tract in which the household is located to the Rio Doce. For households in the control area, we used the distance from the census tract to the nearest main watercourse.

This information is crucial for the econometric impact estimation strategy, which will be detailed in Chapter 5.

4 Descriptive Analysis

This chapter presents descriptive analyses of the data from PDP. The objective is to provide an overview of habits and patterns related to own-use production activities, employment, and educational attendance among the surveyed households. We examine the frequency with which own-use activities are undertaken and their importance in meeting the food needs of families, both in the Rio Doce region and in the comparison area. In addition, we explore which factors—such as household composition, individual characteristics, and geographic conditions—are associated with the likelihood of engaging in own-use production.

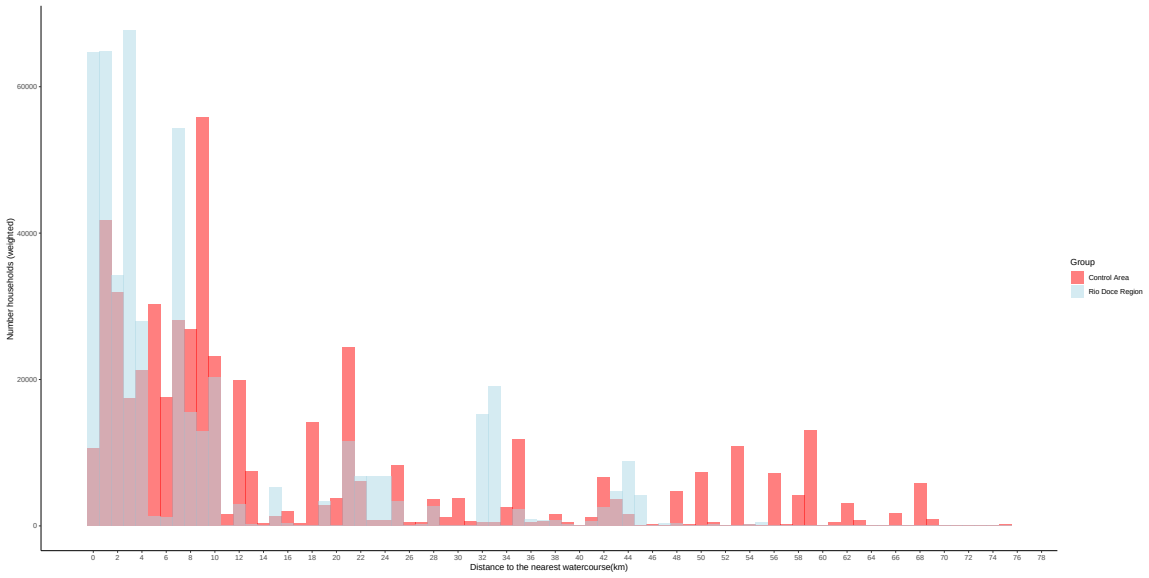

Figure 4 – Household Distance to the Nearest Main Watercourse

For the analyses presented in this chapter, as well as for the models estimated in subsequent chapters, we restrict the sample to households located within 14 kilometers of the Rio Doce (in the affected area) and within 14 kilometers of the nearest watercourse (in the control group). This decision is motivated, first, by theoretical considerations. Including households located farther away would introduce substantial heterogeneity — such as proximity to other rivers and the presence of additional confounding factors—that could compromise the identification of the disaster effect. Second, as shown in Figure 4, the majority of the sample (77.15% in the Rio Doce region and 66.59% in the control area)

are concentrated within a 12 to 14-kilometer radius from the river.

4.1 Own-Use Production

Initially, we sought to understand the proportion of households in the sample that engage in own-use production and how this share varies with distance to the river. Our initial hypothesis is that proximity to the river is positively associated with own-use activities that rely on natural resources, such as Own-Consumption and Extraction.

A key finding is that a significant portion of the subsample engages in own-use production — on average, 25% of households in the control area and 35% in the Rio Doce region. Among the four types of own-use activities, those related to food production are the most commonly practiced, with agricultural production being the most frequent. During the household survey, detailed information was collected on the types of crops produced. Over 150 different agricultural products were reported across the sample, including fruits, vegetables, leafy greens, tubers, herbs, and more than 50 fish species.

Table 1 – Percentage of Households Engaged in Own-Use Production by Distance to the River (Control Area)

	0–2km	2–4km	4–6km	6–8km	8–10km	10–12km	12–14km	14–16km
Own-Use Production	29.35	23.90	22.80	37.61	14.92	30.72	31.04	38.51
Own-Use Consumption	23.60	19.08	14.35	25.75	14.45	25.62	22.27	32.97
Animal Husbandry	7.15	8.22	6.01	5.51	4.95	3.16	13.57	6.02
Agricultural Production	17.62	16.97	10.58	24.05	12.02	21.03	15.39	31.71
Fishing	2.73	0.57	0.08	0.23	0.16	4.35	10.64	2.53
Home-Production	1.72	4.80	3.31	12.16	2.13	2.67	1.61	0.00
Extraction	2.15	3.81	0.77	3.33	0.42	0.89	2.77	3.80
Home-Construction	7.88	3.09	6.75	2.93	0.04	4.75	16.23	9.75
Perc. households (wgt)	13.48	9.16	10.00	9.18	16.40	4.86	3.51	0.26
Num. households in sample	619	497	220	280	205	157	102	42

Table 2 – Percentage of Households Engaged in Own-Use Production by Distance to Rio Doce

	0–2km	2–4km	4–6km	6–8km	8–10km	10–12km	12–14km	14–16km
Own-Use Production	29.75	37.17	32.59	38.50	46.40	85.13	91.36	34.87
Own-Use Consumption	17.35	26.86	31.45	30.42	15.04	85.10	91.36	34.87
Animal Husbandry	5.99	4.16	19.92	10.41	8.29	72.29	77.22	7.94
Agricultural Production	12.25	25.83	22.90	27.31	10.93	57.51	87.83	34.87
Fishing	1.88	3.04	3.83	5.45	0.34	7.54	10.20	3.15
Home-Production	10.28	3.02	2.60	5.42	4.67	7.32	10.88	0.00
Extraction	4.91	4.77	6.80	10.19	5.46	7.75	35.91	1.23
Home-Construction	6.71	11.48	6.22	7.46	24.08	12.33	33.36	1.02
Perc. households (wgt)	32.66	19.96	2.21	14.67	5.07	2.55	0.03	1.14
Num. households in sample	1468	600	276	245	84	62	36	32

We begin the analysis by examining the proportion of households engaged in different types of own-use production in the control region, where the hypothesis that proximity to the river increases engagement in such activities should plausibly hold in the absence of environmental disruption. As shown in Table 1, however, the relationship between the frequency of own-use activities and distance to the river is not as direct or linear as initially expected. For animal husbandry, the proportion of participating households generally decreases with greater distance from the river, yet unusually high values are observed in the 12–14 km band. A similar pattern emerges for agricultural production, with elevated participation rates in the 10–12 km and 14–16 km bands. A closer inspection reveals that households in these distance bands are predominantly located in specific microregions — such as Passos and Campo Belo, in the southeastern part of Minas Gerais — known for their strong agricultural base, particularly in livestock and crop farming. Such regional heterogeneity may obscure an underlying relationship between proximity to the river and engagement in own-use activities. Moreover, there are few observations in these two distance bands, which limits the ability to draw reliable inferences about the relationship between river proximity and the propensity for own-use production.

A comparable pattern is observed in Table 2, which displays the proportion of households engaged in own-use production by distance to the Rio Doce in the treated area. Again, the 10–12 km and 12–14 km distance bands show unexpectedly high participation rates. These bands contain relatively few observations—62 and 36 households, respectively—and are largely composed of households located in specific microregions of Minas Gerais, particularly Aimorés and Ipatinga. The concentration of observations in these areas likely contributes to the elevated proportions observed.

Table 3 – Percentage of Households that Fulfill their Dietary Needs through Own-Use Production by Distance to the River (Control Area)

	0–2km	2–4km	4–6km	6–8km	8–10km	10–12km	12–14km	14–16km
Suff. of agr. products	5.42	5.02	3.44	16.41	2.33	4.98	5.87	11.49
Suff. of animal prod.	3.89	1.39	0.79	0.82	1.87	0.20	0.05	3.01
Perc. households (wgt)	13.48	9.16	10.00	9.18	16.40	4.86	3.51	0.26
Num. households (N)	619	497	220	280	205	157	102	42

Table 4 – Percentage of Households that Fulfill their Dietary Needs through Own-Use Production by Distance to Rio Doce

	0–2km	2–4km	4–6km	6–8km	8–10km	10–12km	12–14km	14–16km
Suff. of agr. products	5.10	10.00	7.17	4.32	5.71	5.29	21.21	13.21
Suff. of animal prod.	1.08	1.71	12.49	1.73	2.28	4.97	13.16	3.15
Perc. households (wgt)	32.66	19.96	2.21	14.67	5.07	2.55	0.03	1.14
Num. households (N)	1468	600	276	245	84	62	36	32

A second piece of information collected in the survey concerns whether the household's production — of both agricultural goods and animal products — is sufficient to meet the family's food needs in these categories. In the control region, as shown in Table 3, 6.72% of households report being able to meet their needs for agricultural goods, and 3.23% for animal products. In the Rio Doce region, the overall results are similar: as shown in Table 4, 6.6% of households report sufficiency in agricultural goods and 2.69% in animal products. Once again, we observe specific distance bands with outlier values, and these cases tend to coincide geographically with microregions where previous patterns of elevated own-use activity were also recorded.

4.2 Employment and Educational Attendance

The following section presents descriptive statistics on employment status, income, and school attendance in the region represented by the sample [1].

[1] In 2019, when the survey was conducted, the minimum wage in Brazil was R$ 998.00.

Table 5 – Descriptive Analysis of Employment, Income, and School Attendance by Distance to the River (Control Area)

	0–2km	2–4km	4–6km	6–8km	8–10km	10–12km	12–14km	14–16km
Employment and Income								
Percentage of adults with paid work	59.98	69.79	64.32	66.80	70.03	63.70	57.60	68.72
Percentage of adults with formal employment (registered jobs)	31.54	35.01	34.81	31.92	35.00	39.32	35.82	42.45
Percentage of adults who are registered entrepreneurs	7.30	6.39	5.95	12.30	14.69	8.61	8.39	7.03
Average monthly income of employed adults	1852	1846	1892	2028	2227	1836	1951	1222
Percentage of adults receiving Bolsa Família	6.59	6.89	9.14	3.63	1.70	9.00	5.30	5.63
Percentage of adults receiving BPC (Benefício de Prestação Continuada)	2.79	1.57	2.45	2.05	2.36	1.16	3.58	3.75
Percentage of adults receiving other social benefits	0.16	2.10	0.04	0.06	0.01	0.17	0.00	0.00
Educational Attendance								
Percentage of children (ages 0–5) attending daycare	52.49	54.03	40.49	53.35	50.19	48.39	62.81	0.00
Percentage of children (ages 6–12) attending school	100.00	92.43	100.00	99.79	99.98	99.16	98.67	93.71
Percentage of youth (ages 13–21) attending school	74.45	65.57	66.10	66.53	82.54	67.08	98.03	84.50
Population Composition								
Percentage of children (ages 0–12)	14.65	12.59	16.95	14.47	14.56	17.27	15.02	13.04
Percentage of youth (ages 13–21)	11.39	12.20	13.53	8.92	10.73	11.03	11.72	11.30
Percentage of adults (ages 18–65)	64.89	63.17	62.21	66.37	66.48	61.87	65.20	65.22
Percentage of elderly (ages 65+)	13.58	16.71	14.15	14.18	13.22	14.87	12.45	16.52
Number of people in the sample	1686	1287	643	684	522	417	273	115

Table 6 – Descriptive Analysis of Employment, Income, and School Attendance by Distance to Rio Doce

	0–2km	2–4km	4–6km	6–8km	8–10km	10–12km	12–14km	14–16km
Employment and Income								
Percentage of adults with paid work	60.80	52.37	61.01	59.24	62.18	44.79	53.86	49.76
Percentage of adults with formal employment (registered jobs)	28.44	28.51	25.26	36.63	36.55	11.77	10.16	8.17
Percentage of adults who are registered entrepreneurs	8.13	6.19	5.74	7.11	8.80	3.34	6.36	2.01
Average monthly income of employed adults	1848	1769	1488	2129	1457	1314	1099	1120
Percentage of adults receiving Bolsa Família	8.66	10.30	10.22	9.17	11.29	13.66	8.12	13.80
Percentage of adults receiving BPC (Benefício de Prestação Continuada)	4.30	2.28	4.42	3.16	0.05	0.09	5.21	3.56
Percentage of adults receiving other social benefits	0.74	0.55	0.14	0	0.05	0	1.22	0
Educational Attendance								
Percentage of children (ages 0–5) attending daycare	56.33	63.43	53.00	56.16	63.68	80.21	70.00	64.99
Percentage of children (ages 6–12) attending school	97.47	91.20	98.38	99.77	99.74	99.62	100.00	88.22
Percentage of youth (ages 13–21) attending school	68.56	62.06	63.75	86.78	62.52	72.01	67.32	63.24
Population Composition								
Percentage of children (ages 0–12)	15.74	16.12	15.42	17.55	18.14	18.18	4.60	14.44
Percentage of youth (ages 13–21)	12.13	10.54	11.93	8.32	6.51	9.66	12.64	8.89
Percentage of adults (ages 18–65)	62.67	64.54	64.34	63.84	64.65	65.34	52.87	66.67
Percentage of elderly (ages 65+)	15.04	13.33	12.60	13.16	12.09	11.93	35.63	14.44
Number of people in the sample	4015	1613	746	661	215	176	87	90

Tables 5 and 6 provide information for the control area and the Rio Doce region, respectively. Overall, the results appear to be similar across both regions. In both areas, approximately 60% of the adult population (aged 18 to 65) engages in some form of paid work, with around half of these individuals formally employed under a signed labor contract. Additionally, about 8% of the adult population operates a formalized business. The average income among employed individuals is approximately R$1,800 (in 2019 prices). Regarding school attendance, nearly all children aged 6 to 12 are enrolled in school, and about half of those under the age of 5 attend daycare. Among adolescents and youth aged 13 to 21, school attendance drops to around 70%.

4.3 Determinants of Own-Use Production

To examine the factors associated with engagement in own-use production, we estimate a Linear Probability Model (LPM). This model is selected due to its simplicity in both estimation and interpretation, making it a suitable choice for analyzing binary outcomes. The set of independent variables includes household composition indicators — such as the number of members, the proportion of elderly individuals, and the share of children — as well as characteristics of the household head[2], including age, race, gender, and education level. In addition, we incorporate locational variables, specifically the microregion in which the household is situated and the distance to the nearest main watercourse, to account for geographic and environmental influences on own-use production decisions.

Aiming to capture this correlation, we estimate the following equation:

$$A_j^k = \beta_0 + \boldsymbol{X_j}\beta_1 + \boldsymbol{X_{ij}}\beta_2 + e_j,$$

where A_j^k is dummy variable indicating whether family j perform activity k; X_j is a vector of household characteristics and X_{ij} is a vector of characteristics of the head of the household.

[2] The head of the household was identified based on the respondent's self-report in the survey. When he was unable to indicate the household's head, we considered the adult with the highest income.

Table 7 – Factors Associated with Engaging in Own-Use Production in the Control Area

	Own-Consumption	Home-Production	Extraction	Home Construction
Distance to nearest main watercourse (km)	-0.006	0.001	-0.002*	-0.003
	(0.006)	(0.002)	(0.001)	(0.003)
Reg. Campo Belo	0.639***	0.005	0.658***	0.079
	(0.063)	(0.029)	(0.069)	(0.056)
Reg. Passos	0.159***	0.048	-0.004	-0.033***
	(0.056)	(0.031)	(0.009)	(0.011)
Num. people in household	0.034**	-0.015*	-0.004*	-0.001
	(0.017)	(0.008)	(0.002)	(0.006)
Perc. of children	-0.099	0.005	0.021*	-0.027
	(0.117)	(0.041)	(0.011)	(0.050)
Perc. of elderly	0.124	0.050	-0.002	0.033
	(0.080)	(0.042)	(0.017)	(0.043)
Log per capita monthly earnings	0.013**	0.004*	-0.001	0.001
	(0.006)	(0.002)	(0.001)	(0.003)
Head of household is woman	-0.046	0.034**	-0.015**	-0.014
	(0.038)	(0.016)	(0.006)	(0.019)
Age of head of household	0.002	0.000	0.000	-0.001
	(0.002)	(0.001)	(0.001)	(0.001)
Head is white	-0.026	0.033	-0.007	-0.007
	(0.037)	(0.020)	(0.005)	(0.018)
Head has college degree	-0.056	0.004	-0.015***	-0.027*
	(0.054)	(0.027)	(0.005)	(0.016)

Notes: ***p≤0.01, **p≤0.05, *p≤0.1. Robust standard errors are reported in parentheses.This regression employs a Linear Probability Model.

Table 8 – Factors Associated with Engaging in Own-Use Production in the Rio Doce Region

	Own-Consumption	Home-Production	Extraction	Home Construction
Distance to Rio Doce(km)	0.012*	-0.009**	-0.004	0.010*
	(0.007)	(0.003)	(0.004)	(0.005)
Region: Aimorés	0.409***	0.023	0.075*	0.192***
	(0.073)	(0.023)	(0.043)	(0.070)
Region: Gov. Valadares	0.077**	0.034	0.030*	0.092***
	(0.036)	(0.025)	(0.015)	(0.028)
Region: Ponte Nova	-0.008	-0.024	-0.007	-0.024
	(0.065)	(0.038)	(0.010)	(0.015)
Region: Ipatinga	0.104**	0.057**	0.083***	0.020
	(0.047)	(0.026)	(0.028)	(0.026)
Region: Caratinga	0.436***	0.025	0.242***	0.182**
	(0.081)	(0.031)	(0.084)	(0.079)
Num. people in household	0.001	0.015	0.000	-0.001
	(0.014)	(0.010)	(0.009)	(0.009)
Perc. of children	-0.048	-0.099	-0.042	-0.028
	(0.108)	(0.063)	(0.059)	(0.068)
Perc. of elderly	0.142**	0.027	0.033	-0.065*
	(0.064)	(0.037)	(0.034)	(0.036)
Log per capita monthly earnings	0.010*	0.004	-0.001	0.007*
	(0.005)	(0.003)	(0.003)	(0.004)
Head is woman	-0.050	0.029	-0.004	0.018
	(0.033)	(0.019)	(0.016)	(0.024)
Age of head	-0.001	0.000	-0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Head is white	-0.009	-0.039**	-0.017	-0.034
	(0.035)	(0.017)	(0.017)	(0.022)
Head has college degree	-0.093*	-0.015	-0.046**	-0.065**
	(0.048)	(0.029)	(0.019)	(0.031)

Notes: ***p≤0.01, **p≤0.05, *p≤0.1. Robust standard errors are reported in parentheses.This regression employs a LPM.

The regression results are presented in Tables 7 and 8. Analyzing these results reveals some patterns that appear consistently across all types of own-use production activities. One of the most notable findings concerns the education level of the household head. The variable college, which indicates whether the household head has completed higher education, is negatively and significantly associated with the likelihood of engaging in own-use production for most activity types, both in the control area and in the Rio Doce region. This result is consistent with household production theory, as higher education is typically associated with higher income, thereby increasing the opportunity cost of allocating time to household production. In this context, the substitution effect — favoring market-purchased goods over self-produced ones — appears to outweigh the income effect.

The number of household members is positively associated with the likelihood of engaging in own-use production in both groups, with statistically significant results in the control area. Larger households may face greater food demand, which in turn increases the probability of producing food domestically to supplement consumption. Kabunga et al. (2014), using data from rural Ugandan households, shows that household size has a positive and significant effect on the probability of a household producing fruits and vegetables.

Gender dynamics within the household also influence patterns of own-use production. The dummy variable indicating whether the household head is female is negatively associated with the probability of engaging in own-consumption, extraction, and home-construction activities, while it is positively associated with home-production — activities that are culturally more often performed by women. The race of the household head also emerges as a significant factor in many of the regressions. Households headed by individuals who self-identify as white are less likely to engage in own-use production compared to those headed by non-white individuals (including those who identify as Black, Pardo, Indigenous, or Asian). This pattern is observed for nearly all types of activities in both regions and is statistically significant in the case of manufacturing. While this may partially reflect differences in income or asset levels, it may also reflect cultural patterns, as traditional and riverside communities—often composed of non-white ethnic groups — often retain stronger ties to subsistence practices as part of their daily lives and collective identity (Acselrad et al., 2009).

When analyzing household characteristics, we observe consistent patterns across regressions for different types of own-use production activities. One key variable is the log of total monthly per capita household income[3], which is positively associated with the likelihood of engaging in own-use production. This result likely reflects that wealthier families have access to larger properties that can accommodate subsistence activities such as animal husbandry and small-scale agriculture. Additionally, higher-income households may have greater flexibility or available time among some members to engage in these practices.

A higher share of elderly household members is positively associated with the likelihood of engaging in own-use production in the Rio Doce region, while the association is not statistically significant in the control area. This pattern may be related to generational

[3] For this regression, we consider only income derived from labor and other productive factors, such as rental income, other earnings, and private pensions. Social benefits are not included.

habits, cultural norms, and the greater availability of discretionary time among older individuals. The greater involvement of older individuals in household production is also supported by the literature. Stancanelli and Van Soest (2012), in a study on France, finds that retirement significantly increases both husbands' and wives' time spent on household production—by more than three hours per weekday for men and by two hours and 40 minutes for women.

Looking specifically at the Rio Doce region, which is largely situated within the Vale do Rio Doce mesoregion in the state of Minas Gerais, certain microregions exhibit a substantially higher probability of engaging in own-use production. In particular, the microregions of Aimorés, Governador Valadares, Caratinga, and Ipatinga stand out for their elevated levels of subsistence activity. These differences likely result from a combination of geographic and climatic conditions, as well as local productive structures that are more favorable to domestic food production. In the comparison region, the microregions of Campo Belo and Passos — located in the southern part of Minas Gerais, near the border with São Paulo — show the highest probabilities of own-use production. These areas are historically known for strong agricultural and livestock sectors, which may facilitate and incentivize subsistence practices among households.

Distance to the river in the control region appears to be negatively associated with own-use production, with a statistically significant effect observed for extraction activities. In the Rio Doce region, a positive and significant relationship is found for own-consumption and home-construction activities, while a negative association is observed for home production.

5 Methodology

To estimate the impact of the Fundão tailing dam collapse on families' own-use production and other allocative decisions, this study proposes a difference-in-differences (DiD) approach. Given that the available data are cross-sectional — comprising observations from both affected and control areas, but only after the disaster—the standard DiD framework, which typically relies on pre- and post-treatment observations, must be adapted. The objective is to adjust the traditional assumptions underlying the DiD model to suit the structure of our data and to interpret the implications of these modifications in the specific context of the disaster.

We adopt a nonlinear difference-in-differences (DiD) model given the binary nature of our outcome variable, which indicates whether household i engaged in own-use production and other time allocation activities. When the dependent variable is limited in range, the Linear Parallel Trends (LPT) assumption becomes potentially problematic, and linear DiD models may produce predicted probabilities outside the $[0, 1]$ interval (Blundell and Powell, 2004; Blundell and Costa Dias, 2009). To address these issues and ensure consistent estimation, we follow the nonlinear DiD framework proposed by Wooldridge (2023).

5.1 Difference-in-Differences Framework

The first adaptation of the traditional DiD model to our framework concerns the interpretation of the time index t. In the standard setting, t indicates the pre- and post-treatment periods; however, in our application, t denotes the geographic location of the observation (household). Specifically, $t = 1$ corresponds to households located farther from the river (either the Rio Doce in the affected area or another river in the control region), which we refer to as the adjacent area. Conversely, $t = 2$ corresponds to households situated near the river, which we refer to as riverbank area. As in the traditional DiD setting, the index D continues to indicate treatment status, where $D = 1$ identifies households in the affected region (the Rio Doce area) and $D = 0$ identifies those in the control area.

Thus, when considering potential outcomes $Y_t(D)$, we associate the indices t and D as follows:

$$D = \begin{cases} 1, & \text{if Rio Doce region} \\ 0, & \text{if control area} \end{cases}$$

$$t = \begin{cases} 1, & \text{if adjacent area} \\ 2, & \text{if riverbank} \end{cases}$$

Thus, $Y_{1i}(0)$ represents the potential outcome of household i in adjacent area and control region, while $Y_{1i}(1)$ represents household i in adjacent area and Rio Doce region. Similarly, $Y_{2i}(0)$ corresponds to the potential outcome f household i in riverbank and control region, and $Y_{2i}(1)$ represents household i in the riverbank and Rio Doce region.

Our objective is to estimate how the environmental disaster affected the engagement in different own-use production activities and other choices related to household time allocation among families living near the Rio Doce. In this context, our parameter of interest is the Average Treatment Effect on the Treated (ATT). The ATT measures the average impact of the treatment on those individuals who were actually exposed to it (Imbens and Wooldridge, 2009). In our setting, assuming the dependent variable is a dummy indicating whether or not a household engaged in own-use production, the ATT corresponds to the expected difference in the probability of own-use production between the observed scenario—where the disaster occurred—and the counterfactual scenario in which the disaster did not occur. Formally, the ATT is defined as:

$$\tau_2 = E[Y_2(1) - Y_2(0)|D = 1]$$

Since $t = 2$ represents households located along the riverbank and $D = 1$ identifies those in the Rio Doce region, the ATT corresponds to the expected difference in the probability of engaging in a specific activity for households living on the riverbank in the Rio Doce region, comparing the observed scenario — where the disaster occurred — with the counterfactual scenario in which the disaster did not take place.

$$\tau_2 = E[Y_2(1)|D = 1] - E[Y_2(0)|D = 1]$$

Expanding the ATT expression:

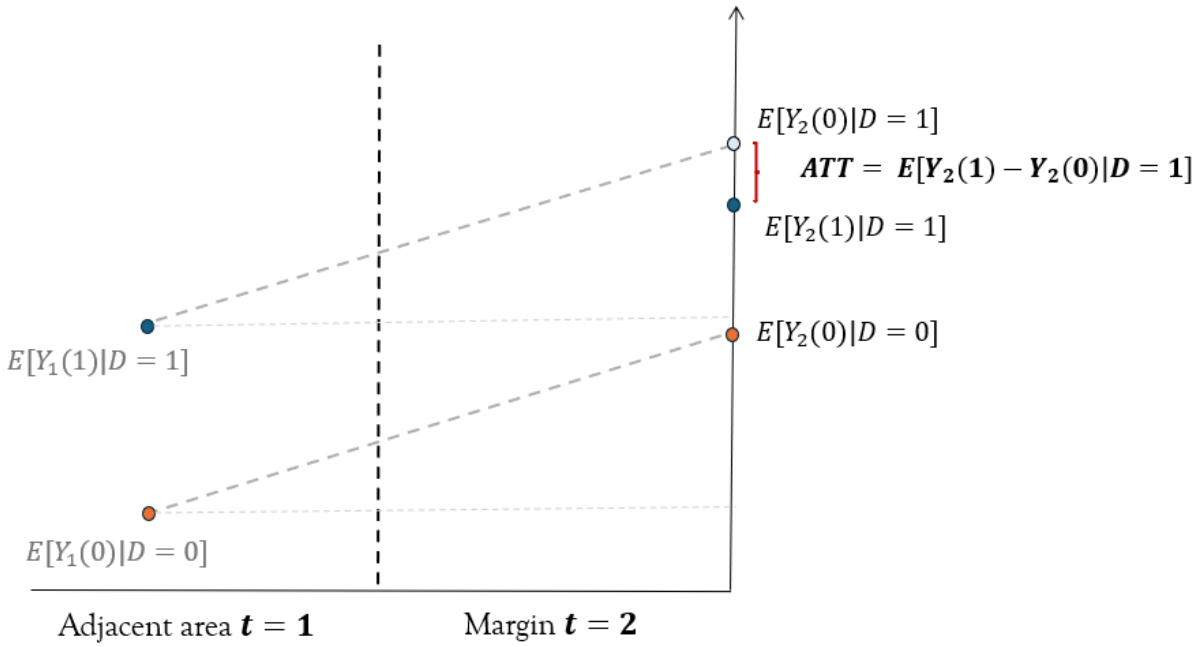

Figure 5 – Visual representation of ATT

The first term, $E[Y_2(1)D = 1]$, represents the population expectation of Y in the riverbank area of the Rio Doce region and can be consistently estimated using its sample equivalent. The second term, $E[Y_2(0)D = 1]$, represents the counterfactual outcome for the same region (Rio Doce riverbank) in the absence of the disaster.

To identify our parameter of interest, we will follow the nonlinear DiD framework developed by Wooldridge (2023). This model allows for unrestricted correlation across regions $t = 1$ and $t = 2$. In our context, this means that there may be correlation between the riverside area and the adjacent area, both in the Rio Doce region and in the control area. This implies that these two regions may have distinct characteristics that influence different habits of engaging in own-use production activities.

5.1.1 Assumptions

To identify the ATT, it is necessary to establish two key assumptions, following the framework outlined by Wooldridge (2023): (1) Conditional No Anticipation and (2) Conditional Parallel Trends. In the next subsection, we will discuss the implications of these assumptions within the proposed framework, as well as the specific constraints they impose given the characteristics of our context and data.

The first assumption, referred to as the Conditional Non-Anticipation (CNA) assumption in the standard two-period DiD framework, can be expressed as follows:

$$E[Y_1(1) - Y_1(0)|D = 1, X] = 0$$
$$E[Y_1(1)|D = 1, X] = E[Y_1(0)|D = 1, X]$$

In the context, this assumption implies that, among observations in the Rio Doce region (where $D = 1$) and located in adjacent areas ($t = 1$), the disaster did not alter the probability of engaging in own-use production. Specifically, it requires that for households located sufficiently far from the river, the tailing dam collapse did not affect their domestic production patterns or other time allocation decisions. This assumption appears plausible, as the primary channel through which the disaster could influence own-use production habits is the direct environmental damage caused by contamination of the river and its surroundings. To better reflect the specificities of our context, we refer to this adapted version as the *Non-Contamination Assumption*.

The second key assumption is that of Parallel Trends (PT). In its linear specification, it can be expressed as:

$$E[Y_t(0)|D, X] = \alpha + \beta D + X\kappa + DX\eta + \gamma_t + X\pi_t$$

α represents individual fixed effects, capturing unobserved characteristics specific to each unit; γ_t corresponds to location fixed effects, controlling for structural differences between the riverbank and the adjacent area; β measures the average effect of being in the Rio Doce region on the outcome variable; κ is the vector of coefficients associated with the covariates, which control for observed factors that vary across units; η may represent additional fixed effects related to spatial subgroups; and π_t captures specific variation associated with the riverbank relative to the adjacent area, accounting for potential spatial heterogeneity in the impact of river proximity.

However, when the outcome variable is limited in range, the Linear Parallel Trends (LPT) assumption may become problematic (Wooldridge, 2023; Blundell and Costa Dias, 2009). As Blundell and Powell (2004) highlight, assuming linearity in this context is particularly unrealistic when the outcome is a binary variable, since linear DiD models can produce predicted probabilities outside the $[0, 1]$ interval. To address this issue, Wooldridge

(2023) proposes relaxing the linearity assumption by introducing a strictly increasing, continuously differentiable function $G(.)$ that applies a nonlinear transformation to the conditional mean of the potential outcome. The only restriction imposed on $G(.)$ is smoothness, ensuring the applicability of standard asymptotic theory.

This new Conditional Parallel Trends assumption can be expressed as follows:

$$E[Y_t(0)|D, X] = G(\alpha + \beta D + X\kappa + DX\eta + \gamma_t + X\pi_t),$$

where, to define α and κ, we normalize $\gamma_1 \equiv 0$ and $\pi - 1 \equiv 0$.

Thus, instead of the PT assumption applying directly to the conditional mean of the outcome variable, it applies to a nonlinear transformation of that mean. In this framework, the LPT assumption no longer holds for $E[Y_t|D]$ itself, but rather for the index inside the transformation function $G(.)$ used in the model. In other words, it is the transformed latent index, not the observed outcome, that satisfies the parallel trends condition.

Since we adopt a function $G(.)$ from the logarithmic family, we interpret the PT assumption as applying to the rate of change of the latent variable rather than directly to its levels. In this setting, the PT assumption operates within the space of the logistic function. This means that, in the absence of treatment (environmental disaster), the relative growth between the treated group (Rio Doce region) and the control group (adjacent area) — as we move from farther to closer proximity to the river — follows the same pattern in terms of log-odds. In other words, the parallel trends assumption is imposed on the exponential growth rate of the mean probability of engaging in own-use production in the untreated state. Practically, this implies that, had the disaster not occurred, the difference in the expected probability of self-production between the riverside and adjacent areas would have been the same in both the Rio Doce region and the control area.

Given these assumptions and the specified transformation function $G(.)$, it is possible to identify the ATT using random samples from the treated and control populations in both the riverside and adjacent areas.

5.2 Identification and estimation

ATT is the difference between the expected treated outcome and the expected untreated outcome, conditional on receiving treatment.

$$\tau_2 = E[Y_2(1) - Y_2(0)|D = 1]$$

$$\tau_2 = E[Y_2(1)|D = 1] - E[Y_2(0)|D = 1]$$

Since we observe treated outcomes for treated units, it follows that

$$E[Y_2(1)|D = 1] = E[Y_2|D = 1]$$

Given a random sample, the expected outcome for treated individuals, $E[Y_2 \mid D = 1]$, can be consistently estimated by the sample average. By the Law of Large Numbers, the sample mean among treated units converges to the true conditional expectation. Slutsky's theorem further ensures that any scaling involved preserves consistency, making the sample mean a reliable estimator.

$$\bar{Y}_{12} \equiv N_1^{-1} \sum_{i=1}^{N} D_i Y_{i2} = \left(\frac{N_1}{N}\right)^{-1} \left(N^{-1} \sum_{i=1}^{N} D_i Y_{i2}\right) \xrightarrow{p} E(Y_2 \mid D = 1)$$

The second term in the ATT expression ($E[Y_2(0)|D = 1]$), which is not directly observed, can be expanded by applying iterated expectations,

$$E[Y_2(0)|D = 1] = E(E[Y_2(0)|D = 1, X]|D = 1])$$

Under the previously defined parametric model, it follows that

$$E[Y_2(0)|D = 1] = E(G(\alpha + \beta + X\kappa + X\eta + \gamma_2 t + X\pi_2)|D = 1])$$

Given that $G(.)$ is assumed known and covariates X are observed, $E[Y_2(0)|D = 1]$ is identified if parameters $(\alpha, \beta, \gamma_2, \kappa, \eta, \pi_2)$ are identified.

Using data from a random sample at $t = 1$ (corresponding to the adjacent area), it is possible to consistently estimate the parameters α and κ. Under the parametric model

specification, the expected outcome for untreated individuals in adjacent area, conditional on covariates X, is given by

$$E[Y_1(0)|D = 0, X] = G(\alpha + X\kappa)$$

Thus, the parameters α and κ can be identified by inverting the known link function $G(.)$ and regressing the transformed expected outcomes on covariates X.

$$\alpha + X\kappa = G^{-1}(E[Y_1|D = 0, X])$$

To estimate the remaining parameters, we rely on the CNA assumption. At $t = 1$, the expected outcome for treated individuals conditional on covariates X can be written as

$$E[Y_1|D = 1, X] = E[Y_1(1)|D = 1, X] = E[Y_1(0)|D = 1, X]$$

Applying the parametric model, the expected outcome for treated individuals at $t = 1$, conditional on covariates X, can be expressed as

$$E[Y_1(0)|D = 1, X] = G(\alpha + \beta + X\kappa + X\eta)$$

Consequently, by applying the inverse of the link function, we obtain

$$\alpha + \beta + X(\kappa + \eta) = G^{-1}(E[Y_1|D = 1, X])$$

So, β and η can be identified by comparing treated (Rio Doce region) and untreated (control area) individuals at $t = 1$ (adjacent area).

To estimate the remaining parameters, we rely on the CNA assumption. Under this assumption, at $t = 2$ (riverbank region), the expected outcome for treated individuals, conditional on covariates X, can be expressed as

$$E[Y_2|D = 0, X] = E[Y_2(0)|D = 0, X]$$

Applying the parametric model,

$$E[Y_2|D=0,X] = G(\alpha + X\kappa + \gamma_2 + X\pi_2)$$

Applying the inverse of the link function,

$$\alpha + \gamma_2 + X(\pi_2 + \kappa) = G^{-1}(E[Y_2|D=0,X])$$

Since α and κ are identified from the estimation at $t = 1$, this allows for the identification of γ_2 and π_2 as well.

Finally, the ATT is obtained by subtracting the estimated counterfactual mean from the observed mean among treated individuals, leading to a sample estimator that combines the empirical mean of outcomes for the treated with the average predicted counterfactual outcomes based on the estimated model parameters.

$$\tau_2 = E[Y_2(1)|D=1] - E[Y_2(0)|D=1]$$

$$\tau_2 = E[Y_2(1)|D=1] - E(E[Y_2(0)|D=1,X]|D=1])$$

$$\tau_2 = E[Y_2(1)|D=1] - E(G(\alpha + \beta + X\kappa + X\eta + \gamma_2 t + X\pi_2)|D=1]$$

$$\hat{\tau_2} = \bar{Y_{12}} - N_1^{-1} \sum_{i=1}^{N} D_i(G(\hat{\alpha} + \hat{\beta} + \hat{\gamma_2} + X_i(\hat{\kappa} + \hat{\eta} + \hat{\pi_2})))$$

6 Results

This section presents and discusses the estimated ATT parameters, as outlined in the identification strategy. Since our dependent variables are binary — indicating whether household i engaged in a given activity — the ATT reflects the average treatment effect on the treated (i.e., households in the Rio Doce riverbank), interpreted in terms of probabilities. The first section is dedicated to presenting the estimated impacts on own-use production, disaggregated by activity type. The second section investigates potential shifts in time allocation to other domains. Specifically, we analyze changes in labor market participation and school attendance among children and adolescents.

An important part of the analysis was to define the distance range considered as *riverbank*. We defined initially the riverbank as the territorial strip up to 2 kilometers. Accordingly, households located within 2 kilometers of the Doce River in the treated area, and within 2 kilometers of the nearest watercourse in the control area, are considered riverbank observations. Initially, we compare households in the riverbank zone (0–2 km) with those in the immediately adjacent range (2–4 km). Subsequently, we expand the comparison to include the entire remaining portion of the subsample (2–14 km). This allows us to vary the definition of the adjacent area used for comparison.

Next, we examine the sensitivity of the results to the definition of the observation window—that is, the geographic boundaries used to define the riverbank and adjacent areas. To this end, we replicate the main analysis using alternative thresholds for the riverbank, specifically adopting 1.5 km and 2.5 km cutoffs. The purpose of this sensitivity analysis is to evaluate whether the results remain qualitatively consistent when the spatial bandwidth is modified.

For most of the dependent variables, we use the logistic function as the link function, given its suitability for modeling the probability of an event occurring. However, in cases where the incidence of a particular own-use activity was exceptionally low, we encountered convergence issues with the logistic model. Therefore, for such concentrated outcomes, specifically fishing and extraction activities, we used the Poisson model. This choice is justified by the desirable properties of the Poisson estimator in the context of rare events. Even when the dependent variable is binary, the Poisson estimator still provides consistent

estimates of the parameters of interest, as long as the conditional mean is correctly specified (Santos Silva and Tenreyro, 2006).

It is essential to avoid the inclusion of bad controls — variables that may be endogenous to the disaster and potentially bias the estimated effects. With this concern in mind, we estimate the ATT using four different model specifications, each incorporating a distinct set of covariates. Model 1 includes no controls and serves as a baseline. Model 2 introduces controls for the characteristics of the household head, including gender, age, race, and educational attainment. Model 3 adds controls for household characteristics and composition, such as the number of residents, the proportion of children and elderly, natural strata, and whether the household is located in a rural or urban area. Finally, Model 4 combines both sets of covariates, accounting for characteristics of the household and its head.

In our analysis, we test hypotheses related to three main activities: own-use production, paid work, and education. Although this involves multiple hypothesis testing, these outcomes pertain to distinct dimensions of household behavior, which does not pose concerns regarding the validity of our estimates or their confidence intervals. However, when we disaggregate own-use production into its various components, we introduce the issue of testing multiple hypotheses within the same conceptual domain, own-use production. To address this concern and ensure more robust inference, we apply the Bonferroni correction in the disaggregated analysis of own-use production types, thereby adjusting for multiple comparisons and yielding more reliable confidence intervals.

6.1 Own-use Production

We begin by presenting the overall results. The own-use production variables are defined at the household level. Specifically, we observe whether at least one member of the household engaged in any own-use production activity during the week in which the survey was conducted, and, if so, which type of activity was performed. Own-use production activities comprise four main groups: (i) Own-Consumption, (ii) Home-Production, (iii) Home-Construction, and (iv) Extraction activities. In the following subsections, we present the estimated impact of the disaster on each type of own-use activity individually.

Overall, the results suggest that the disaster had a negative effect on the likelihood of engaging in own-use production activities, as presented in Table 9. The estimated

Table 9 – Own-use Production - Main Results

		ATT			
t = 2	**t = 1**	(1)	(2)	(3)	(4)
0 - 2km	2 - 4km	-0.1004	-0.0967	-0.166**	-0.1495**
0 - 2km	+2km	-0.0938**	-0.0832*	-0.1024**	-0.0923**
0 - 1.5km	1.5 - 3km	-0.1317*	-0.1119	-0.1417**	-0.1195*
0 - 1.5km	+1.5km	-0.0788**	-0.0619*	-0.0813**	-0.0691*
0 - 2.5km	2.5 - 5km	-0.0664	-0.056	-0.0831	-0.0758
0 - 2.5km	+2.5km	-0.0778	-0.0716	-0.0389	-0.0356

Notes: The regressions employ a logit model. Model 1 includes no controls. Model 2 includes controls for the characteristics of the household head (gender, age, race, and educational attainment). Model 3 includes controls for household characteristics (number of residents, the proportion of children and elderly, natural strata, and whether the household is located in a rural or urban area). Model 4 combines both sets of covariates, household and its head. Standard errors are clustered at the census tract level.***p≤0.01, **p≤0.05, *p≤0.1.

ATT ranges from –0.097 to –0.15 and is statistically significant in most specifications for the 0–2 km and 0–1.5 km distance bands. Focusing on areas located closest to the river, the estimated reduction in the probability of participating in own-use production reaches approximately 10 to 15 percentage points. When riverbank is is compared to the broader sample, the magnitude of the effect decreases slightly but remains negative and statistically significant across all four model specifications. When the riverbank is defined using the broader 0–2.5 km range, the ATT loses statistical significance, although the point estimates remain negative with a slightly smaller magnitude.

6.1.1 Own-Consumption Activities

The results for Own-Consumption activities closely mirror the overall estimates, which is expected given that the general effects are largely driven by this category. Among households engaged in own-use production, the majority report participation in Own-Consumption activities.

Table 10 – Own-Consumption - Main Results

t = 2	t = 1	ATT (1)	p-value	Adj. p-value	ATT (2)	p-value	Adj. p-value	ATT (3)	p-value	Adj. p-value	ATT (4)	p-value	Adj. p-value
0 - 2km	2 - 4km	-0.107	0.027	0.107	-0.097	0.038	0.152	-0.144	0.003	0.011	-0.134	0.010	0.040
0 - 2km	+2km	-0.103	0.004	0.014	-0.088	0.009	0.035	-0.097	0.001	0.004	-0.090	0.002	0.009
0 - 1.5km	1.5 - 3km	-0.177	0.001	0.002	-0.160	0.002	0.007	-0.165	0.000	0.002	-0.162	0.002	0.008
0 - 1.5km	+1.5km	-0.104	0.000	0.001	-0.086	0.002	0.009	-0.087	0.001	0.002	-0.081	0.001	0.006
0 - 2.5km	2.5 - 5km	-0.079	0.118	0.470	-0.068	0.172	0.686	-0.078	0.086	0.345	-0.069	0.125	0.501
0 - 2.5km	+2.5km	-0.095	0.018	0.073	-0.089	0.019	0.074	-0.052	0.126	0.505	-0.052	0.120	0.478

Notes: The regressions employ a logit model. Model 1 includes no controls. Model 2 includes controls for the characteristics of the household head (gender, age, race, and educational attainment). Model 3 includes controls for household characteristics (number of residents, the proportion of children and elderly, natural strata, and whether the household is located in a rural or urban area). Model 4 combines both sets of covariates, household and its head. Adjusted p-values refer to p-values that have been corrected using the Bonferroni adjustment method. Standard errors are clustered at the census tract level.***p≤0.01, **p≤0.05, *p≤0.1.

The estimated ATT values are negative, with their magnitude decreasing as control variables are introduced. In areas closest to the river, specifically within the 0–2 km range, the probability of engaging in Own-Consumption activities declines by approximately 9 to 14 percentage points, as shown in Table 10. When narrowing the riverbank to the 0–1.5 km range, the negative effect becomes stronger — ranging from 9 to 17 percentage points — and remains statistically significant across all model specifications. Expanding the riverbank to 0–2.5 km leads to a loss in both statistical significance and effect size, although the point estimates remain negative, with values around –0.07.

Table 11 – Agriculture Production - Main Results

t = 2	t = 1	ATT (1)	p-value	Adj. p-value	ATT (2)	p-value	Adj. p-value	ATT (3)	p-value	Adj. p-value	ATT (4)	p-value	Adj. p-value
0 - 2km	2 - 4km	-0.103	0.008	0.023	-0.105	0.007	0.021	-0.145	0.000	0.001	-0.145	0.001	0.003
0 - 2km	+2km	-0.089	0.001	0.004	-0.088	0.001	0.004	-0.091	0.000	0.000	-0.089	0.000	0.001
0 - 1.5km	1.5 - 3km	-0.149	0.000	0.001	-0.151	0.001	0.002	-0.176	0.000	0.000	-0.184	0.000	0.000
0 - 1.5km	+1.5km	-0.086	0.000	0.001	-0.081	0.001	0.002	-0.087	0.000	0.000	-0.088	0.000	0.000
0 - 2.5km	2.5 - 5km	-0.090	0.055	0.165	-0.089	0.050	0.101	-0.104	0.020	0.060	-0.092	0.042	0.085
0 - 2.5km	+2.5km	-0.085	0.011	0.034	-0.093	0.005	0.015	-0.052	0.083	0.250	-0.052	0.085	0.255

Notes: The regressions employ a logit model. Model 1 includes no controls. Model 2 includes controls for the characteristics of the household head (gender, age, race, and educational attainment). Model 3 includes controls for household characteristics (number of residents, the proportion of children and elderly, natural strata, and whether the household is located in a rural or urban area). Model 4 combines both sets of covariates, household and its head. Adjusted p-values refer to p-values that have been corrected using the Bonferroni adjustment method. Standard errors are clustered at the census tract level.***p≤0.01, **p≤0.05, *p≤0.1.

Table 12 – Animal Husbandry - Main Results

t = 2	t = 1	ATT (1)	p-value	Adj. p-value	ATT (2)	p-value	Adj. p-value	ATT (3)	p-value	Adj. p-value	ATT (4)	p-value	Adj. p-value
0 - 2km	2 - 4km	0.017	0.474	1.000	0.016	0.577	1.000	-0.014	0.679	1.000	-0.007	0.894	1.000
0 - 2km	+2km	-0.037	0.033	0.098	-0.030	0.142	0.425	-0.038	0.076	0.229	-0.046	0.061	0.182
0 - 1.5km	1.5 - 3km	-0.012	0.610	1.000	-0.039	0.231	0.694	-0.073	0.023	0.070	-0.056	0.153	0.458
0 - 1.5km	+1.5km	-0.044	0.002	0.005	-0.040	0.029	0.086	-0.037	0.037	0.111	-0.047	0.025	0.075
0 - 2.5km	2.5 - 5km	0.004	0.876	1.000	-0.007	0.804	1.000	-0.046	0.117	0.352	-0.059	0.142	0.285
0 - 2.5km	+2.5km	-0.054	0.003	0.008	-0.047	0.012	0.036	-0.039	0.061	0.183	-0.044	0.082	0.247

Notes: The regressions employ a logit model. Model 1 includes no controls. Model 2 includes controls for the characteristics of the household head (gender, age, race, and educational attainment). Model 3 includes controls for household characteristics (number of residents, the proportion of children and elderly, natural strata, and whether the household is located in a rural or urban area). Model 4 combines both sets of covariates, household and its head. Adjusted p-values refer to p-values that have been corrected using the Bonferroni adjustment method. Standard errors are clustered at the census tract level.***p≤0.01, **p≤0.05, *p≤0.1.

Table 13 – Fishing - Main Results

t = 2	t = 1	ATT (1)	p-value	Adj. p-value	ATT (2)	p-value	Adj. p-value	ATT (3)	p-value	Adj. p-value	ATT (4)	p-value	Adj. p-value
0 - 2km	+2km	-0.033	0.001	0.002	-0.043	0.000	0.002	-0.592	0.000	0.001	-0.390	0.000	0.000
0 - 1.5km	+1.5km	-0.033	0.001	0.001	-0.033	0.000	0.003	-0.672	0.001	0.000	-0.630	0.000	0.000
0 - 2.5km	+2.5km	-0.020	0.001	0.003	-0.048	0.000	0.000	-1.399	0.002	0.000	-1.538	0.002	0.003

Notes: The regressions employ a Poisson model. Model 1 includes no controls. Model 2 includes controls for the characteristics of the household head (gender, age, race, and educational attainment). Model 3 includes controls for household characteristics (number of residents, the proportion of children and elderly, natural strata, and whether the household is located in a rural or urban area). Model 4 combines both sets of covariates, household and its head. Adjusted p-values refer to p-values that have been corrected using the Bonferroni adjustment method. Standard errors are clustered at the census tract level.***p≤0.01, **p≤0.05, *p≤0.1..

Own-Consumption activities were further disaggregated into three main categories: (i) Agricultural Production, (ii) Animal Husbandry, and (iii) Fishing. All three activities exhibit negative and statistically significant ATT estimates. For agricultural production, the ATT values range from –0.09 to –0.14 when considering the 0–2 km range (Table 11). When the riverbank is alternatively defined using 1.5 km and 2.5 km thresholds, the estimates remain negative and statistically significant. The effect is strongest within the 1.5 km range, showing a reduction of 9 to 18 percentage points depending on the model specification and the comparison group used.

In the case of animal husbandry, we observe a consistent decline in participation. However, in specification 4, the ATT is statistically significant only when the entire subsample (up to 14 km) is used as the comparison group. The magnitude of this reduction is smaller, ranging from approximately 3 to 4 percentage points (Table 12). Fishing was

also negatively affected, with ATT estimates indicating reductions of around 5 percentage points when the adjacent area is defined as the 2–4 km band (Table 13). This negative effect in fishing activities aligns with expectations, not only due to the decline in aquatic fauna caused by the disaster, but also because of widespread concerns about water contamination — particularly from toxic metals such as lead — which contributed to reduce the demand for freshly caught fish (Zonta and Trocate, 2016).

6.1.2 Home-Production

Table 14 – Home-Production - Main Results

t = 2	t = 1	ATT (1)	p-value	Adj. p-value	ATT (2)	p-value	Adj. p-value	ATT (3)	p-value	Adj. p-value	ATT (4)	p-value	Adj. p-value
0 - 2km	2 - 4km	0.065	0.179	0.716	0.034	0.574	1.000	0.068	0.206	0.822	0.051	0.518	1.000
0 - 2km	+2km	0.046	0.105	0.420	0.039	0.154	0.614	0.043	0.222	0.888	0.038	0.269	1.000
0 - 1.5km	1.5 - 3km	0.046	0.362	1.000	-0.017	0.769	1.000	-0.007	0.919	1.000	-0.028	0.705	1.000
0 - 1.5km	+1.5km	0.035	0.147	0.587	0.032	0.147	0.589	0.012	0.722	1.000	0.010	0.736	1.000
0 - 2.5km	2.5 - 5km	0.059	0.325	1.000	0.042	0.421	1.000	0.059	0.303	1.000	0.059	0.727	1.000
0 - 2.5km	+2.5km	0.047	0.136	0.542	0.046	0.119	0.477	0.043	0.288	1.000	0.039	0.388	1.000

Notes: The regressions employ a logit model. Model 1 includes no controls. Model 2 includes controls for the characteristics of the household head (gender, age, race, and educational attainment). Model 3 includes controls for household characteristics (number of residents, the proportion of children and elderly, natural strata, and whether the household is located in a rural or urban area). Model 4 combines both sets of covariates, household and its head.Adjusted p-values refer to p-values that have been corrected using the Bonferroni adjustment method. Standard errors are clustered at the census tract level.***p≤0.01, **p≤0.05, *p≤0.1..

Home-production activities — which include the manufacturing of household goods such as furniture, textiles, pottery, and clothing — were the only own-use activity category to exhibit a positive effect on the probability of engagement following the disaster. However, none of the estimated effects are statistically significant, as shown in Table 14. The estimated increase in the probability of engaging in home-production activities ranges from 3.4 to 6 percentage points when comparing households located 0–2 km from the river to those 2–4 km away. A similar increase of approximately 4 percentage points is observed when the 0–2 km group is compared to the entire sample. This pattern is consistent with the nature of the disaster, as manufacturing activities are generally less dependent on natural resources directly affected by the tailing dam collapse. Furthermore, the observed increase in domestic production of goods may reflect a compensatory strategy adopted by households in response to higher food expenditures or potential income losses.

6.1.3 Home-Construction

Table 15 – Home-Construction - Main Results

t = 2	t = 1	ATT (1)	p-value	Adj. p-value	ATT (2)	p-value	Adj. p-value	ATT (3)	p-value	Adj. p-value	ATT (4)	p-value	Adj. p-value
0 - 2km	2 - 4km	-0.136	0.000	0.000	-0.143	0.000	0.000	-0.321	0.000	0.000	-0.303	0.000	0.000
0 - 2km	+2km	-0.079	0.000	0.000	-0.063	0.002	0.008	-0.136	0.000	0.000	-0.123	0.000	0.000
0 - 1.5km	1.5 - 3km	-0.018	0.591	1.000	0.000	0.997	1.000	-0.191	0.000	0.000	-0.150	0.015	0.061
0 - 1.5km	+1.5km	-0.028	0.079	0.314	-0.008	0.703	1.000	-0.048	0.025	0.101	-0.024	0.443	1.000
0 - 2.5km	2.5 - 5km	-0.065	0.095	0.379	-0.078	0.034	0.134	-0.086	0.036	0.144	-0.118	0.021	0.086
0 - 2.5km	+2.5km	-0.054	0.028	0.111	-0.038	0.128	0.510	-0.081	0.005	0.022	-0.076	0.010	0.041

Notes: The regressions employ a logit model. Model 1 includes no controls. Model 2 includes controls for the characteristics of the household head (gender, age, race, and educational attainment). Model 3 includes controls for household characteristics (number of residents, the proportion of children and elderly, natural strata, and whether the household is located in a rural or urban area). Model 4 combines both sets of covariates, household and its head. Adjusted p-values refer to p-values that have been corrected using the Bonferroni adjustment method. Standard errors are clustered at the census tract level.***p≤0.01, **p≤0.05, *p≤0.1..

Home-Construction activities experienced the largest reductions in the probability of being carried out. The estimated ATT values range from –0.13 to –0.30 when comparing households located 0–2 km from the river to those 2–4 km away. In the comparison between the 0–2 km band and the rest of the subsample, the reduction varies from 6.25 to 13.5 percentage points, depending on the model specification, as shown in Table 15. One possible explanation for this sharp decline is that the construction of dwellings and other communal spaces often takes place through collective efforts, such as community-based building projects. The social disruption caused by the disaster — including the displacement of entire villages and communities — may have weakened local cohesion and reduced the feasibility of such collaborative practices. Environmental degradation and migration pressures may also have contributed to the decline in home-construction activities.

When analyzing the results for Own-Consumption, Home Production, and Home Construction, we observe that the estimated effect of the disaster on the probability of engaging in these activities is stronger when comparing the 0–2 km band to the 2–4 km band than when comparing the 0–2 km band to the rest of the sample (2–14 km). The magnitude of the ATT is greater when the comparison is restricted to the areas closest to the river—negative in the case of Own-Consumption and Home Construction, and positive in the case of Home Production. Several factors may explain this pattern. First, households located farther from the Rio Doce may be influenced by proximity to other rivers or be subject to distinct regional dynamics. In particular, the control areas include

microregions with a strong agricultural tradition, which may contribute to differences in own-use behavior. Additionally, the larger comparison group (2–14 km) introduces more heterogeneity, whereas comparisons between geographically closer areas may capture a cleaner impact.

6.1.4 Extraction

Table 16 – Extraction - Main Results

t = 2	t = 1	ATT (1)	p-value	Adj. p-value	ATT (2)	p-value	Adj. p-value	ATT (3)	p-value	Adj. p-value	ATT (4)	p-value	Adj. p-value
0 - 2km	2 - 4km	0.016	0.000	0.000	0.014	0.000	0.000	-0.058	0.000	0.000	-0.069	0.000	0.000
0 - 2km	+2km	-0.019	0.000	0.000	-0.019	0.000	0.000	-0.161	0.000	0.000	-0.194	0.000	0.000
0 - 1.5km	1.5 - 3km	-0.004	0.010	0.042	-0.022	0.000	0.000	-0.179	0.000	0.000	-0.207	0.000	0.000
0 - 1.5km	+1.5km	-0.023	0.000	0.000	-0.029	0.000	0.000	-0.236	0.000	0.000	-0.294	0.000	0.000
0 - 2.5km	2.5 - 5km	0.014	0.000	0.000	0.015	0.000	0.000	-0.241	0.000	0.000	-0.214	0.000	0.000
0 - 2.5km	+2.5km	-0.027	0.000	0.000	-0.030	0.000	0.000	-0.047	0.000	0.000	-0.064	0.000	0.000

Notes: The regressions employ a Poisson model. Model 1 includes no controls. Model 2 includes controls for the characteristics of the household head (gender, age, race, and educational attainment). Model 3 includes controls for household characteristics (number of residents, the proportion of children and elderly, natural strata, and whether the household is located in a rural or urban area). Model 4 combines both sets of covariates, household and its head. Adjusted p-values refer to p-values that have been corrected using the Bonferroni adjustment method. Standard errors are clustered at the census tract level.***p≤0.01, **p≤0.05, *p≤0.1.

Extraction activities — which involve the collection of natural materials such as charcoal, firewood, water, sand, clay, and seeds — were negatively affected by the disaster, with a decline in the average probability of these activities being carried out. When comparing the two bands closest to the river (0–2 km and 2–4 km), the estimated ATT ranges from –0.016 to –0.034. A similar reduction is observed when comparing the 0–2 km band to the full subsample, with an average decrease of approximately 2 percentage points, as shown in Table 16. This result is consistent with expectations, given that these activities depend heavily on the availability of natural resources, which were directly impacted by the environmental collapse.

6.2 Other Allocative Choices

To analyze school attendance and labor market participation, we constructed an individual-level dataset, in contrast to the household-level approach used for own-use production activities. For each adult household member, we observe whether they are engaged in paid work, and for children and youth, whether they are enrolled in school or

another educational institution. For labor market outcomes — specifically employment and formal employment — we restrict the sample to working-age adults between 16 and 65 years old. For the estimation of the DiD model on school attendance, we focus on adolescents and youth aged 13 to 21. This age group was selected because nearly all children under the age of 12 in both the Rio Doce and control groups were already regularly attending school.

6.2.1 Educational Attendance

Table 17 – Educational Attendance - Main Results

		ATT			
t = 2	**t = 1**	(1)	(2)	(3)	(4)
0 - 2km	2 - 4km	-0.0215	-0.0643	0.138	0.0706
0 - 2km	+2km	-0.0293	0.0077	0.0240	0.0223
0 - 1.5km	1.5 - 3km	0.0762	0.0212	0.1923*	0.0731
0 - 1.5km	+1.5km	0.0395	0.0391	0.0416	0.0420
0 - 2.5km	2.5 - 5km	-0.0308	0.0091	-0.0055	0.072
0 - 2.5km	+2.5km	-0.0362	0.01496	-0.0122	0.0011

Notes: The regressions employ a logit model. Model 1 includes no controls. Model 2 includes controls for the characteristics of the household head (gender, age, race, and educational attainment). Model 3 includes controls for household characteristics (number of residents, the proportion of children and elderly, natural strata, and whether the household is located in a rural or urban area). Model 4 combines both sets of covariates, household and its head. Standard errors are clustered at the household level.***p≤0.01, **p≤0.05, *p≤0.1.

When examining the estimated ATT for school attendance among adolescents and youth — corresponding roughly to the final years of lower secondary education, upper secondary education, and potential entry into higher education — there is no consistent evidence of an impact. The ATT estimates are statistically insignificant across nearly all specifications and model variants (Table 17). Moreover, the direction of the estimated effect is sensitive to model specification, indicating a lack of robustness in the results.

6.2.2 Employment

Table 18 – Paid Work - Main Results

		ATT			
t = 2	**t = 1**	(1)	(2)	(3)	(4)
0 - 2km	2 - 4km	0.1122**	0.1109**	0.0436	0.0525
0 - 2km	+2km	0.0546*	0.0457	0.0054	0.0076
0 - 1.5km	1.5 - 3km	0.0871*	0.104**	0.0954**	0.1277***
0 - 1.5km	+1.5km	0.0462*	0.0397	0.0109	0.010528
0 - 2.5km	2.5 - 5km	0.0462	0.046	-0.0533	-0.0421
0 - 2.5km	+2.5km	0.0339	0.0252	-0.0422	-0.0400

Notes: The regressions employ a logit model. Model 1 includes no controls. Model 2 includes controls for the characteristics of the household head (gender, age, race, and educational attainment). Model 3 includes controls for household characteristics (number of residents, the proportion of children and elderly, natural strata, and whether the household is located in a rural or urban area). Model 4 combines both sets of covariates, household and its head. Standard errors are clustered at the household level.***p≤0.01, **p≤0.05, *p≤0.1.

Table 19 – Formal Employment - Main Results

		ATT			
t = 2	**t = 1**	(1)	(2)	(3)	(4)
0 - 2km	2 - 4km	0.0151	0.0047	-0.002	-0.0008
0 - 2km	+2km	0.0117	0.0050	0.0039	-0.0009
0 - 1.5km	1.5 - 3km	0.0182	0.0237	0.0491	0.068
0 - 1.5km	+1.5km	0.0104	0.0109	0.0032	0.0047
0 - 2.5km	2.5 - 5km	-0.054	-0.0715	-0.0908**	-0.103**
0 - 2.5km	+2.5km	-0.0072	-0.0178	-0.0412	-0.0531*

Notes: The regressions employ a logit model. Model 1 includes no controls. Model 2 includes controls for the characteristics of the household head (gender, age, race, and educational attainment). Model 3 includes controls for household characteristics (number of residents, the proportion of children and elderly, natural strata, and whether the household is located in a rural or urban area). Model 4 combines both sets of covariates, household and its head. Standard errors are clustered at the household level.***p≤0.01, **p≤0.05, *p≤0.1.

Regarding labor market outcomes, there is evidence suggesting an increase in the probability of having any paid employment following the disaster. However, this potential increase does not appear to be driven by formal employment. When using a binary

dependent variable indicating whether the individual engaged in any form of monetized work during the survey reference week, the ATT estimates are mostly positive, with some statistically significant results depending on the specification, as shown in Table 18. Comparing the 0–2 km and 2–4 km distance bands, the estimated increase in the probability of paid work ranges from 5 to 11 percentage points, depending on the model specification. This magnitude remains relatively stable when the riverbank is redefined as 1.5 km. However, when the threshold is expanded to 2.5 km, the estimates become negative in specifications 3 and 4, suggesting that the effect is sensitive to the choice of the spatial comparison window.

In contrast, when the dependent variable is defined as a binary indicator for formal employment — whether through a formal job contract or a formalized business — the results are less consistent. Most of the ATT estimates are statistically insignificant (Table 19). In the 1.5 km band, we observe positive effects, while the estimates turn negative when using the 2.5 km threshold. For the 2 km band, results are mixed across specifications.

A caveat must be noted regarding the labor market outcomes. The non-contamination assumption — discussed in Section 5.1.1 — may be violated due to the fact that the tailing dam collapse likely affected the structure of wages and prices not only in the riverbank region but also in the adjacent area. Given their geographic proximity and economic integration, these two regions effectively constitute a single labor market. This overlap may represent a potential channel through which the disaster influenced own-use production in both regions.

6.3 Robustness Check

A robustness check is conducted to support the validity of the parallel trends assumption underlying the identification strategy. This assumption posits that, in the absence of the disaster, the gradient of the probability of engaging in own-use production would have evolved similarly across the treatment and control areas. Since this hypothesis cannot be directly tested in areas near the Rio Doce due to the disaster's impact, the test is implemented using geographic bands located farther from the river — regions where the effects on natural resources, and thus on own-use production activities, are expected to be minimal or absent.

Table 20 – Own-use Production - robustness test

		ATT			
t = 2	**t = 1**	(1)	(2)	(3)	(4)
4–6km	6–8km	0.0483	0.0704	-0.0042	0.0097
6–8km	8–10km	-0.2706	-0.3037**	0.0833	-0.0101

Notes: The regressions employ a logit model. Model 1 includes no controls. Model 2 includes controls for the characteristics of the household head (gender, age, race, and educational attainment). Model 3 includes controls for household characteristics (number of residents, the proportion of children and elderly, natural strata, and whether the household is located in a rural or urban area). Model 4 combines both sets of covariates, household and its head. Standard errors are clustered at the census tract level.***p≤0.01, **p≤0.05, *p≤0.1.

Table 20 reports the estimated ATT values for areas situated farther from the river. We begin by examining the 4–6 km and 6–8 km distance bands, followed by the 6–8 km and 8–10 km intervals. The results are largely statistically insignificant, and both the direction and magnitude of the estimated effects vary considerably depending on the set of covariates included. When controlling for household and household head characteristics, the ATT estimates remain consistently insignificant and of small magnitude, reinforcing the hypothesis that the disaster did not affect the likelihood of engaging in own-use production among households located farther from the Rio Doce. Robustness checks for other types of own-use production activities and additional allocative choices are provided in the Appendix (Tables 25 to 33).

7 Conclusions

The environmental disaster caused by the collapse of the Fundão tailing dam had severe and far-reaching consequences, affecting multiple dimensions of life for the impacted population. This study provides empirical evidence that the environmental degradation resulting from the contamination of the Doce River adversely affected own-use production practices among communities located near the river. Specifically, activities related to Home-Construction, Own-Consumption, and Extraction were negatively impacted. On average, for food-related own-use activities, we estimate a reduction of approximately 5 to 10 percentage points in the probability of participation among individuals residing within 2 kilometers of the Doce River, compared to those living at a similar distance from a river in the control area.

This finding raises important questions about the potential welfare implications for the affected households. As highlighted in the literature, food production activities play a key role in promoting dietary diversity and nutritional adequacy, particularly in regions where subsistence practices are widespread and characterized by a variety of cultivated crops. The loss of access to these practices may therefore result in a deterioration of food security and nutrition. On the other hand, we find some evidence of an increase in the likelihood of employment, seemingly driven by participation in informal labor markets. This observation prompts the question of whether the reduction in own-use production may have been offset by an increase in labor supply, as household members sought to compensate for the loss of household production output through paid work.

Nevertheless, there is no evidence that the disaster resulted in an expansion of employment opportunities, particularly within the informal sector. If such opportunities were already accessible prior to the disaster, and households nonetheless chose to engage in own-use production, this behavior — under the principle of revealed preference — suggests that domestic production represented the preferred allocation of time and resources. In this context, the observed shift from own-use activities to labor market participation is unlikely to reflect a voluntary reoptimization, but rather a constrained response to environmental and economic disruptions. Such involuntary adjustments in household behavior may therefore indicate a deterioration in overall welfare among the affected population.

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Appendix

APPENDIX A – Tables and Figures

A.1 Descriptive Analyses

Table 21 – Factors Associated with Engaging in Own-Consumption Activities in the Rio Doce Region

	Agricultural Production	Animal Husbandry	Fishing
Intercept	0.039	-0.029	-0.010
	(0.0866)	(0.0591)	(0.0320)
Distance to nearest river (km)	0.007	0.026***	0.001
	(0.0069)	(0.0057)	(0.0035)
Reg. Aimorés	0.396***	0.197***	-0.007
	(0.0758)	(0.0612)	(0.0120)
Reg. Gov. Valadares	0.098***	0.000	-0.008
	(0.0347)	(0.0187)	(0.0081)
Reg. Ponte Nova	-0.059**	0.027	0.017
	(0.0248)	(0.0476)	(0.0323)
Reg. Ipatinga	0.127***	-0.067**	0.016
	(0.0460)	(0.0276)	(0.0221)
Reg. Caratinga	0.458***	0.146*	0.212***
	(0.0840)	(0.0771)	(0.0764)
Num. people in household	0.000	0.014	-0.006
	(0.0133)	(0.0097)	(0.0039)
Perc. of children	-0.032	-0.140**	0.025
	(0.1026)	(0.0633)	(0.0470)
Perc. of elderly	0.112*	0.056	-0.052**
	(0.0608)	(0.0468)	(0.0230)
Log per capita monthly earnings	0.013**	0.004	0.002
	(0.0053)	(0.0029)	(0.0023)
Head is woman	-0.033	0.000	0.008
	(0.0317)	(0.0225)	(0.0143)
Age of head	0.000	0.000	0.001**
	(0.0015)	(0.0011)	(0.0005)
Head is white	0.008	-0.005	-0.017
	(0.0340)	(0.0245)	(0.0116)
Head has college degree	-0.057	-0.056***	-0.017*
	(0.0477)	(0.0211)	(0.0100)

Notes: The regression employs a logit model. ***p≤0.01, **p≤0.05, *p≤0.1. Robust standard errors are reported in parentheses.

Table 22 – Factors Associated with Engaging in Own-Consumption Activities in the Control Area

	Agricultural Production	Animal Husbandry	Fishing
Intercept	-0.104	0.096*	0.040
	(0.117)	(0.051)	(0.028)
Distance to nearest river (km)	-0.003	-0.002	-0.002
	(0.005)	(0.003)	(0.002)
Reg. Campo Belo	0.542***	0.726***	0.125***
	(0.076)	(0.066)	(0.046)
Reg. Passos	0.138***	0.017	0.016
	(0.052)	(0.031)	(0.018)
Num. people in household	0.027*	0.018**	-0.004
	(0.015)	(0.009)	(0.004)
Perc. children	-0.071	-0.071	0.013
	(0.109)	(0.066)	(0.010)
Perc. elderly	0.138*	0.079*	-0.021
	(0.076)	(0.041)	(0.026)
Log per capita monthly earnings	0.015***	0.001	0.000
	(0.005)	(0.003)	(0.002)
Head is woman	-0.018	-0.048***	-0.015*
	(0.034)	(0.017)	(0.009)
Head's age	0.003	-0.001	0.000
	(0.002)	(0.001)	(0.001)
Head is white	-0.033	0.012	0.007
	(0.034)	(0.021)	(0.014)
Head has college degree	-0.015	-0.062***	-0.016
	(0.052)	(0.014)	(0.010)

Notes: The regression employs a logit model. ***p≤0.01, **p≤0.05, *p≤0.1. Robust standard errors are reported in parentheses.

A.2 Sufficiency

We estimated the DiD model for outcomes related to the sufficiency of household production in meeting families' needs for agricultural goods and animal products. As expected, the environmental disaster led to a decline in the probability that households could satisfy their food needs through own-use production. For the sufficiency of animal products, the results are consistently negative and statistically significant. In specification 4, the estimated reduction ranges from 7 to 14 percentage points when comparing shorter distance bands (Table 23). In the case of agricultural production sufficiency (Table 24),

the estimates are also consistently negative; however, their magnitude varies considerably depending on the observation window and model specification. In specification 4, only the 1.5 km riverbank definition yields statistically significant results.

Table 23 – Sufficiency in Animal Products - Main Results

		ATT			
t = 2	**t = 1**	(1)	(2)	(3)	(4)
0 - 2km	2 - 4km	-0.026***	-0.149***	-0.0888***	-0.1403***
0 - 2km	+2km	-0.038624***	-0.0456***	-0.0513***	-0.0427***
0 - 1.5km	1.5 - 3km	-0.0354***	-0.1178***	-0.0884***	-0.0891***
0 - 1.5km	+1.5km	-0.038402***	-0.0402***	-0.0421***	-0.0273***
0 - 2.5km	2.5 - 5km	-0.0278***	-0.061***	-0.0576***	-0.0769***
0 - 2.5km	+2.5km	-0.032741***	-0.0396***	-0.0311***	-0.0400***

Notes: The regressions employ a logit model.Model 1 includes no controls. Model 2 includes controls for the characteristics of the household head (gender, age, race, and educational attainment). Model 3 includes controls for household characteristics (number of residents, the proportion of children and elderly, natural strata, and whether the household is located in a rural or urban area). Model 4 combines both sets of covariates, household and its head. Standard errors are clustered at the census tract level.***p≤0.01, **p≤0.05, *p≤0.1.

Table 24 – Sufficiency of Agriculture Production - Main Results

		ATT			
t = 2	**t = 1**	(1)	(2)	(3)	(4)
0 - 2km	2 - 4km	-0.04	-0.0518*	-0.0438	-0.0532
0 - 2km	+2km	-0.0081	-0.0043	-0.0149	-0.01379
0 - 1.5km	1.5 - 3km	-0.0635	-0.0643*	-0.2148***	-0.2101***
0 - 1.5km	+1.5km	-0.0085	-0.0067	-0.0246	-0.0313*
0 - 2.5km	2.5 - 5km	-0.026	-0.039	-0.0215	-0.0965**
0 - 2.5km	+2.5km	-0.0065	-0.0026	0.0070	0.0084

Notes: The regressions employ a logit model. Model 1 includes no controls. Model 2 includes controls for the characteristics of the household head (gender, age, race, and educational attainment). Model 3 includes controls for household characteristics (number of residents, the proportion of children and elderly, natural strata, and whether the household is located in a rural or urban area). Model 4 combines both sets of covariates, household and its head. Standard errors are clustered at the census tract level.***p≤0.01, **p≤0.05, *p≤0.1.

A.3 Robustness Test

Table 25 – Own-Consumption - Robustness Test

		ATT			
t = 2	**t = 1**	(1)	(2)	(3)	(4)
4–6km	6–8km	0.0742	0.1137	0.0653	0.0692
6–8km	8–10km	0.0281	-0.053	0.0433	0.0895

Notes: The regressions employ a logit model. Model 1 includes no controls. Model 2 includes controls for the characteristics of the household head (gender, age, race, and educational attainment). Model 3 includes controls for household characteristics (number of residents, the proportion of children and elderly, natural strata, and whether the household is located in a rural or urban area). Model 4 combines both sets of covariates, household and its head. Standard errors are clustered at the census tract level.***p≤0.01, **p≤0.05, *p≤0.1.

Table 26 – Animal Raising - Robustness Test

		ATT			
t = 2	**t = 1**	(1)	(2)	(3)	(4)
4–6km	6–8km	0.0456	0.0673	0.0283	0.0476
6–8km	8–10km	0.0092	-0.1111	0.0999	0.1604

Notes: The regressions employ a logit model. Model 1 includes no controls. Model 2 includes controls for the characteristics of the household head (gender, age, race, and educational attainment). Model 3 includes controls for household characteristics (number of residents, the proportion of children and elderly, natural strata, and whether the household is located in a rural or urban area). Model 4 combines both sets of covariates, household and its head. Standard errors are clustered at the census tract level.***p≤0.01, **p≤0.05, *p≤0.1.

Table 27 – Sufficiency in Animal Products - Robustness Test

		ATT			
t = 2	**t = 1**	(1)	(2)	(3)	(4)
4–6km	6–8km	0.0574	0.0742	0.0784	0.0817
6–8km	8–10km	0.0054	-0.0139	-0.0026	-0.0232

Notes: The regressions employ a logit model. Model 1 includes no controls. Model 2 includes controls for the characteristics of the household head (gender, age, race, and educational attainment). Model 3 includes controls for household characteristics (number of residents, the proportion of children and elderly, natural strata, and whether the household is located in a rural or urban area). Model 4 combines both sets of covariates, household and its head. Standard errors are clustered at the census tract level.***p≤0.01, **p≤0.05, *p≤0.1.

Table 28 – Agriculture Production - Robustness Test

		ATT			
t = 2	**t = 1**	(1)	(2)	(3)	(4)
4–6km	6–8km	0.0561	0.0784	0.0161	0.0277
6–8km	8–10km	0.0384	-0.0734	-0.0045	-0.0148

Notes: The regressions employ a logit model. Model 1 includes no controls. Model 2 includes controls for the characteristics of the household head (gender, age, race, and educational attainment). Model 3 includes controls for household characteristics (number of residents, the proportion of children and elderly, natural strata, and whether the household is located in a rural or urban area). Model 4 combines both sets of covariates, household and its head. Standard errors are clustered at the census tract level.***p≤0.01, **p≤0.05, *p≤0.1.

Table 29 – Sufficiency of Agriculture Production - Robustness Test

		ATT			
t = 2	**t = 1**	(1)	(2)	(3)	(4)
4–6km	6–8km	0.0337	0.0354	-0.0433	-0.0396
6–8km	8–10km	-0.2157***	-0.2636***	0.0404	0.0599
14–16km	16–18km	0.0491	0.0435	-0.1105***	-0.0742***

Notes: The regressions employ a logit model. Model 1 includes no controls. Model 2 includes controls for the characteristics of the household head (gender, age, race, and educational attainment). Model 3 includes controls for household characteristics (number of residents, the proportion of children and elderly, natural strata, and whether the household is located in a rural or urban area). Model 4 combines both sets of covariates, household and its head. Standard errors are clustered at the census tract level.***p≤0.01, **p≤0.05, *p≤0.1.

Table 30 – Home-Production - Robustness Test

		ATT			
t = 2	**t = 1**	(1)	(2)	(3)	(4)
4–6km	6–8km	0.0064	0.0067	-0.0103	-0.0629
6–8km	8–10km	-0.1366***	-0.1021	-0.0337	-0.0284

Notes: The regressions employ a logit model. Model 1 includes no controls. Model 2 includes controls for the characteristics of the household head (gender, age, race, and educational attainment). Model 3 includes controls for household characteristics (number of residents, the proportion of children and elderly, natural strata, and whether the household is located in a rural or urban area). Model 4 combines both sets of covariates, household and its head. Standard errors are clustered at the census tract level.***p≤0.01, **p≤0.05, *p≤0.1.

Table 31 – Home-Construction - Robustness Test

		ATT			
t = 2	**t = 1**	(1)	(2)	(3)	(4)
4–6km	6–8km	-0.0528*	-0.1753***	-0.1325***	-0.1248**
6–8km	8–10km	-0.6627***	-0.5517***	-0.6773***	-0.6446

Notes: ***p≤0.01, **p≤0.05, *p≤0.1. Standard errors are clustered at the census tract level.

Table 32 – Paid Work - Robustness Test

		ATT			
t = 2	**t = 1**	(1)	(2)	(3)	(4)
4–6km	6–8km	0.0183	0.0595	0.0485	0.0521
6–8km	8–10km	0.0118	0.0578	-0.1007	-0.064

Notes: The regressions employ a logit model. Model 1 includes no controls. Model 2 includes controls for the characteristics of the household head (gender, age, race, and educational attainment). Model 3 includes controls for household characteristics (number of residents, the proportion of children and elderly, natural strata, and whether the household is located in a rural or urban area). Model 4 combines both sets of covariates, household and its head. Standard errors are clustered at the census tract level.***p≤0.01, **p≤0.05, *p≤0.1.

Table 33 – Formal Employment - Robustness Test

		ATT			
t = 2	**t = 1**	(1)	(2)	(3)	(4)
4–6km	6–8km	-0.0415	-0.0212	0.0602	0.0644
6–8km	8–10km	0.0361	0.0409	-0.0266	-0.0239

Notes: The regressions employ a logit model. Model 1 includes no controls. Model 2 includes controls for the characteristics of the household head (gender, age, race, and educational attainment). Model 3 includes controls for household characteristics (number of residents, the proportion of children and elderly, natural strata, and whether the household is located in a rural or urban area). Model 4 combines both sets of covariates, household and its head. Standard errors are clustered at the census tract level.***p≤0.01, **p≤0.05, *p≤0.1.

Table 34 – Youth Educational Attendance - robustness test

		ATT			
t = 2	**t = 1**	(1)	(2)	(3)	(4)
4-6km	6-8km	-0.1409	-0.1237	-0.0033	-0.0988
6-8km	8-10km	0.363***	0.2227***	0.1129*	0.2134***

Notes: The regressions employ a logit model. Model 1 includes no controls. Model 2 includes controls for the characteristics of the household head (gender, age, race, and educational attainment). Model 3 includes controls for household characteristics (number of residents, the proportion of children and elderly, natural strata, and whether the household is located in a rural or urban area). Model 4 combines both sets of covariates, household and its head. Standard errors are clustered at the household level.***p≤0.01, **p≤0.05, *p≤0.1.