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The Value of Clean Water:

Evidence from an Environmental Disaster

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Abstract[1]

Clean water has a largely unknown economic value, particularly to small communities whose agricultural activities take place on river shores. In November 2015, the rupture of a mining tailings dam in the municipality of Mariana led to a record disposal of toxic residuals in southeast Brazil. A mud avalanche ran out for 600 km (373 miles) until it reached the Atlantic Ocean, leaving behind extreme ecological and economic damage in the Doce River basin. This is the largest environmental disaster in Brazil to date. We quantify the negative externalities using rich, identified, and comprehensive data from firm-to-firm electronic payments and individual-level consumer credit usage. We find that agricultural producers in affected municipalities received cumulatively 41% to 60% fewer inflows (income) from customer firms outside the affected zone three years after the disaster. Effects are driven by municipalities where the river shore is larger relative to the farming area. In these municipalities, individuals also faced an 8% fall in their credit card and consumer finance expenditures. This result is stronger for non-formal and high-risk workers. Thus, water contamination led to (first) production and (later) consumption decline with real effects on municipality-level agriculture and services' output, causing a 7% decline in local GDP.

JEL Classification: C63, G01, G20, G21, G28, O16, O40
Keywords: Water, Environmental disaster, Agriculture, Consumer credit, Payment system

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1 Introduction

Access to clean water is important for human well-being and economic activity, while contaminated water has adverse effects on human health (Smith et al., 2010; Ward et al., 2018), education (Akter, 2019), agricultural output (Khan et al., 2008; Meng et al., 2016; Sharma et al., 2006), property value (Nicholls and Crompton, 2018) and general economic activity (Desbureaux et al., 2019). As a consequence, it is also relevant for public policy (Carson and Mitchell, 1993; Keiser and Shapiro, 2019; Sigman, 2002).

This paper explores a catastrophic environmental disaster in Brazil—the Mariana's mining tailing dam collapse—using comprehensive microdata, including firm-to-firm financial transactions and individual-level credit card consumption. We show the negative externalities introduced by water pollution disrupted agricultural firms' supply chain, led to consumption decline, and destroyed wealth with sizeable effects on the GDP of more affected shore municipalities. We start by evaluating the broader real effects on affected municipalities, particularly on agricultural activities. We then turn to microdata to quantify the negative externalities to firms' supply chains in the affected municipalities using comprehensive data from the Brazilian payment system, including identified firm-to-firm electronic transfers used to settle business transactions. Moreover, we turn to the credit registry of the Banco Central do Brasil (BCB) to explore consumer credit expenditure, including each individual's non-interest-bearing credit card usage. The rich dataset allows us to disentangle some of the transmission channels and study how and to what extent water contamination impoverished the affected riverside municipalities.

In November 2015, the rupture of a mining tailings dam in the municipality of Mariana led to a record disposal of toxic residuals in southeast Brazil. This is the largest environmental disaster in the country to date (Veja, 2017) and the largest of its kind (Azevedo, 2016). A mud avalanche ran out for 600 km (373 miles)—roughly the distance between San Francisco and Los Angeles, Frankfurt and Milan, or New York and Montreal—until it reached the Atlantic Ocean, leaving behind extreme ecological and economic damage in the shore cities of the Doce River basin. Moreover, the disaster caused 19 deaths and is associated with increased health and mental problems in the affected region[2].

This paper aims at estimating the economic effects of the contaminated water throughout the affected municipalities focusing on the agricultural sector, by far the most directly affected by water contamination[3]. A survey carried out by Greenpeace and the Federal University of Rio de Janeiro highlights the majority of small producers did not abandon their lands but faced financial difficulties due to soil and water contamination. "Indeed, 88% of interviewed producers claim to have changed their crops following the disaster." While 98% of agricultural producers claimed to have used water from Doce River directly for economic activities prior to the disaster, only 36% are still using it for the same purposes. Within this group, "87% use

[2]Another catastrophic mining disaster happened in a nearby location, Brumadinho, in 2019. The Brumadinho disaster caused at least 270 deaths and extensive environmental damage, but it had more limited economic externalities because the damage was less geographically widespread. It also happened after the time span of our analysis.

[3]Direct effects to the mining sector are also relevant but beyond the scope of this paper. See FGV (2020) for an assessment of these effects.

the water for irrigation, but 60% consider it unsuitable for consumption" (Torres et al., 2017). The study also finds evidence that not only the Doce River shore but also artesian wells were partially contaminated by manganese (Mn) and iron (Fe) because the drying of contaminated water caused metals to infiltrate the soil. This is corroborated by Coelho et al. (2020), which identifies soil and plant tissues had increased content of several metals—chromium (Cr), copper (Cu), manganese (Mn), and iron (Fe)—in affected areas. Empresa Brasileira de Pesquisa Agropecuária (Embrapa), a relevant think tank in agriculture, states in a technical report that, beyond toxic metals in the soil, land productivity is compromised due to the lack of quality of the mud layer now covering the soil. "Organic material in sedimentation does not present conditions for germination of seeds or to the radicular development of plants. Beyond fertility and difficulties for (rain) water to infiltrate the soil, the low levels of organic material needed for soil microbiotic life to develop compromise productivity (Empresa Brasileira de Pesquisa Agropecuária - Embrapa, 2015)."

Along these lines, we explore water dependence for agriculture and related negative externalities of water contamination to firms and individuals. We use a propensity score matching strategy to identify control municipalities in the same affected states (Minas Gerais and Espírito Santo) but out of the Doce River basin and start by evaluating the broader losses to local GDP and its main components. We find a cumulative loss of 14% in the value-added of agriculture in the 37 affected[4] municipalities. This result is mainly led by more affected municipalities, where the freshwater area was (one standard deviation) larger relative to the total farm area, and where agricultural value-added declined by 18%[5]. Results on the value-added from industries were muted as we excluded the industrial city of Mariana (the disaster's epicenter) from the sample. Importantly, as a consequence of such steep losses in rural areas, services were also affected. In the more affected municipalities, value-added from services declined by 6% in three years. The combination of these effects led to an overall GDP decline of 7%[6]. As previously explained, the transmission channel to agriculture is a consequence of two aspects: contaminated water (including high levels of heavy metals) dried and metals infiltrated the soil; and the mud on top of the soil, which was poor in nutrients compromising crop development. Both aspects compromised the performance of the crops already established, leading to changes in the agricultural mix in the following years. Consistently, we document a strong decline in the total farmed area of beans, coffee, and corn— the three most relevant crops in the region—and an increase in sugar cane.

While these results provide a picture of the extension of losses to these communities, disentangling the channels and properly measuring those losses requires microdata. For identification, we turn to the payment system and the credit register of the BCB. Our first approach explores the negative production

[4]For identification, we exclude the industrial city of Mariana, the epicenter of the disaster.

[5]Distance from the epicenter is not relevant for this particular disaster. For instance, in the municipality of Colatina, 400 km away from the dam, water is found to contain 5 times the allowed amount of Mn in its dwellings. Toxic mud contaminated the soil to the point of reaching subterranean water (Associação Brasileira de Engenharia Sanitária e Ambiental - ABES, 2017). We take the Water/Farm area ratio, with both areas measured in ha and taken from MapBiomas, as a superior proxy of disaster intensity because it more clearly communicates to the relative extension of exposure to water contamination.

[6]Using a sample of 19 countries, Desbureaux et al. (2019) find national GDP growth declines by 0.8% to 2% when rivers become heavily polluted (i.e., with high levels of biological oxygen demand, BOD).

shock to agriculture using a rich set of controls and fixed effects on firm-to-firm financial transactions data. Relatively to the same consumer firm, agricultural producers in affected municipalities experienced a 41% income loss (i.e., a fall in payment inflows from firms across the country but outside the Doce River basin) compared to producers in unaffected municipalities in the following three years. These results are driven by municipalities with larger river shore-to-farm area ratios.

To quantify the effects on consumption, we turn to the credit registry of the BCB and explore credit lines directly attached to consumption, including non-interest-bearing credit card expenditures from over seven hundred thousand individuals. We find an average consumption fall of 8% in the more affected municipalities. Importantly, high-risk individuals without a formal job[7] face a 13% consumption fall in the same more affected municipalities with larger river shore/farm areas. Thus, non-formal workers, whose income is directly or indirectly dependent on sowing, harvesting, transporting or selling the crops, consume less relatively to similar individuals in unaffected cities, confirming water pollution not only impoverished formal agricultural producers but also families, directly and indirectly, reliant on their outcomes. These economic impacts are related and interact with other consequences of the disaster, such as adverse health outcomes[8] likely to have magnified the economic impact.

We make four contributions to the literature. First, the sizeable economic impact of the Mariana disaster raises a different perspective on the problem of valuing clean water and the benefit/cost of related public policies. Keiser and Shapiro (2019) turn to this problem by exploring the U.S. Clean Water Act, a large and controversial program to restore river water quality, but concludes the program failed to achieve any acceptable cost/benefit ratio[9]. On the other hand, Christensen et al. (2022) explores a poor public policy introduced in the US city of Flint. To save on water treatment, Flint switched its drinking water supply from the Detroit water system to the contaminated waters of the Flint River, exposing residents to dangerous lead levels. Remediation measures worth 400M far exceeded the city savings with this switch (about 5M) and caused a long-lasting fall in home prices. Similarly to the authors, we turn to the problem of assessing clean water value, but we explore an environmental disaster with steep negative externalities to economic activity. Importantly, looking at the economic effects raises a different but related question to policymakers: how much is worth spending on water river surveillance?

Second, our work relates to a stream of the empirical literature assessing the propagation of shocks in supply-chain networks (e.g. Barrot and Sauvagnat, 2016; Carvalho, 2014)[10], particularly following disas-

[7]We define high-risk individuals as those with interest rates on their bank products above the median before the disaster. To identify individuals with formal job relationships, we merge the credit registry data with comprehensive employer-employee data from the Ministry of Labor and Employment.

[8]Matsunaga (2020) finds an increase in mental disorder hospitalizations, 2 to 4 times higher in affected municipalities in the state of Minas Gerais. Rocha et al. (2016) reports a substantial increase in diarrhea (173%), fever (133%), and skin infection (35%) cases in the (affected) riverside population of Colatina, state of Espírito Santo.

[9]She et al. (2020) explore government-oriented environmental regulations on water pollution in China and finds mixed results on their effectiveness. Similarly, Greenstone et al. (2021) finds more effectiveness of regulation on air pollution than in water pollution in China. Using cross-country data, Sigman (2002) finds river water pollution spillovers on country borders, suggesting international environmental treaties are poorly enforced.

[10]See Carvalho and Tahbaz-Salehi (2019) for a comprehensive review on the topic of propagation of shocks in networks.

ters. Boehm et al. (2018) and Carvalho et al. (2020) investigate the economic effects of the 2011 Japanese earthquake on firms' supply chain and document that the disruption caused by the disaster propagated upstream and downstream along the supply chain, affecting suppliers and customers of disaster-stricken firms. Instead, this paper turns to an environmental disaster and a different problem, i.e., water contamination as a production shock to agriculture, with similarly strong downstream effects on firms' supply chains. We also explore a richer dataset, with complete identification of firms and amounts transferred[11].

Third, we explore unique, comprehensive, and identified data on individuals' credit card and consumer credit usage to quantify how disasters affect consumption. Using microdata from tax returns, Deryugina et al. (2018) examine Hurricane's Katrina long-term economic impacts on its victims and finds small and transitory effects on individuals' income. In contrast, the Mariana environmental disaster led to extensive river water pollution with strong effects on individuals' consumption, particularly from more vulnerable citizens. This consumption decline was broad enough to reflect in the performance of the broad services sector in more affected municipalities.

Fourth, we turn to agriculture, its dependence on clean water, soil quality, and related implications. Xiao (2011) explores the 1993 Midwestern flood in the U.S. and finds temporary effects on municipality-level income but persistent effects on agricultural employment and income and concludes rural areas are less resilient to environmental shocks. Our results corroborate these findings. Effects on agriculture are stronger, more persistent, and span to the services sector, in urban areas. On the other hand, industries more easily turn to consumers in outer municipalities mitigating the effects of local consumption decline.

The paper proceeds as follows. Section 2 describes the mining disaster. Section 3 explores effects on GDP, its main components, and crops. Section 4 presents the microdata, Section 5 shows the production shock results, and Section 6 analyzes the consumption shock. Section 7 concludes.

2 The Mariana Mining Disaster

In November 2015, an iron ore tailings dam in Bento Rodrigues, a village in the municipality of Mariana, Minas Gerais, Brazil, suffered a catastrophic failure. This dam contained waste from processing iron ore from mines owned by Samarco, a joint venture of Vale and BHP Billiton, two of the world's largest mining companies. The burst of the Bento Rodrigues tailings dam has broken several negative records, including the volume of residuals released (60 million cubic meters) and run-out[12](600 km). The disaster affected the whole Doce River basin, with 84 thousand km^2 drainage area in the Brazilian States of Minas Gerais and Espírito Santo. The hydrographic basin had a population of around 3.6 million inhabitants in the 2010 census (Instituto Brasileiro de Geografia e Estatistica, 2010). This is the largest environmental disaster in Brazil's history and the largest accident of the kind in terms of residuals released. The second

[11]The aforementioned papers are constrained to the most relevant consumer/supplier or binary information about the existence of a transaction between firms, compromising quantification of the effects.

[12]Run-out is the maximum distance traveled by residuals.

largest happened on August 4, 2014, in the Canadian mine of Mount Polley, in British Columbia, and the volume of residuals reached 17 million cubic meters (Azevedo, 2016).

The burst occurred in the afternoon of November 5, 2015. The rupture released a torrent of sludge with waste, which flowed through three rivers—Gualaxo do Norte, do Carmo and Santarém—and their flood plains for 77 km until it reached Doce River (Agência Nacional de Águas - ANA, 2016). From this point, the mud avalanche stretched to an area of about 1,500 hectares and devastated the village of Bento Rodrigues, where 207 out of 251 buildings were destroyed, and 19 people died (Instituto Brasileiro de Meio Ambiente, 2015; Silva, 2016).

Some kilometers after reaching the Doce River, the flood wave lost part of its strength as approximately 30% the residuals were retained in the Candonga reservoir, which serves the Risoleta Neves hydroelectric power plant, located about 120 km from the accident epicenter (Agência Nacional de Águas - ANA, 2016). After the Candonga reservoir, the wave moved faster and with a lower sediment concentration without causing floods. However, a sediment plume with extremely high turbidity moved slower until reaching the Atlantic Ocean mouth of the Doce River in Linhares, Espírito Santo (Agência Nacional de Águas - ANA, 2016). In total, the waste residuals traveled more than 600 km from the dam to the ocean. According to the Companhia de Pesquisa de Recursos Minerais (2015), the flood wave took 4 days to reach the ocean, while the sediment plume took 17 days. The flood contaminated 170 km of beaches.

On the Brazilian coast, the mudslide also reached the Comboios Biological Reserve, situated between the municipalities of Aracruz and Linhares, at Espírito Santo state. This reserve is a coastal conservation biome that protects the only regular nesting site of the leatherback sea turtle on the Brazilian coast. Furthermore, the mud flood has reached two other federal conservation units: the Environmental Protection Area of Costa das Algas and the Wildlife Refuge of Santa Cruz (Miranda and Marques, 2016). On the ocean coast, it affected beaches and, consequently, tourism (Universidade Federal do Espírito Santo, 2015). Figure 1 shows satellite images before and after the disaster.

Besides dislodging numerous families, the disaster has deeply affected river fishery and compromised access to clean water for hundreds of thousands of residents in riverside communities. The effects on agriculture, which we explore in the following sections, are particularly severe for producers relying on water from the Doce River basin. Water contamination infiltrated the soil, drastically reducing productivity. Livestock breeding was also affected because the sources of livestock drinking water were contaminated. Besides the contamination of the Doce River, there is evidence that artesian wells were also affected by manganese (Mn) and iron (Fe), as reported in Torres et al. (2017). River water contamination lasted at least two years, according to Queiroz et al. (2021).

The economic impact of the disaster was sizable. Using a general equilibrium model, FGV (2020) estimates a negative effect of 6.3% of the disaster on the GDP of the affected areas. This estimation encompasses all effects, including the interruption of mining activities. However, in our study, we are interested in the effects that can be traced to the contaminated waters of the Doce River. While FGV

Figure 1: *Satellite Images before (left panel) and after (right panel) the Mining Disaster. Creative Commons – CC BY 3.0 – Google Earth*

(2020) quantifies the impact of the disaster with a model, we turn to comprehensive data in a difference-in-differences strategy to identify the impacts of contaminated water through the supply chain of agriculture and related effects on consumption. We describe our identification strategy in the following sections.

2.1 Which Municipalities Were Affected?

After the tailings dam failure, in March 2016, Samarco, its shareholders (Vale and BHP Billiton) and 14 public authorities and agencies signed a Framework Agreement (TTAC, *Termo de Transação e de Ajustamento de Conduta* in Portuguese[13]) in order to assure the implementation of the actions required to treat the impacts of the disaster. To implement these compensations, Samarco created the *Fundação Renova*, a not-for-profit private foundation responsible for managing and executing all of the remediation and compensatory measures sated in the recovery plans. In 2023, the *Fundação Renova* is still paying remediation and compensatory measures.

The Framework Agreement delineated the geographic scope of the socioeconomic and socioenvironmental remediation and compensation programs. We identify the municipalities affected by the disaster using the "area of socioeconomic scope" defined in the Framework Agreement, which comprises localities and communities adjacent to the channel of the rivers Doce, Carmo, Gualaxo do Norte and the Santarém creek, in addition to estuarine, coastal and marine areas. This area includes 39 municipalities[14]. Because

[13]available at https://www.fundacaorenova.org/wp-content/uploads/2016/07/ttac-final-assinado-para-encaminhamento-e-uso-geral.pdf

[14]It also includes one small district, Barra do Riacho, belonging to the municipality of Aracruz. As we cannot identify districts in our dataset, we leave it out of our affected list.

we are interested in the externalities of river water contamination, we exclude from this list the municipality of Mariana, the disaster's epicenter. Mariana is an industrial city and was directly affected by the mud avalanche and relevant economic losses related to the Samarco closure. Moreover, we also exclude from the affected list the municipality of Linhares because it is the only coastal city in the sample and differs from the remaining in several aspects used for matching. Therefore, we have a total of 37 treated municipalities in our sample. Appendix A contains a list of all affected municipalities considered in this paper.

The initial 2016 Framework Agreement was followed by further negotiations and litigation regarding repairment and compensations[15]. To address transparency and accountability issues, in June 2018 another Framework Agreement (*TTAC Governanca*) was signed to set up better governance of the reparations process, including greater participation by the affected population. Even after this TTAC, legal action continued, with Public Prosecutor's Offices and Public Defenders' Offices questioning the amount of reparations and advertising expenditures by *Fundação Renova*[16]. After this intense questioning, reparations and compensations amounts, which had increased only slowly from 2016 to 2020, jumped in 2021 (see Figure 2).

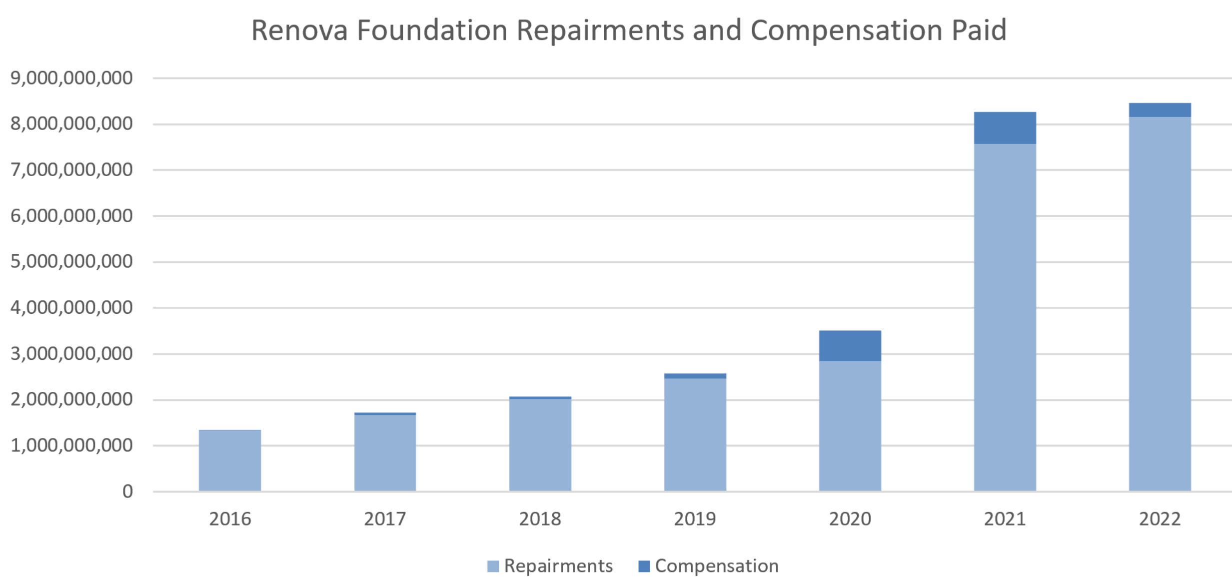

Figure 2: *Reparations and Compensation in Brazilian Reais. Source: Renova Foundation.*

We were not able to obtain reparations and compensation amounts by municipality[17], and we are not able to control for this in our econometric setup. Therefore, our estimates for the effects are likely to be downward biased. Most of our analyses is carried out until 2018, prior to the Brumadinho disaster and before the bulk of the reparations (75%) was implemented.

[15] Repairment refers to the actions targeted to the directly affected actors and infrastructure. Compensation includes more general actions to improve affected areas like road building or education programs.

[16] See the public civil suit: https://defensoria.mg.def.br/wp-content/uploads/2021/05/ACP-propaganda-assinada-protocolo.pdf.

[17] The authors made several attempts to contact *Fundação Renova* and obtain the data, but without success.

2.2 Municipality Matching Procedure

We run a propensity score matching (PSM) at the municipality level in order to build the control group. The search for control group municipalities is performed over the two affected states, Minas Gerais and Espírito Santo. We exclude from the PSM municipalities located in the 8 micro-regions where affected municipalities are located since these adjacent municipalities are also likely to be indirectly affected through spillovers. Moreover, we exclude one ocean coast municipality from PSM[18]. Thus, we load PSM with 400 municipalities to build the control group.

The variables used in the PSM are the following: population, GDP per capita, the share of agriculture in GDP, water area, farming area, the share of the urban area to total municipality area, share of the irrigated area to farming area, and the ratio of water area to farming area. These variables are devised to produce control municipalities of similar size, similar economic dependence on agriculture, similar river water extension, and similar farming area. In this way, our treated and control groups should be comparable not only in terms of socioeconomic characteristics but also in terms of land usage and water landscape.

After the PSM procedure, we ended up with a sample of 190 municipalities, 37 affected and 153 control municipalities. All regressions are further estimated with the related municipality weights.

Besides affected and control groups, we have a set of outer municipalities, composed of the PSM unmatched and municipalities in other states of Brazil[19].

2.3 Municipality Summary Statistics

In Table 1, we show municipality-level summary statistics. Population and GDP-related variables are available from the *Instituto Brasileiro de Geografia e Estatística* (IBGE) reports of 2014, except for IDH and Gini coefficients from the 2010 census. Variables related to land cover and usage are extracted from MapBiomas project (collection 6.0), also from 2014. Irrigation area data come from the *Atlas da Irrigação* published by *Agencia Nacional de Aguas* (ANA)[20].

Table 1 shows the mean and standard deviation for variables in both affected and unaffected (matched) municipalities. For all variables, the test for the difference in the mean of affected and unaffected municipalities does not reject the null hypothesis of equal means. It is important to highlight that the share of agriculture in the GDP is similar in affected (0.133) and unaffected (0.118) municipalities. Thus, the relative economic importance of agriculture in these two groups is comparable. The municipalities are also

[18]Our water variables may not be representative in the case of ocean water, which is not used for farming. Our only affected coastal city is removed for consistency.

[19]We use inflows from outer municipalities to proxy for income. The adjacent municipalities, in the 8 micro-regions of the Doce River basin, are totally excluded, as well as Mariana and Linhares, the only ocean coast affected municipality.

[20]The irrigation "atlas" was first published in 2017 with 2015 data. Thus, data from previous years are not available. We cannot guarantee data collection precedes November 2015 in the states of Minas Gerais and Espirito Santo. This "atlas" is not periodical, but a second one was published in 2021 with 2019 data. See more in https://metadados.snirh.gov.br/geonetwork/srv/por/catalog.search/metadata/c639ac44-8151-421d-a1ed-c333392d76a9

comparable among other dimensions not explicitly introduced in the matching procedure, such as human development (IDH) and income concentration (Gini coefficient). Importantly, cities are also comparable in terms of the relative importance of their six main crops, which altogether represent over 91% of the total farmed area in affected municipalities.

Table 1: *Municipality-level Summary Statistics*

	Unaffected		Affected	
	Mean	Std. Dev.	Mean	Std. Dev.
Panel A: Economic Variables				
Population	36,187	77,713	32,519	62,339
GDP Level (R$ thous.)	695,194	2,323,223	712,938	1,753,052
GDP per Capita (R$)	13,247	7,912	13,092	8,559
IDH	0.674	0.049	0.669	0.039
Gini Index	0.479	0.056	0.477	0.044
Agricultural GDP (share)	0.118	0.084	0.133	0.088
Panel B: Land Use and Cover Variables				
Farming Area (ha)	35,641	41,345	39,017	40,262
Water Area (ha)	945	2,591	749	723
Water Area/Farming Area	0.028	0.062	0.029	0.031
Water Area (share)	0.016	0.037	0.017	0.010
Urban Area (share)	0.035	0.093	0.018	0.049
Irrigation Area (share)	0.023	0.059	0.029	0.068
Panel C: Land Use variables for Crops (% of total area)				
Main crops (%)	86.836	23.775	91.931	12.996
Corn (%)	33.734	21.679	34.327	22.430
Coffee (%)	19.883	27.063	20.690	29.341
Beans (%)	12.475	11.522	13.532	12.095
Sugar cane (%)	10.686	15.340	13.934	22.359
Banana (%)	5.104	12.911	3.282	8.022
Manioc (%)	4.954	8.578	6.166	12.556
# Municipalities	153		37	

Notes: For all variables, the test for the difference in the mean of affected and unaffected municipalities does not reject the null hypothesis of equal means.

3 Aggregated Analysis

In this section, we turn to the aggregated real effects of the disaster using municipality-level data. We estimate a standard difference-in-differences (DiD) taking as pre-period the three years before the disaster (2013-2015) and as post-period the following three years (2016-2018). We consider a baseline specification and an additional with the Water/Farm area interaction, which serves as a proxy for farm land exposure to water pollution[21]. The more complete specification is the following:

$$\begin{aligned} y_{m,t} =& \beta \text{ Affected}_m \cdot \text{Post}_t + \gamma \text{ Post}_t \cdot \text{Water/Farm Area}_m \\ & + \theta \text{ Affected}_m \cdot \text{Post}_t \cdot \text{Water/Farm Area}_m + \delta_m + \zeta_t + \varepsilon_{m,t}, \end{aligned} \tag{1}$$

in which m is the municipality, t is a three-year time period (either 2013-2015 or 2016-2018), Affected_m is equal to one if municipality m was affected by the disaster, and zero if it is a matched municipality, $y_{m,t}$ is the three-year cumulative GDP for municipality m or related components in log format. The dependent variables $y_{m,t}$ are GDP, and its three main components, the value-added from agriculture, services, and industry. Water/Farm area_m is the ex-ante ratio of freshwater to the farming area, which has been de-meaned and standardized to facilitate interpretation. The interaction of Affected_m with Water/Farm Area_m and Post_t explores real effects in municipalities more exposed to water pollution. The regressions use municipality (δ_m) and time (ζ_t) fixed effects, and standard errors are clustered at the municipality level.

The baseline results are in the odd columns of Table 2. It depicts strong negative effects of -14% on the agriculture GDP (i.e., the value-added from agriculture in log format) for affected municipalities relative to (matched) unaffected municipalities three years after the disaster (Column 1). However, baseline coefficients are not statistically significant for industry (column 3), services (column 5), or broad municipality-level GDP (column 7). Our empirical evidence shows that the shock directly and strongly affected the agriculture sector.

Nonetheless, heterogeneities related to water contamination exposure are relevant. In order to explore this channel, we add interactions with $\text{Freshwater/Farm Area}_m$ to the baseline regressions to check whether municipalities with more ex ante shore water area relative to farm area are more deeply affected. The triple interaction coefficient θ from Affected_m * Water/Farm Area_m * Post_t in Table 2 shows negative values across all sectors and is statistically significant for agriculture, services, and overall GDP. In this way, municipalities more reliant on freshwater (with one standard deviation higher Water/Farm Area) faced an additional 18% fall in agricultural GDP (column 2) relative to unaffected municipalities with a similar

[21] The ideal proxy would be the shore area effectively dedicated to farming. But Mapbiomas, our information source, provides only municipality-level proxies of areas (in ha) estimated from satellite images. As a consequence, we take the total water area and total farming area to create this proxy. Other water sources, such as lakes, are included, but the Doce River is the largest in the region.

shore to farming area[22]. Moreover, we find economic spillovers to the services sector on more affected municipalities, as coefficient θ indicates a 6% relative fall in services (column 6) and a broad 7% drop for the overall GDP (column 8). Thus, municipalities more exposed to water pollution face negative effects beyond agricultural activities, suggesting a fall in consumption that we explore with microdata in the following sections.

Table 2: *GDP Effects*

Dependent Variable:	Agric. GDP	Agric GDP	Indust. GDP	Indust. GDP	Serv. GDP	Serv. GDP	Overall GDP	Overall GDP
Specification:	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Variables								
Affected$_m$ × Post	-0.14**	-0.06	-0.04	-0.06	0.00	0.03	-0.02	0.00
	(0.068)	(0.101)	(0.057)	(0.057)	(0.017)	(0.023)	(0.015)	(0.019)
Post ×		0.05*		-0.01		0.00		0.02**
Water/Farm area		(0.031)		(0.029)		(0.007)		(0.011)
Affected$_m$ × Post ×		-0.18*		-0.04		-0.06**		-0.07***
Water/Farm area		(0.101)		(0.118)		(0.026)		(0.025)
Fixed effects								
Municipality	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Post	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Statistics								
# Observations	380	380	380	380	380	380	380	380
R-squared	0.951	0.953	0.985	0.985	0.998	0.999	0.998	0.998
# Municipalities	190	190	190	190	190	190	190	190
# Affected Muni	37	37	37	37	37	37	37	37

Note: This table reports results for specification (1) at the municipality level. The dependent variable is the cumulative 3-year municipality GDP and its main components. Standard errors in parentheses are clustered at the municipality level. *, **, *** denote statistical significance of 10%, 5%, and 1%, respectively.

To consider possible pre-trends in agriculture GDP, we run an econometric specification with dynamic coefficients for Affected$_m$, i.e., we interact Affected$_m$ with each year dummy from 2010 to 2018. The year 2014 is the base-case year. Figure 3 shows that there is no pre-trend and that the intensity of the relative negative effects is growing over time.

These negative effects are even more pronounced when we analyze the land area used for agriculture. Figure 4 depicts the dynamic coefficients using the agricultural land area as the dependent variable. We see a sharp decline in the area used for agriculture in the affected municipalities. Importantly, the steep decline in land usage for farming (Figure 4) in affected municipalities suggests the fall in Agriculture GDP is more related to quantity than to price (Figure 3).

The planted areas dedicated to the main three crops in affected municipalities—corn, coffee, and

[22] Water/Farm Area$_m$ has been de-meaned and standardized to facilitate interpretation of the real effects in all Tables.

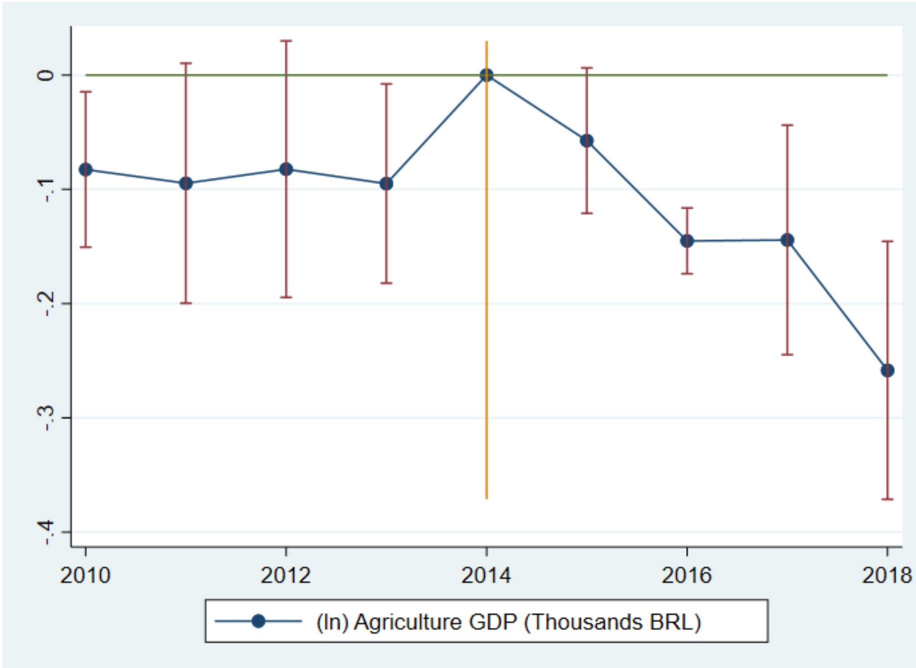

Figure 3: *This figure shows the effects on the Agriculture GDP of the Mariana disaster. The horizontal axis indicates the year, and the vertical axis encodes the coefficient estimates of Affected$_m$ interacted with the respective year(solid blue points) and the associated 95% confidence interval (vertical red bars), all relative to the observed value in 2014 (reference).*

beans—declined drastically in the years following the disaster (Figure 5), but compositional changes across crops are relevant. As we can see in the lower right graph of Figure 5, sugarcane had a steep increase in 2017 and 2018. There are two important reasons for the sugar cane increase. First, in Brazil, sugar cane is used for ethanol production, and most automobiles can run on ethanol fuel. Heavy metal contamination becomes negligible if production is to be fermented into ethanol rather than consumed as sugar (Wang et al., 2017a). Second, sugar cane crops can be used for phytoremediation[23] of the soil. Empirical evidence by Wang et al. (2017b) shows that heavy metal soil concentration declines with sugarcane phytoremediation as compared to areas without sugarcane treatment.

One important issue in agricultural area usage is the timing of changes. The accident happened in November 2015, compromising mostly future outputs. Perennial crops like coffee—the most important in the region—take time, effort and resources to be first removed and then replaced, which helps explain the strong reduction of coffee planted areas only in 2017 and 2018, as shown in Figure 5.

Overall, this section suggests the disaster directly affected agriculture, with stronger effects on more exposed municipalities (i.e., with more freshwater-to-farm area ratio). There are also implications for consumption reflected in the services sector. In the following sections, we turn to microdata for clearer identification of these effects.

[23]Phytoremediation is a technique that uses plants to clean up contaminated environments. Certain crops can help clean up many types of contaminants, including metals, pesticides, explosives, and oil.

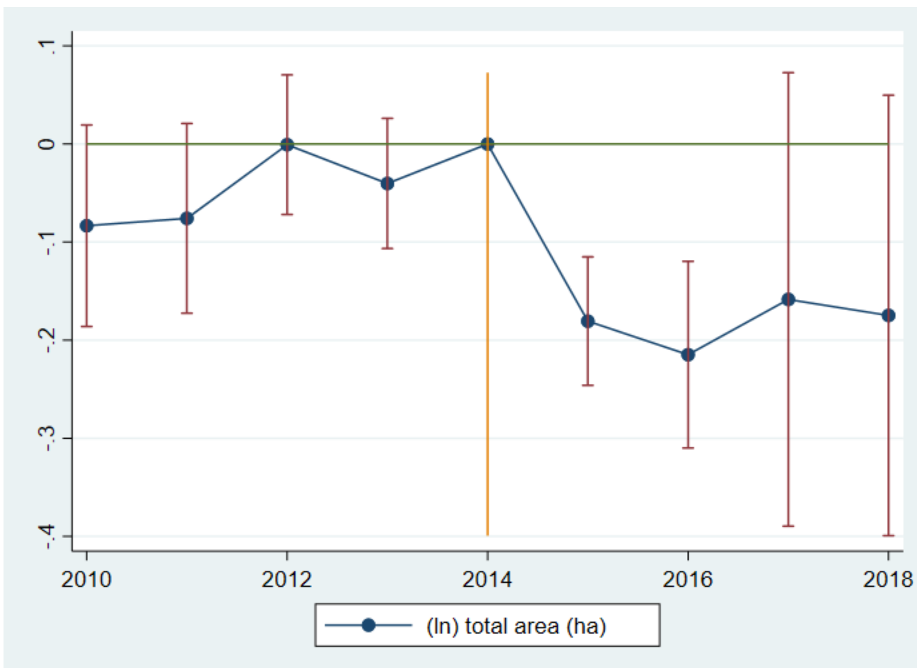

Figure 4: *This figure shows the effects on the Land area used for agriculture. The horizontal axis indicates the year, and the vertical axis encodes the coefficient estimates of Affected$_m$ interacted with the respective year(solid blue points), and the associated 95% confidence interval (vertical red bars), all relative to the observed value in 2014 (reference).*

Figure 5: *This Figure shows the effects of the Mariana disaster on the planted area for the six main crops. The horizontal axis indicates the year, and the vertical axis encodes the coefficient estimates of Affected$_m$ interacted with the respective year(solid blue points), and the associated 95% confidence interval (vertical red bars), all relative to the observed value in 2014 (reference).*

4 Microdata Description

To explore the externalities of the disaster to the real economy, we combine two micro-data sources: the payment system and the credit registry augmented with employer-employee data. The aforementioned municipality-level controls from IBGE and Census are also introduced. We explore these data and related identification strategies in the two following subsections: (4.1) Payment System and (4.2) Credit Registry.

4.1 Payment System

The Brazilian Payment System, more specifically the *Sistema de Transferência de Reservas* (STR) and *Sistema de Transferência de Fundos* (CIP-Sitraf), are our main datasets. Both STR and CIP-Sitraf are real-time gross settlement payment systems that record all electronic interbank transactions in Brazil above a certain limit (set to 1 cent in 2016). The data contain information on the date of the transaction and identifiers for "creditors" and "debtors," i.e., the tax id of cash receivers and payers, respectively. We use these transaction-level data to measure cash inflows and outflows across identified firm pairs, which proxies for amounts received and paid by each firm due to ordinary business.

For identification, we focus on transactions between firms in the affected or unaffected control municipalities against those outside these areas (the outer group described in section 2.2), thus eliminating transactions between and inside affected and control groups. We also eliminate all transactions with the public sector, the financial sector, NGOs, and firms related to mining activities. Including those does not change our main results.

Following the direction of money transfers, we are able to classify firms as suppliers or customers and navigate their supply chains. Suppliers are receivers of money and therefore are on the creditor side of the monetary transaction in the payment system. Customers are those transferring money, thus on the debtor side of the transaction.

We navigate *downstream* in the supply chain to identify firm income focusing on transactions between suppliers in affected/unaffected municipalities and its customers in outer municipalities (i.e., "local" exports). A rich set of customer fixed effects captures all remaining firm-level demand shocks, sharpening the identification of the *production shock* to firms in the affected/unaffected area[24].

4.2 Credit Registry data

For identification of the *consumption shocks*, we turn to the Brazilian Credit Registry, *Sistema de Informações de Crédito* (SCR), which tracks credit operations in Brazil. SCR is provided and managed by the Central Bank of Brazil in its role as bank supervisor, and records identified loan-level transactions between firms or individuals and all financial intermediaries in Brazil. Each financial intermediary

[24] The identification strategy follows Khwaja and Mian (2008) but applied to payment data instead of loan-level data.

reports monthly all credit exposures above a certain threshold to SCR[25]. The data include bank and individuals' tax ID numbers and loan-level characteristics, such as credit type, interest rates charged, limits, and drawn/undrawn credit amounts. We take data on drawn consumer credit (including from non-interest-bearing credit card expenditures)[26] to proxy individual-level consumption. Finally, we augment the dataset with employer-employee information from *Relação Anual de Informações Sociais* (RAIS), containing detailed information on formal job relationships including income, sex, type of job contract, and occupation, all matched by the tax ID of both employer and employee. This registry is available from the Ministry of Labor and Employment in its role as labor supervisor. Because providing information to RAIS once a year is mandatory for all firms[27], we take all individuals not matched as non-formally employed.

5 The Production Shock

This section analyzes the effects of the mining disaster on supply chains, i.e., the negative production shock on suppliers in affected areas. We resort to transaction-level (firm-to-firm) payment data, observing bilateral monetary flows between economic agents: the *customer*, the transaction payer/debtor (who pays money and receives products), and the *supplier*, the transaction receiver/creditor (who receives money and provides products).

We focus on transactions between *supplier firms* either in the affected (treatment group) or unaffected (control group) municipalities with *customer firms* in the outer area, i.e., located in municipalities other than those in our treatment or control group. Thus, our empirical strategy eliminates transactions between customer and supplier firms within affected and unaffected groups for clear identification of the mining disaster as a production shock on local producers selling to outside customers (not affected by disaster-related demand contraction). To ensure that electronic transfers primarily reflect the flow of goods and services, we exclude firms from the public administration and financial sectors. Additionally, we eliminate firms from the mining sector[28] to capture the water value to local riverside economies and not direct effects of the dam collapse, which also halted municipalities such as Mariana, very dependent on the performance of the mining industry.

Since the mining disaster deeply affected the agricultural sector, we first focus on the affected agricultural producers. We build the following event study to examine affected agri-firms (suppliers located in municipalities bordering the Doce River) and unaffected agri-firms (suppliers located in matched unaffected

[25]Up to June 30, 2016, this threshold limit was BRL 1,000 (USD 300), and after it became BRL 200 (USD 300) or more. Therefore, most of the data we assess have been retrieved under this rule.

[26]We do not observe credit card transactions, only end-of-month total drawn amounts from each individual credit card account. This information is available only for credit cards issued by financial institutions under the supervision of the Central Bank of Brazil.

[27]RAIS is an end-of-year picture of all formal job relationships in the country but contains detailed information on job changes across the year, including dates of job creation and termination. We use these data to create the picture of September 2015 and merge it with the credit registry. Thus, having a formal job relationship is measured at this point.

[28]This includes firms directly affected by the disaster, such as Samarco and its controllers, Vale and BHP Billiton, as well as all firms in the mining sector.

but similar municipalities, i.e., the downstream effects)[29]:

$$\ln\left(y_{c,s,m,t}\right) = \zeta \text{ Affected}_s + \sum_{\substack{k\in\mathscr{T} \\ k\neq 2015Q3}} \beta_k \, \mathbb{1}_{\{k=t\}}\text{Affected}_s + \sigma \text{ Controls}_{s,m} + \eta_{\text{sec}(c),\text{muni}(c)} + \gamma_t + \varepsilon_{c,s,m,t}, \quad (2)$$

in which c indexes the outside customer firm (located in outer municipalities, of any economic sector), s the inside agricultural supplier in affected or unaffected (matched) municipalities m, and t time (quarters). $\mathbb{1}_{\{\text{argument}\}}$ is the indicator function that yields one when the argument is true, and zero otherwise. $\mathscr{T} = \{2013Q1, 2013Q2, \ldots, 2018Q4\}$. The dependent variable is the volume of payments from the outside customer firm c to the inside agricultural supplier s during the year-quarter t. The binary dummy variable Affected_s is equal to one when the supplier s's municipality borders the Doce River in the path of the mudwave caused by the Mariana dam collapse and zero when the supplier s is in a matched unaffected municipality. The vector $Controls_{s,m}$ includes the following set of control variables with values fixed before the mining disaster: supplier s's number of inflow transactions (which serves as a proxy of size); and supplier's municipality-level controls: population (in log), GDP *per capita*, freshwater to farming area ratio, urban and farming areas as a share of the total municipality's area, value-added in agriculture as a share of GDP, and irrigated area as a share of farm area $\varepsilon_{c,s,t}$ is the error term. Standard errors are clustered at the municipality and time dimension. The fixed effects customer sector $\times$ municipality $\eta_{\text{sec}(c),\text{muni}(c)}$ serve as demand controls (in the spirit of Degryse et al., 2019) and proxy for differential local demand for agricultural outputs in outer cities.

We also introduce a set of pulse time dummies β_k from 2013Q1 to 2018Q4 in equation (2) to examine how payments from outside customers to inside producers behave before and after the dam collapse. We take as reference the year-quarter 2015Q3, which is the quarter before the disaster of November 5^{th}, 2015. A necessary and testable condition is that these payments should trend similarly before the disaster, i.e., $\beta_k = 0$ before the disaster. Our identification hypothesis is that such a variable would have trended similarly between affected and unaffected supplier agri-firms *ex-post* in the absence of the mining disaster (non-testable).

Figure 6 displays β_k. Electronic transfers from outside customers to affected agri-firms are not statistically different from those of unaffected municipalities in the quarters preceding the mining disaster. However, β_k reduced steeply following the dam collapse, confirming the income of the agricultural sector in affected municipalities was deeply affected.

We extend the downstream analyses with a difference-in-differences (DiD) approach concentrating on the three years before and after Mariana's dam collapse. We aggregate three-year payments of every pair of $\langle\text{customer}, \text{supplier}\rangle$ before and after the dam collapse, resulting in two observations for each pair

[29] See more on Boehm et al. (2018) and Carvalho et al. (2020).

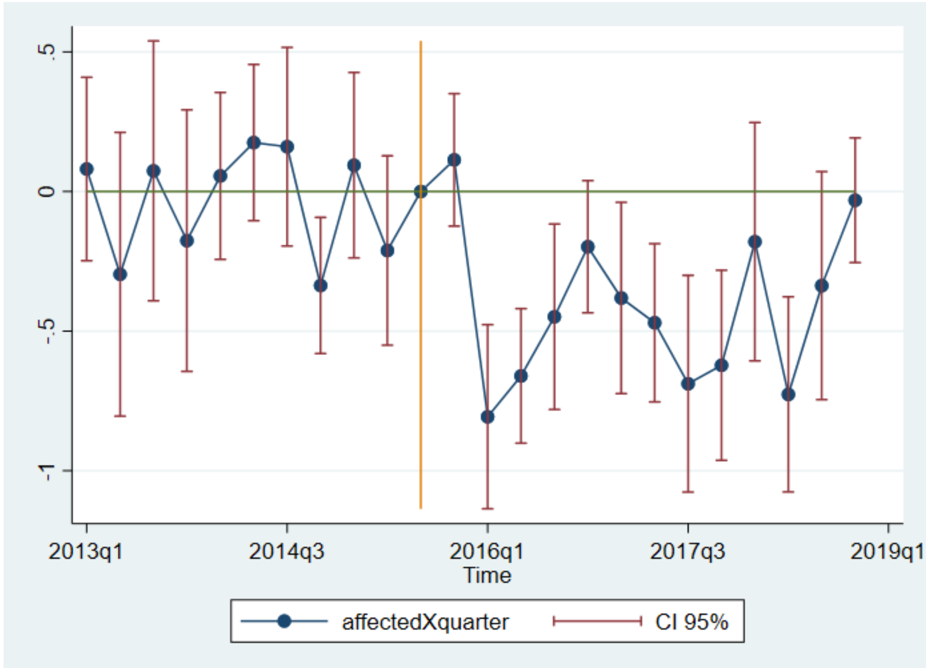

Figure 6: *Event study on electronic transfers from outside customers to inside agri-firms in affected and (matched) unaffected municipalities before and after Mariana's dam collapse in 2015Q4. The horizontal axis indicates year-quarter, and the vertical axis encodes the coefficient estimates of β_k in Specification (2) (solid blue points), the associated 95% confidence interval (vertical red bars), all relative to the reference value of 2015Q3 (yellow bar).*

(*ex-ante* and *ex-post* the event). Thus, this setup reduces to a traditional two-period DiD analysis, which we operationalize with the following econometric specification:

$$\ln(y_{c,s,m,t}) = \zeta \text{ Affected}_s + \lambda \text{Post}_t + \beta \text{ Post}_t \cdot \text{Affected}_s + \sigma \text{ Controls}_{c,s,m} + \kappa_c + \varepsilon_{c,s,m,t}, \tag{3}$$

in which c, s, m, and t index the outside customer firm (located in outer municipalities, from any economic sector), the inside supplier firm (affected or matched municipalities, from any economic sector), the affected/unaffected municipality and time (two periods: before and after the dam collapse), respectively. The binary dummy variable Post$_t$ equals one when t is after the dam collapse (2016Q1–2018Q4), and zero otherwise (2013Q1–2015Q4). As we expect water-dependent sectors to be hit harder by water contamination, we start by analyzing agriculture and then industry and services. We provide summary statistics for the sub-sample of firms in the agricultural sector in Table 3. Our coefficient of interest in equation (3) is β, which captures the effect on suppliers' cash inflows (income) from outside customers to agricultural producers in affected relatively to unaffected municipalities after the shock.

Columns (I) to (IV) of Table 4 show coefficient estimates for variations of the baseline downstream regression (3) in the agricultural sector. Column (I) shows a baseline regression without controls or fixed effects. Column (II) introduces municipality-level controls, and Columns (III) and (IV) demand controls (customer sector × municipality fixed effects). In Column (V), we introduce customer fixed effects, i.e.,

Table 3: Summary Statistics: Payment Transactions

	P1	P10	P50	Mean	P90	P99	Std. Dev.
Dependent variable							
ln(inflows)	5.93	8.41	11.41	11.36	14.31	16.27	2.30
Main independent variable							
Affected Municipality	0.00	0.00	0.00	0.28	1.00	1.00	0.45
Control variables							
Water/Farm area	0.00	0.00	0.01	0.04	0.07	0.32	0.07
Irrigation area (Share)	0.00	0.00	0.01	0.03	0.05	0.12	0.07
Population (ln)	8.30	8.87	10.94	10.70	12.53	12.87	1.28
GDP *per capita*	5779.16	8227.43	15821.78	16635.31	28448.78	40871.77	7578.34
Agriculture GDP (share)	0.00	0.01	0.08	0.10	0.26	0.29	0.09
Farm/Municipality area (share)	0.15	0.35	0.68	0.62	0.80	0.89	0.18
Urban/Municipality area (share)	0.00	0.00	0.01	0.03	0.04	0.27	0.06
Number of transactions	1.00	1.17	2.48	3.77	6.79	19.35	4.87
Observations			2,263				

Notes: This downstream summary represents the sample of consumer firms in outer municipalities that buy simultaneously from at least two agricultural producers in affected/unaffected municipalities. On downstream regressions, we explore the effects of the Mariana disaster on supplying firms (producers). Hence, the dependent variable, Log(Inflows$_{s,c,m,t}$), is the natural logarithm of total payment inflows to each supplying firm s in an affected or unaffected municipality m from an outer consumer firm c, i.e. it proxies for firm s local exports. For identification, we consider only consumer firms outside the Doce River. We accumulate the inflows of 2016, 2017 and 2018 in the post period and the inflows of 2013, 2014 and 2015 in the pre-period. N transactions is the average number of electronic transfers a producer used to receive up to 2015, which serves as a proxy of producer size. The municipality-level controls are taken from December 2014 except for irrigation, which is from 2015.

one fixed effect for each consumer firm, which fully controls for demand at the firm level (in the spirit of Khwaja and Mian, 2008). It should be noted that the number of customers falls by half after this additional layer of demand controls is imposed.

Our results show that agriculture suppliers in affected municipalities received on average 40 to 64% less payments from outside customers than agriculture suppliers in (matched) unaffected areas in the three years following the dam collapse.

Even among riverside municipalities impacted by the mud wave, the damage caused by water contamination may vary depending on the shore extension. We explore this heterogeneity again by using the municipality's ratio of freshwater area to the farming area. The higher this value, the (likely) greater the dependence of local agricultural activities on the river freshwaters[30]. We use the following empirical specification to characterize this heterogeneity:

[30]Strictly speaking, the freshwater area may also include other local river systems that traverse the areas of the affected municipalities. However, the Doce River basin is the largest in the region. Moreover, we exclude municipalities with ocean coasts, and our proxy effectively measures the dependency of the municipality's agricultural activities on the Doce River water.

Table 4: Payment Transaction Data: Effects of the Mining Disaster on Agriculture

Dependent variable:	$\ln\left(\text{Outside Customer}_c \xrightarrow[\text{flows}]{\$} \text{Inside Supplier}_s\right)$				
Specification:	(I)	(II)	(III)	(IV)	(V)
Variables					
Affected$_s$	0.12	0.25	0.51*	0.46	0.42
	(0.240)	(0.317)	(0.282)	(0.277)	(0.269)
Post$_t$	-0.27**	-0.24**	-0.11	-0.10	-0.06
	(0.114)	(0.106)	(0.091)	(0.088)	(0.092)
Post$_t$ $\times$ Affected$_s$	-0.64*	-0.61*	-0.41*	-0.28	-0.03
	(0.358)	(0.341)	(0.224)	(0.229)	(0.174)
Post$_t$ $\times$ Affected$_s$ $\times$ Water/Farm area$_s$				-0.26*	-0.32**
				(0.152)	(0.133)
Affected$_s$ $\times$ Water/Farm area$_s$				0.05	0.08
				(0.135)	(0.121)
Post$_t$ $\times$ Water/Farm area$_s$				-0.07	-0.07
				(0.081)	(0.082)
Fixed effects and controls					
Controls	No	Yes	Yes	Yes	Yes
Demand Controls	No	No	Yes	Yes	—
Customer Firm FE	No	No	No	No	Yes
Statistics					
Observations	2,899	2,899	2,899	2,899	2,263
R-squared	0.02	0.17	0.59	0.59	0.67
N suppliers	486	486	486	486	443
N customers	1,321	1,321	1,321	1,321	685
N cities	108	108	108	108	101
N affected cities	20	20	20	20	20

Note: This table reports coefficient estimates for variations of the baseline downstream specification in (3) (Columns (I)–(III)) and (4) (Columns (IV)–(V)) at the electronic transaction level. The dependent variable is the sum of all electronic transfers observed between each customer c outside the affected (treatment group) and the matched unaffected municipalities (control group) to inside agri-firm suppliers s. We aggregate payments in two periods t: the *ex-ante* period (2013Q1–2015Q3) and the *post* period (2016Q1–2018Q4). The binary dummy variable Affected$_s$ is equal to one when supplier s's municipality borders the Doce River in the downstream path of the mudwave caused by the Mariana dam collapse and zero when the supplier s is in a matched unaffected municipality. The vector $Controls_{c,s,m}$ includes the following set of control variables with values fixed before the mining disaster, the number of electronic transactions received by the supplier s, and the following supplier's municipality controls: population (in log), GDP *per capita*, freshwater as a share of the total farm area, urban and farming areas as a share of the total municipality's area, value-added in agriculture as a share of GDP, and irrigated area as a share of the farm area. Demand controls represent customer's industry $\times$ municipality fixed effects. All controls are winsorized at the 1% level and Water/Farm area is de-meaned and standardized to facilitate interpretation of the real effects. Standard errors are three-way cluster to accommodate possible demand shocks from the consumer, thus we use the supplier's municipality and sector as well as the consumer's municipality. *, **, *** denote statistical significance of 10%, 5%, and 1%, respectively.

$$
\begin{aligned}
\ln\left(y_{c,s,m,t}\right) = \zeta\ \text{Affected}_s + \lambda \text{Post}_t + \beta\ \text{Post}_t \cdot \text{Affected}_s + \\
+ \delta\ \text{Post}_t \cdot \text{Water/Farm area}_s + \gamma\ \text{Affected}_s \cdot \text{Water/Farm area}_s + \\
+ \theta\ \text{Post}_t \cdot \text{Affected}_s \cdot \text{Water/Farm area}_s + \sigma\ \text{Controls}_{s,m} + \kappa_c + \varepsilon_{c,s,t},
\end{aligned}
\tag{4}
$$

in which c, s, m, and t index the outside customer firm, the inside supplier firm, the supplier´s municipality, and time, respectively. Our prediction is that θ is negative, meaning that the municipality's dependency on freshwater acts as an amplifying transmission channel of the water contamination to firms located in affected municipalities.

Columns (IV) and (V) of Table 4 show the coefficient estimates of equation (4). These results are statistically and economically significant. Freshwater/farm area has been de-meaned and standardized to facilitate the interpretation of results. Agricultural producers (suppliers) in more affected municipalities (one standard deviation higher water/farm area ratio) experience an additional reduction in their cash inflows (income) from outer customers of 26% to 32% compared to suppliers equally dependent on river freshwater in unaffected municipalities. In column (V), we introduce customer fixed effects, thus relative to the same consumer firm, agricultural producers in more affected cities and similarly dependent on river water face 32% fall in cash inflows.

We highlight that the DiD coefficient $\text{Post}_t \times$ Affected_s becomes insignificant once the freshwater heterogeneity is introduced, indicating that the extension of freshwater contamination on the soil used for agriculture is the main driver of the production shock to agriculture. The abrupt inflow reduction to affected suppliers reveals the devastating impact of water contamination on water-dependent agricultural activities.

Importantly, agriculture, particularly in this region, is largely informal. Although we find data on agricultural GDP and crops in all affected and unaffected cities from IBGE, we could find formal agricultural producers in only 20 of our affected municipalities (Table 4). In Appendix B1, we provide robustness tests running Column (V) in different windows of DiD, i.e., using not only a three-year window but also one, two, and four years before and after the disaster. The results are in line.

We also provide empirical evidence of the effects of water contamination on other economic sectors in Table 5. Again, our focus is on "local exports," as all customers are outside the affected areas and not affected by the disaster. We should not find any negative spillover effects, because the production shock does not directly affect industries (other than mining) and services (typically non-tradable and driven by local demand).

Columns (I) and (III) of Table 5 show coefficient estimates of equation (3) for supplier firms in the industry (I) and services (III) sectors. There is no effect on services but a positive economically and statistically significant effect of 13% on industries as the tradable sector more easily shifts production to outer municipalities. We also explore the municipality's dependence on freshwater as a source of heterogeneity in Columns (II) and (IV). Again, positive effects measured by θ in equation (4) are stronger in more affected municipalities (those with one standard deviation higher freshwater/farm area ratio) but only in the industry. After the disaster, the average industrial firm in more affected municipalities exports 15% more (Column II). This result helps explain why the aggregated effects in the industry are more muted in Table 2.

Table 5: Payment Transaction Data: Effects of the Mining Disaster on Industry and Services

Dependent variable:	$\ln\left(\text{Outside Customer}_c \xrightarrow[\text{flows}]{\$} \text{Inside Supplier}_s\right)$			
Sample:	Industry		Services	
Specification:	(I)	(II)	(III)	(IV)
Variables				
Affected$_s$	-0.05	-0.06	-0.04*	-0.07***
	(0.045)	(0.047)	(0.027)	(0.024)
Post$_t$	-0.40***	-0.40***	-0.54***	-0.54***
	(0.043)	(0.034)	(0.035)	(0.036)
Post$_t$ × Affected$_s$	0.13**	0.13**	-0.00	0.00
	(0.061)	(0.055)	(0.027)	(0.030)
Post$_t$ × Affected$_s$ × Water/Farm area$_s$		0.15***		0.03
		(0.028)		(0.032)
Affected$_s$ × Water/Farm area$_s$		-0.10*		-0.09***
		(0.057)		(0.033)
Post$_t$ × Water/Farm area$_s$		-0.07***		-0.00
		(0.012)		(0.010)
Fixed effects and controls				
Controls	Yes	Yes	Yes	Yes
Customer Firm FE	Yes	Yes	Yes	Yes
Statistics				
Observations	170,444	170,444	475,952	475,952
R-squared	0.53	0.53	0.45	0.45
N suppliers	14,431	14,431	54,670	54,670
N customers	34,791	34,791	65,552	65,552
N cities	174	174	190	190
N affected cities	34	34	37	37

Note: This table reports coefficient estimates for variations of the baseline downstream specification in equation (3) (Columns (I) and (III)) and equation (4) (Columns (II) and (IV)) at the electronic transaction level. The dependent variable is the sum of all electronic transfers observed between each outer customer c and supplier s of the industry and services sectors in either affected or (matched) unaffected municipalities. We aggregate payments in two periods t: the *ex-ante* period (2013Q1–2015Q4) and the *ex-post* period (2016Q1–2018Q4). The binary dummy variable Affected$_s$ is equal to one when the supplier s's municipality borders the Doce River in the downstream path of the mudwave caused by the Mariana dam collapse and zero when the supplier s is in a matched unaffected municipality following the methodology in Section 2.2. The vector $Controls_{s,m}$ includes the following set of control variables with values fixed before the mining disaster, the number of electronic transactions received by the supplier s as well as the following supplier's municipality controls: population (in log), GDP *per capita*, freshwater as a share of the total farm area, urban and farming areas as a share of the total municipality's area, value-added in agriculture as a share of GDP, and irrigated area as a share of the farm area. All regressions have customer fixed effects. All controls are winsorized at the 1% level and de-meaned and standardized to facilitate interpretation of the reall effects. Standard errors are three-way cluster to accommodate possible demand shocks from the consumer, thus we use supplier's municipality and sector as well as consumer's municipality. *, **, *** denote statistical significance of 10%, 5%, and 1%, respectively.

6 The Consumption Shock

In this section, we explore the effects on households' consumption. Results of Section 3 show more affected municipalities faced an average aggregate decline in the services sector of 6% (Table 2). These firms were also unable to compensate the lack of income with exports, possibly due to its non-tradable nature (Table 5). If individuals consume less in more affected municipalities, with consequences for their broad services' performance, it should be possible to find these effects turning to consumer credit data from individuals located in affected and unaffected municipalities.

We start by analyzing an event study of the consumption effects on affected municipalities quarter by quarter using the following econometric specification:

$$\ln\left(y_{i,m,t}\right) = \zeta \text{ Affected}_i + \sum_{\substack{k \in \mathscr{T} \\ k \neq 2015Q3}} \beta_k \, \mathbb{1}_{\{k=t\}} \text{Affected}_i + \sigma \text{ Controls}_m + \varepsilon_{i,m,t}, \tag{5}$$

in which i indexes the individual, m the affected or unaffected municipality in which i has a bank account and t the quarter. $y_{i,m,t}$ represents the log of quarterly consumption proxied by the drawn amounts from non-interest-bearing credit cards and consumer credit lines directly associated with consumption[31]. Affected_i takes the value of 1 if the consumer is in an affected municipality m and 0 if the consumer is in an unaffected municipality. $\mathbb{1}_{\{\text{argument}\}}$ is the indicator function that yields one when the argument is true, and zero otherwise. $\mathscr{T} = \{2013Q1, 2013Q2, \ldots, 2018Q4\}$. Controls_m is a vector of control variables used in the previous regressions.

We run this regression in four subsets, splitting individuals by formal/non-formal worker and high-risk/low-risk. We match the credit register to employer-employee data containing all formal employees as of September 2015. They represented 47% of our consumer finance sample (Table 6). The remaining group (non-formal) includes informal workers, unemployed, self-employed, or retirees with active credit card or consumer finance accounts. As we know nothing about these individuals, we use data provided by banks on interest rates available for each individual before the disaster to split them into two groups, high-risk (interest rates above median) and low-risk (interest rates below median). Because informal workers are commonly engaged in agriculture, and this particular labor force is less educated and poor, we expect stronger effects among the risky and non-formal.

Results for the dynamic coefficients β_k are shown in Figure 7. The upper left presents the consumption trend for high-risk and non-formal individuals, and we can see a statistically significant negative effect on the consumption levels of this group after the shock. Importantly, consumption decline seems to follow the

[31] The ideal consumption data would relate to consumption expenditures and possibly include related cash, credit and debit card usage. Yet, we only observe drawn amounts from individuals credit cards at end-of-month and do not observe individuals' transactions. We also do not observe cash or debit card usage. To proxy for consumption with means of payment other than credit cards, we add drawn amounts from a consumer credit line typically offered in Brazil, "consignado".

production shock, with stronger effects starting in mid-2017. In the remaining three plots, coefficients are negative but not statistically significant. In this way, the disaster seems to affect disproportionately more vulnerable individuals in affected municipalities, likely directly or indirectly more dependent on agricultural performance to complement income.

Figure 7: *Event study on credit card consumption from customers from affected and matched unaffected municipalities in the surroundings of Mariana's dam collapse, which occurred in 2015Q4. The horizontal axis indicates the year-quarter and the vertical axis encodes the coefficient estimates of* β_k *in Specification* (5) *(solid blue points), and the associated 95% confidence interval (vertical red bars) are all relative to the observed values of 2015Q3 (reference). Standard errors are two-way clustered at the municipality and quarter dimensions.*

As in the previous sections, we extend our consumption analysis with a difference-in-differences (DiD) strategy concentrating on the three years before and after Mariana's disaster. We aggregate every individual's three-year consumer credit usage before and after the dam collapse, resulting in two observations for each. This setup reduces to a traditional two-period DiD analysis, which we operationalize with the following two equations:

$$\ln(y_{i,m,t}) = \zeta \text{ Affected}_i + \lambda \text{Post}_t + \beta \text{ Post}_t \cdot \text{Affected}_i + \sigma \text{ Controls}_m + \varepsilon_{i,m,t}, \tag{6}$$

$$\begin{aligned}\ln\left(y_{i,m,t}\right) = \zeta \text{ Affected}_i + \lambda \text{Post}_t + \beta \text{ Post}_t \cdot \text{Affected}_i + \\ + \delta \text{ Post}_t \cdot \text{Water/Farm area}_i + \gamma \text{ Affected}_i \cdot \text{Water/Farm area}_m + \\ + \theta \text{ Post}_t \cdot \text{Affected}_i \cdot \text{Water/Farm area}_i + \sigma \text{ Controls}_{m,i} + \varepsilon_{i,m,t},\end{aligned} \tag{7}$$

where $y_{i,m,t}$ represents the log of individual i's (located at affected/unaffected municipality m) consumption during the two periods t (i.e., three years before and after the disaster), which is proxied by his drawn amounts from consumer credit lines. $Controls_{m,i}$ is a vector including all municipality-level controls from the previous regressions, the number of credit products each individual used in the three years before the disaster and the ln of its ex-ante debt commitments. We provide all summary statistics in Table 6.

Our coefficient of interest in equation (6) is β, which captures the average individual consumption effects in affected relatively to unaffected municipalities after the shock. In equation (7), we are interested in the parameter θ, which depicts the effects on the more affected municipalities.

Table 6: *Summary Statistics: Consumption*

	p1	p10	p50	mean	p90	p99	sd
Dependent variable							
Consumption (ln)	1.96	6.07	8.52	8.30	10.41	11.89	1.91
Main independent variable							
Affected Municipality	0.00	0.00	0.00	0.48	1.00	1.00	0.50
Control variables							
Water/Farm area	0.00	0.00	0.02	0.03	0.06	0.10	0.03
Irrigation area (share)	0.00	0.00	0.01	0.03	0.09	0.12	0.04
Population (ln)	8.36	9.79	12.05	11.72	12.87	13.37	1.23
GDP *per capita*	6312.14	10701.91	20091.64	22254.81	36040.84	40871.77	9975.59
Agriculture GDP (share)	0.00	0.00	0.01	0.03	0.12	0.27	0.06
Farm/Municipality Area (share)	0.21	0.23	0.50	0.52	0.77	0.87	0.22
Urban/Municipality area (share)	0.00	0.00	0.03	0.14	0.40	0.52	0.17
High risk (1/0)	0.00	0.00	1.00	0.53	1.00	1.00	0.50
Formal (1/0)	0.00	0.00	0.00	0.47	1.00	1.00	0.50
Number of products	2.00	3.00	14.00	21.17	48.00	95.00	20.36
Debt commitments (ln)	0.00	5.72	8.70	8.39	10.81	12.43	2.26
Observations			1,270,483				

Notes: This summary table shows the mains statistics for the consumption sample. The dependent variable Consumption is the natural logarithm of drawn consumption credit in affected and unaffected municipalities. The post period is 2016 to 2018 and the pre period from 2013 to 2015. The municipality-level controls are taken from December 2014 except for irrigation, which is only available in 2015. The individual controls, Number of products and Debt Commitments are from September 2015. One-way (Municipality) standard errors in parentheses with *, **, *** denoting statistical significance of 10%, 5%, and 1%, respectively.

Table 7 presents results for the consumption regressions. Columns I and II show the overall effects on consumption across all individuals. While β is negative but not statistically significant, introducing the triple interaction coefficient θ on Column II shows a positive coefficient for β and a negative θ, suggesting the average consumption fall is led by municipalities (one standard deviation) more dependent on river freshwater for farming. Individuals in these cities face an average consumption decline of 8%[32]. β is statistically significant and strong only among the risky and non-formal. This group faces an average 5% consumption fall across all affected municipalities (Column III). Even in this sub-sample, the result is led by the triple interaction θ (Column IV). In municipalities likely more affected by water contamination, consumption declined by 13% (Column IV). In this sub-sample of vulnerable individuals, we are likely to find the very informal workers whose income is directly and indirectly dependent on sowing, harvesting, transporting and selling crops. In Appendix B2, we present a robustness exercise reproducing Table 7 with non-interest-bearing credit cards alone. Results are qualitatively and quantitatively similar and consumption among the risky and non-formal declined by 11%, although the number of individuals in the sample declines from 773 thousand to 568 thousand.

The results of this section provide evidence of a local consumption shock, confirming that water pollution not only impoverished formal agricultural producers, but also families directly and indirectly reliant on agricultural outputs.

[32]Water/Farm area is de-meaned and standardized to facilitate direct interpretation of the results

Table 7: *Consumption*

Dependent Variable:	Consumption$_{i,t}$									
Sample:	Overall	Overall	Risky & Non-Formal	Risky & Non-Formal	Non-Risky & Non-Formal	Non-Risky & Non-Formal	Risky & Formal	Risky & Formal	Non-Risky & Formal	Non-Risky & Formal
Specification:	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)	(X)
Variables										
Affected$_i$	-0.08***	-0.16***	-0.13***	-0.24***	-0.10***	-0.19***	-0.00	-0.05	-0.07***	-0.14***
	(0.024)	(0.026)	(0.036)	(0.032)	(0.035)	(0.029)	(0.031)	(0.038)	(0.024)	(0.027)
Post$_t$	0.08	0.07	-0.11	-0.12	0.01	0.02	0.23**	0.17**	0.24**	0.23**
	(0.094)	(0.087)	(0.093)	(0.086)	(0.081)	(0.079)	(0.099)	(0.086)	(0.100)	(0.094)
Post$_t$ $\times$ Affected$_i$	-0.01	0.05**	-0.05**	0.03	-0.04	0.01	-0.06**	0.04	0.04*	0.11***
	(0.016)	(0.019)	(0.021)	(0.021)	(0.023)	(0.019)	(0.025)	(0.028)	(0.023)	(0.017)
Water/Farm area$_i$	0.03***	0.03**	0.03	0.02	0.05**	0.06**	0.03**	0.02	0.02**	0.02**
	(0.012)	(0.016)	(0.020)	(0.023)	(0.024)	(0.026)	(0.013)	(0.020)	(0.009)	(0.012)
Post$_t$ $\times$		-0.03**		-0.01		-0.05***		-0.05		-0.04***
Water/Farm area$_i$		(0.013)		(0.012)		(0.014)		(0.028)		(0.012)
Affected$_i$ $\times$		0.03		0.02		0.02		0.03		0.06
Water/Farm area$_i$		(0.049)		(0.063)		(0.058)		(0.064)		(0.070)
Post$_t$ $\times$ Affected$_i$		-0.08**		-0.13***		-0.07		0.01		-0.12
$\times$ Water/Farm area$_i$		(0.031)		(0.033)		(0.059)		(0.055)		(0.078)
Fixed effects and controls										
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
All control interactions	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Statistics										
Observations	1,270,483	1,270,483	353,197	353,197	319,192	319,192	318,069	318,069	280,021	280,021
R-squared	0.20	0.20	0.18	0.18	0.19	0.20	0.21	0.21	0.26	0.26
N individuals	772,842	772,842	222,499	222,499	193,689	193,689	189,854	189,854	166,796	166,796
N cities	190	190	190	190	190	190	190	190	190	190
N affected cities	37	37	37	37	37	37	37	37	37	37

Note: This table reports coefficient estimates of equation (6) (Columns I, III, V, VII and IX) and equation (7) (Columns II, IV, VI, VIII and X) at the consumer i level. The dependent variable is the sum of drawn amounts of non-interest-bearing credit card and consumer credit lines in log format. We aggregate those in two periods t: the *ex-ante* period (2013Q1–2015Q4) and the *ex-post* period (2016Q1–2018Q4). The binary dummy variable Affected$_i$ is equal to one when consumer i is in an affected municipality and zero when i is in a matched unaffected municipality following the methodology in Section 2.2. The vector $Controls_{m,i}$ includes the following set of control variables with values fixed before the mining disaster, municipality controls: population (in log), GDP *per capita*, freshwater as a share of the total farm area, urban and farming areas as a share of the total municipality's area, value-added in agriculture as a share of GDP, and irrigated area as a share of the farm area, and individual controls: Number of ex ante credit products and Debt commitments from September 2015. All controls are winsorized at the 1% level and de-meaned and standardized to facilitate interpretation of the real effects. Standard errors are two-way cluster to accommodate differential wealth from the consumer, thus we use Number of products, consumer's municipality. *, **, *** denote statistical significance of 10%, 5%, and 1%, respectively.

7 Final Remarks

Water pollution is detrimental to economic activity through several channels that we explore in this paper. In November 2015, the rupture of a mining tailings dam in the municipality of Mariana led to a record disposal of toxic residuals in southeast Brazil, leaving behind ecological and economic damage in the affected municipalities of the Doce River basin. We start by showing Agricultural GDP in affected municipalities declined by 14% in the following three years, which can be traced to a fall in planted area, particularly for the three main regional crops: beans, coffee, and corn. The technical literature details the channel: soil contamination follows water contamination, and the mud covering the soil in farms along the shore is poor in nutrients, affecting productivity. Second-order effects also follow, with a decline in consumption among individuals in the more affected municipalities, leading to a decline in services GDP and municipality-level GDP.

We turn to microdata to disentangle and explore the related transmission channels. Formal agricultural producers selling to outer municipalities saw a 41% to 64% decline in cash inflows (income) in the three following years. These results are led by agricultural producers in municipalities where the river shore was larger relative to the farming area, supporting the identification of a production shock in agriculture caused by water pollution and related impoverishing of the soil. Whereas industries and services in more affected municipalities do not face a production shock, industries increase their exports to outer municipalities, alleviating the effects of local consumption decline.

To shed more light on the consumption shock, we turn to credit card and consumer finance usage and find an average contraction of 5% among riskier and not formally employed individuals. In more affected municipalities, this effect is larger, 13%. These results confirm a consumption shock follows a production shock, particularly among municipalities where Water/Farm area ratio is larger. In these municipalities, the average consumption across all individuals declined by 8%.

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Appendix A List of treated municipalities

We list the treated municipalities employed in this work, which comprises all municipalities within the area of socioeconomic scope in the Framework Agreement, except for the Mariana municipality:

- Aimorés
- Alpercata
- Baixo Guandu
- Barra Longa
- Belo Oriente
- Bom Jesus do Galho
- Bugre
- Caratinga
- Colatina
- Conselheiro Pena
- Córrego Novo
- Dionísio
- Fernandes Tourinho
- Galiléia
- Governador Valadares
- Iapu
- Ipaba
- Ipatinga
- Itueta
- Marilândia
- Marliéria
- Naque
- Periquito
- Pingo-d'Água
- Raul Soares
- Resplendor
- Rio Casca
- Rio Doce
- Santa Cruz do Escalvado
- Santana do Paraíso
- São Domingos do Prata
- São José do Goiabal
- São Pedro dos Ferros
- Sem-Peixe
- Sobrália
- Timóteo
- Tumiritinga

Appendix B Robustness Exercises

In Table B1, we present results for the production shock in agricultural firms, using alternative estimating windows, from one year before and after the mining disaster to four years before and after. The baseline is a three-year window in Table 4. We replicate the last and most saturated regression specification from equation (4). In Table B2, we reproduce Table 7, which represents the consumption shock, but using only credit card transactions at the individual level.

Table B1: *Robustness Test: Downstream Propagation on Agri-firms (multiple years).*

Dependent variable:	$\ln\left(\text{Outside Customer}_c \xrightarrow[\text{flows}]{\$} \text{Inside Supplier}_s\right)$			
Time Window:	± 1 year	± 2 years	± 3 years	± 4 years
Specification:	(I)	(II)	(III)	(IV)
Variables				
Affected$_s$	0.64	0.49	0.42	0.37
	(0.564)	(0.402)	(0.269)	(0.320)
Post$_t$	-0.11	-0.08	-0.06	-0.01
	(0.081)	(0.081)	(0.092)	(0.103)
Post$_t$ × Affected$_s$	0.02	0.11	-0.03	-0.15
	(0.172)	(0.187)	(0.174)	(0.223)
Post$_t$ × Affected$_s$ × Water/Farm area$_s$	-0.24*	-0.31**	-0.32**	-0.32**
	(0.140)	(0.129)	(0.133)	(0.131)
Affected$_s$ × Water/Farm area$_s$	0.13	0.01	0.08	0.04
	(0.167)	(0.168)	(0.121)	(0.131)
Post$_t$ × Water/Farm area$_s$	-0.05	-0.09	-0.07	-0.07
	(0.055)	(0.068)	(0.082)	(0.078)
Fixed effects and controls				
Controls	Yes	Yes	Yes	Yes
Customer Firm FE	Yes	Yes	Yes	Yes
Statistics				
Observations	1,159	1,698	2,263	2,737
R-squared	0.79	0.72	0.67	0.64
N suppliers	292	374	443	511
N customers	394	537	685	802
N cities	86	95	101	110
N affected cities	18	20	20	22

Note: This table reports coefficient estimates for the downstream specification in (4) at the electronic transaction level for different time windows centered at 2015: ± 1 year (Column I), ± 2 years (Column II), ± 3 years (Column III), ± 4 years (Spec IV). The dependent variable is the sum of all electronic transfers observed between each customer c outside the affected (treatment group) and the matched unaffected municipalities (control group) to inside agri-firm suppliers s. We aggregate payments in two periods t: the *ex-ante* period and the *post* period, following the size of the analyzed time window. The binary dummy variable Affected$_s$ is equal to one when supplier s's municipality borders the Doce River in the downstream path of the mudwave caused by the Mariana dam collapse, and zero when supplier s is in a matched unaffected municipality. The vector $Controls_{c,s,m}$ includes the following set of control variables with values fixed before the mining disaster, the number of electronic transactions received by the supplier s and the following supplier's municipality controls: population (in log), GDP *per capita*, freshwater as a share of the total farm area, urban and farming areas as a share of the total municipality's area, value-added in agriculture as a share of GDP, and irrigated area as a share of the farm area. Demand controls represent customer's industry × municipality fixed effects. Standard errors are three-way cluster to accommodate possible demand shocks from the consumer, thus we use supplier's municipality and sector as well as consumer's municipality). *, **, *** denote statistical significance of 10%, 5%, and 1%, respectively.

Table B2: *Robustness Test: Credit Card Consumption*

Dependent Variable:	Consumption$_{i,t}$									
Sample:	Overall	Overall	Risky & Non-Formal	Risky & Non-Formal	Non-Risky & Non-Formal	Non-Risky & Non-Formal	Risky & Formal	Risky & Formal	Non-Risky & Formal	Non-Risky & Formal
Specification:	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)	(X)
Variables										
Affected$_i$	-0.12***	-0.14***	-0.17***	-0.22***	-0.15***	-0.17***	-0.01	-0.01	-0.04**	-0.06***
	(0.028)	(0.028)	(0.032)	(0.031)	(0.034)	(0.029)	(0.050)	(0.053)	(0.017)	(0.020)
Post$_t$	0.21	0.20	0.00	-0.04	0.17	0.17	0.43	0.41	0.35	0.34
	(0.284)	(0.281)	(0.258)	(0.259)	(0.243)	(0.244)	(0.390)	(0.373)	(0.279)	(0.270)
Post$_t$ × Affected$_i$	-0.02	0.02	-0.10***	0.01	-0.06	-0.03	-0.03	-0.00	0.01	0.05***
	(0.024)	(0.025)	(0.033)	(0.025)	(0.040)	(0.035)	(0.082)	(0.065)	(0.016)	(0.013)
Water/Farm area$_i$	0.04**	0.04**	0.04	0.03	0.07**	0.06**	0.01	0.01	0.01	0.02**
	(0.017)	(0.017)	(0.025)	(0.019)	(0.032)	(0.025)	(0.013)	(0.014)	(0.005)	(0.011)
Post$_t$ × Water/Farm area$_i$		-0.05***		0.01		-0.02		-0.08***		-0.08***
		(0.018)		(0.014)		(0.021)		(0.019)		(0.025)
Affected$_i$ × Water/Farm area$_i$		0.01		0.05		-0.00		0.05		-0.06
		(0.060)		(0.068)		(0.049)		(0.068)		(0.072)
Post$_t$ × Affected$_i$ ×		-0.01		-0.11**		-0.04		0.12**		0.03
× Water/Farm area$_i$		(0.048)		(0.054)		(0.043)		(0.047)		(0.038)
Fixed effects and controls										
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
All control interactions	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Statistics										
Observations	910,963	910,963	269,208	269,208	222,562	222,562	209,875	209,875	209,317	209,317
R-squared	0.40	0.40	0.34	0.34	0.31	0.31	0.51	0.51	0.43	0.44
N individuals	568,498	568,498	170,541	170,541	137,703	137,703	130,368	130,368	129,885	129,885
N cities	190	190	190	190	190	190	190	190	190	190
N affected cities	37	37	37	37	37	37	37	37	37	37

Note: This table reports coefficient estimates of equation (6) (Columns I, III, V, VII and IX) and equation (7) (Columns II, IV, VI, VIII and X) at the consumer i level. The dependent variable is the sum of drawn amounts of non-interest-bearing credit card in log format. We aggregate those in two periods t: the *ex-ante* period (2013Q1–2015Q4) and the *ex-post* period (2016Q1–2018Q4). The binary dummy variable Affected$_i$ is equal to one when consumer i is in an affected municipality and zero when i is in a matched unaffected municipality following the methodology in Section 2.2. The vector $Controls_{m,i}$ includes the following set of control variables with values fixed before the mining disaster, municipality controls: population (in log), GDP *per capita*, freshwater as a share of the total farm area, urban and farming areas as a share of the total municipality's area, value-added in agriculture as a share of GDP, and irrigated area as a share of the farm area, and individual controls: Number of ex-ante credit products and Debt commitments from September 2015. All controls are winsorized at the 1% level and de-meaned and standardized to facilitate interpretation of the real effects. Standard errors are two-way cluster to accommodate differential wealth from the consumer, thus we use Number of products, consumer's municipality. *, **, *** denote statistical significance of 10%, 5%, and 1%, respectively.