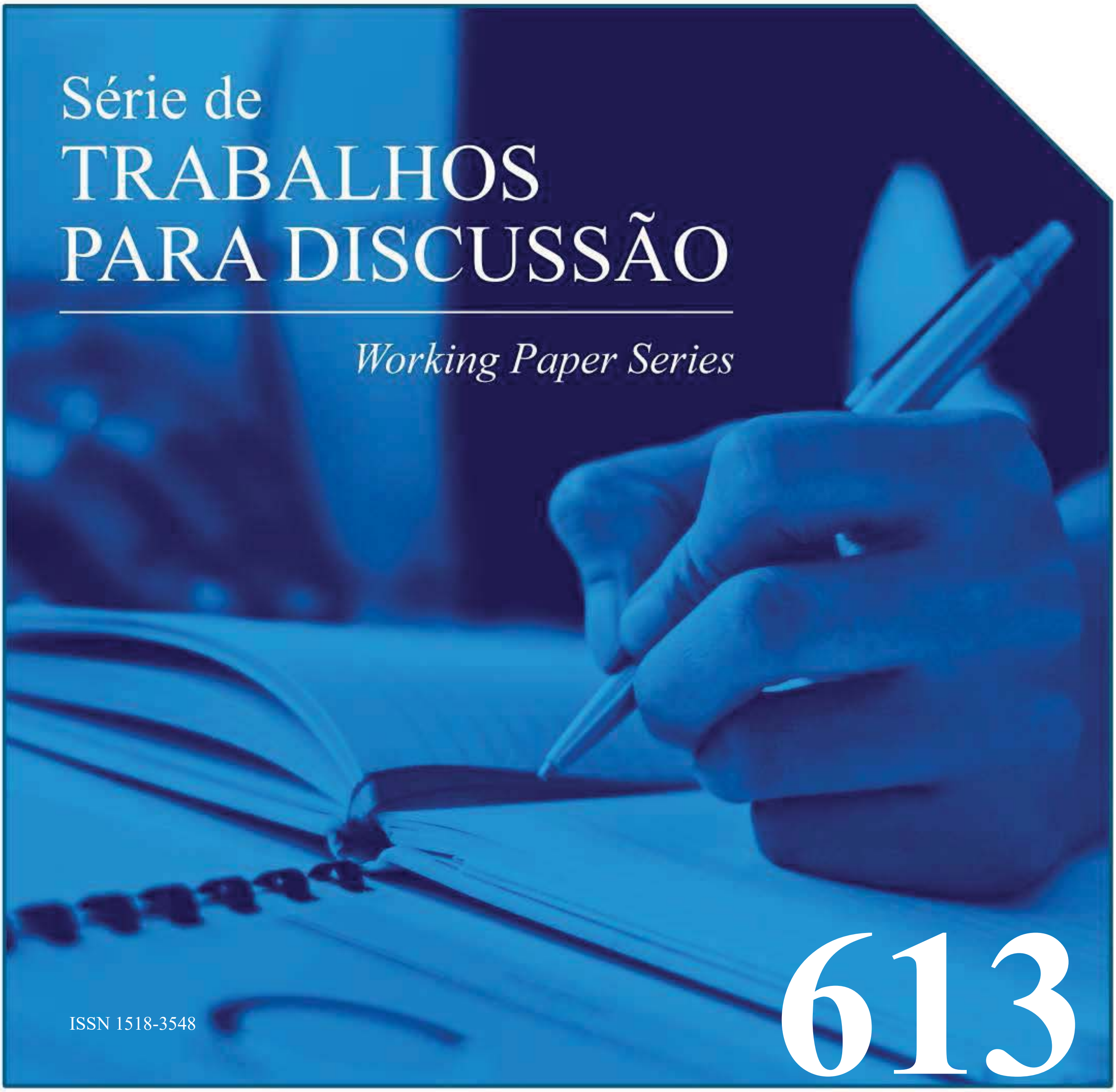


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# Weathering the Storm: how supply chains adapt to extreme climate events

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## Non-Technical Summary

The effects and consequences of extreme climate events have garnered increasing interest from both the academic community and society. These events can cause significant disruptions in cities or regions, critically affecting the operations of local firms. Firms outside the disaster area but connected to the affected firms can experience substantial demand and supply shocks, leading to the propagation of disaster impacts through the supply chain. This problem may be exacerbated if these firms face difficulties and limitations in replacing affected clients or suppliers with unaffected ones. Additionally, disruptions in the activities of affected firms can lead to increased demand for liquidity to manage cash flow interruptions or finance recovery plans. Banks may exhibit reluctance to grant loans due to heightened credit risk, thus limiting access to credit precisely when firms need it most, thereby worsening the situation. Our study reveals fundamental insights into the causal impact of extreme climate events on the supply chain and its adaptation to demand and supply shocks.

We map the Brazilian supply chain in an unprecedented manner by combining proprietary granular data on inter-firm payments and borrower-lender credit relationships from banking institutions in Brazil with extreme climate event records. Our study covers the 30 most severe extreme climate events during 2020 and 2021, including episodes of heavy rains, floods, and flash floods in microregions of the North, Northeast, and Southeast of the country. Our analysis is performed from two perspectives. From the downstream, the extreme climate event affects suppliers in a specific microregion, creating a supply shock for customers outside the affected area. Conversely, from the upstream perspective, the event disrupts customers, resulting in a demand shock that impacts outside suppliers. We utilize difference-in-differences specifications to infer the causal effects of these extreme climate events on affected firms and the supply chain.

Our main findings are threefold. First, outside customers reduce payments to affected suppliers after a climate event, with initial reductions averaging up to 8%. We find significant heterogeneity: affected suppliers in agriculture face reductions near 20%, five times greater than the average. Second, affected firms increase indebtedness post-disaster, relying more on credit for immediate liquidity needs. Third, while firms generally adapt by replacing affected partners, certain sectors face up to 10 p.p. substitution frictions, amplifying extreme climate event impacts.

We offer several key takeaways. While the Brazilian supply chain generally exhibits notable adaptability to climate-induced shocks, firms directly impacted by such events often face a permanent loss of market share—a challenge that banks' provision of liquidity does not fully mitigate. A critical task for policymakers is to develop strategies aimed at helping affected firms recover market share, thereby safeguarding competitiveness and economic dynamism in impacted regions. This is particularly crucial in areas prone to severe climate events. Without policy support, these regions risk falling into underdevelopment traps triggered by successive intense weather episodes. Despite the overall resilience of the supply chain, it is essential to implement policies that address the challenges faced by sectors with limited adaptive capacity to extreme climate-induced shocks, preventing undesirable sector-specific disruptions.

# Sumário Não Técnico

Os efeitos e consequências dos eventos climáticos extremos têm atraído crescente interesse da sociedade em geral. Eles podem causar interrupções significativas em regiões, afetando criticamente as operações das empresas locais. Empresas fora da área de desastre, mas conectadas às empresas afetadas, podem experimentar choques substanciais de demanda e oferta, fazendo com que os impactos do desastre se propaguem pela cadeia de suprimentos. Esse problema pode ser exacerbado se essas empresas enfrentarem dificuldades em substituir parceiros afetados por outros não afetados. Além disso, as interrupções nas atividades das empresas afetadas podem levar a um aumento na demanda por liquidez. Os bancos podem mostrar relutância em conceder empréstimos devido ao aumento do risco de crédito. Nosso estudo revela *insights* fundamentais sobre o impacto causal dos eventos climáticos extremos na cadeia de suprimentos e como ela se adapta a choques de oferta e demanda.

Mapeamos a cadeia de suprimentos brasileira de maneira inédita, combinando dados granulares proprietários sobre pagamentos entre empresas e relações de crédito entre credores e tomadores de todas as instituições bancárias no Brasil com registros de desastres naturais. Nosso estudo abrange os 30 desastres naturais mais severos ocorridos durante 2020 e 2021, incluindo episódios de chuvas intensas, enchentes e inundações repentinas. Sob a perspectiva *downstream*, o evento climático extremo afeta fornecedores em uma microrregião específica, criando um choque de oferta para clientes fora da área afetada. Inversamente, sob a perspectiva *upstream*, o evento abala clientes, resultando em um choque de demanda que impacta fornecedores externos.

Nossos principais resultados são três. Primeiro, clientes externos reduzem pagamentos a fornecedores afetados após um evento climático, com reduções iniciais em média de até 8%. Observamos heterogeneidade significativa: fornecedores afetados na agricultura enfrentam reduções próximas a 20%, cinco vezes maiores que a média. Segundo, empresas afetadas aumentam o endividamento após o desastre, dependendo mais de crédito para necessidades imediatas de liquidez. Terceiro, embora as empresas geralmente se adaptem substituindo parceiros afetados, certos setores enfrentam fricções de substituição de até 10 p.p., amplificando os impactos de eventos climáticos extremos.

Oferecemos diversas conclusões importantes. Embora a cadeia de suprimentos brasileira geralmente demonstre notável adaptabilidade a choques induzidos pelo clima, empresas diretamente impactadas por tais eventos enfrentam uma perda potencial de participação de mercado—um desafio que a provisão de liquidez por bancos não mitiga completamente. Uma tarefa crítica para os formuladores de políticas é desenvolver estratégias destinadas a ajudar empresas afetadas a recuperarem sua participação de mercado, salvaguardando assim a competitividade e o dinamismo econômico em regiões impactadas. Isso é particularmente crucial em áreas propensas a eventos climáticos severos. Sem apoio, essas regiões correm o risco de cair em armadilhas de subdesenvolvimento desencadeadas por sucessivos episódios climáticos intensos. Apesar da resiliência geral, é essencial implementar políticas que abordem os desafios enfrentados por setores com capacidade adaptativa limitada, prevenindo disrupções indesejáveis específicas do setor.

# Weathering the Storm:
# How Supply Chains Adapt to Extreme Climate Events

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## Abstract

This paper examines the causal impact of extreme climate events—intense rains, floods, and flash floods—on the supply chain. We map the Brazilian supply network in a unique and comprehensive way using proprietary granular data on over 1.7 billion inter-firm payments composed of fast payments (Pix), boletos (invoices), and wire transfers (TEDs). Our analysis reveals that supply shocks follow extreme climate events, with outside-the-affected-area customers reducing payments to affected suppliers by up to 8% in the immediate aftermath, compared to unaffected ones within the same industry. We document significant heterogeneities across sectors, with some affected suppliers in agriculture experiencing reductions in payments nearing 20%, five times greater than the average. Leveraging granular data on borrower-lender credit relationships from banking institutions in Brazil, we find affected firms experience increased indebtedness post-disaster, especially in credit types related to immediate liquidity needs. We observe a remarkable ability of the supply chain to adapt to these shocks: outside-the-affected-area firms are often able to replace affected partners with low friction. However, some sectors, such as construction, face substantial difficulties. In this industry, consumers exhibit a substitution friction of approximately 10 p.p. This demonstrates how indirect effects can amplify the direct impacts of extreme climate events on the supply chain. While overall resilience is crucial for maintaining operability, directly affected firms are likely to experience a permanent loss of market share as unaffected firm counterparts shift their economic transactions away from them, leading to harmful consequences in areas affected by extreme climate events. Our research may support policymakers in designing strategies to aid affected firms in restoring market share and mitigating frictions in sectors less prone to partner replacement.

**Keywords:** Physical climate risk; Extreme weather; Supply chain; Shock propagation; Resilience; Credit.
**JEL Classification**: Q54; L14; D22; G21; D85.



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# 1 Introduction

Extreme climate events pose significant threats to both society and the economy. For instance, the 2024 rainfall and floods in Rio Grande do Sul in Brazil highlighted the severe damages caused by such events. They can critically disrupt supply chains, leading to delays, increased costs, and shortages of essential goods and services, thereby hampering economic performance (Botzen et al., 2019; Felbermayr and Gröschl, 2014).

The production system of a country is a key feature of its economy (Gloria et al., 2024). While complex supply chains can enhance productivity, they also heighten macroeconomic fragilities as input-output linkages amplify shocks (Acemoglu et al., 2012; Acemoglu and Tahbaz-Salehi, 2024; Carvalho et al., 2021). Empirical literature demonstrates these fragilities, with firm-level shocks disrupting production networks and affecting the broader economy (Barrot and Sauvagnat, 2016; Carvalho, 2014; Carvalho et al., 2021). Given the increasing frequency of climate events (IPCC, 2023), assessing their losses—both direct, such as asset destruction, and indirect, which can have long-term economic impacts—is complex (Botzen et al., 2019; Felbermayr and Gröschl, 2014). Understanding these impacts is crucial for designing strategies to mitigate damage from natural disasters and for developing effective policies for climate change adaptation and mitigation (Annan and Schlenker, 2015; Carleton and Hsiang, 2016).

Our study investigates the causal impact of extreme climate events, particularly floods and heavy rainfall, on Brazil's supply chain using a unique dataset of inter-firm payments. The dataset allow us to evaluate how payments received by affected suppliers and made by affected customers are impacted by extreme climate events. We find payments received by affected suppliers decrease significantly, with sectoral heterogeneities in payment dynamics. Additionally, using identified borrower-lender credit relationships from Brazilian commercial banking institutions, we show firms in affected areas experience increased indebtedness post-event, with notable increases in loans designed to address immediate liquidity needs, such as working capital loans. This illustrates the crucial role of bank-firm relationships in mitigating financial fragility in the short term. Furthermore, our study uncovers an indirect reallocation effect, where outside firms shift their payments away from affected firms towards unaffected ones, showcasing the broader implications of climate-induced disruptions on supply chain structure and resilience.

The literature on extreme climate events and shock propagation in production networks is well-developed, yet their intersection remains somewhat unexplored. Studies such as Carvalho (2014) and Acemoglu et al. (2012) analyzed shock propagation in production networks, while others like Dell et al. (2014) focused on the economic impacts of climate change.[1] Some exceptions are Barrot and Sauvagnat (2016); Boehm et al. (2019); Carvalho et al. (2021), who leverage natural disasters to study firm-level shock propagation across the production network. Due to data limitations, they rely on binary relationships between customers and suppliers: only the existence or absence of connections are mapped.

We complement this emerging literature by examining how climate-induced shocks propagate through supply chains using a more detailed dataset, where the links convey the monetary value of customer-supplier relationships. Considering monetary values in the links, rather than merely the existence or absence of connections, allows us to capture the intensity and economic significance of each relationship. This detail is crucial for understanding how shocks propagate not just through the presence of connections but through the actual financial impact these connections have on firms' operations and resilience. We build this network by leveraging a unique dataset composed of payments from fast payments (Pix), boletos (invoices), and wire transfers (TEDs) to construct the supply chain structure in Brazil. The main features of this dataset[2] are its high quality and granularity, which provide a significant advantage compared to similar studies in the field.[3] Our dataset offers a comprehensive and dynamic view of the supply chain by capturing actual payment transactions in real time, enabling a robust analysis of shock propagation and supply chain dynamics.

Our identification strategy operates through two lenses: the downstream and upstream perspectives.[4] From the downstream perspective, we view the extreme climate event as a supply

[1]Some studies address how risks from changes in environmental regulations (transition risks) impact firms, rather than focusing on the effects of changes in physical climate parameters (Cohen and Tubb, 2018; Ginglinger and Moreau, 2023; Nguyen and Phan, 2020).

[2]To the best of our knowledge, the unique study that employs this dataset to investigate supply chain disruptions is Silva and de Almeida (2024), in the context of COVID-19 shocks.

[3]Mapping supply chain networks are pervasive in the production networks literature, but data limitation is a common challenge among existing research. For example, studies such as Er Kara et al. (2021) and Jira and Toffel (2013) utilize firm-level surveys where firms report their top suppliers or customers to map out supply chains. While these studies provide valuable insights, their reliance on self-reported data can lead to incomplete or biased representations of supply networks. Additionally, using surveys often limits the temporal granularity and real-time accuracy of the data (Van der Vaart and Van Donk, 2008). Antràs et al. (2012) and Alfaro-Urena et al. (2022) utilized international trade data and customs records to map supply chains. Still, these sources often lack the comprehensive coverage and real-time insights provided by our payment data.

[4]In this paper, "downstream perspective" refers to production shocks that are received by customers, i.e., firms

shock, such as a production shock. We compare payments received by affected suppliers to those received by unaffected suppliers from the exact same customer outside the affected region.[5] Fixing the same outside customer enables us to control for any customer-specific time-varying shocks unrelated to the climate event. Therefore, the changes observed in the payment pattern to affected versus unaffected suppliers by the same customer should be due to the extreme climate event impacting the supplier side. We further mitigate potential omitted variable biases across different suppliers by comparing sets of suppliers within the same industry and adding a comprehensive set of controls and fixed effects. From the upstream perspective, the extreme climate event is seen as a demand shock.

Our empirical framework relies on a multiperiod difference-in-differences (DiD) approach.[6] Since extreme events can occur at different times, we stack different extreme event episodes into a pooled panel-data DiD analysis. The analysis uses the relative time to the extreme event rather than the absolute time to accommodate extreme events occurring at different moments. For every extreme event, we consider a one-year window before and after the event. The treatment variable is specific to the firm and a particular shock. The treatment group for a given shock consists of firms in the microregion affected by that shock. The control group for that shock comprises firms outside the affected microregion, excluding those in other microregions affected by different extreme climate events within a one-year window relative to the analyzed shock.[7] We call these firms "outside firms" for short. Including multiple extreme events in our empirical analysis provides a more robust and reliable picture of how such events impact the supply chain.

We select natural disasters that occurred in 2020 and 2021 due to the availability of payment data. In line with our identification strategy, we exclude the following disaster categories: Dry Spell, Drought, and Viral Infectious Diseases. We develop a ranking system to classify these nat-

that purchase goods from "affected suppliers" and make payments to them. A similar reasoning applies to the upstream propagation in the supply chain: we simply switch the customer and supplier roles.

[5]Throughout our analysis, "customer" refers to a customer firm, and "supplier" refers to a supplier firm. The omission of the word "firm" is for conciseness, but it is implicit in all references.

[6]Our empirical strategy builds on the framework established by Khwaja and Mian (2008). However, while Khwaja and Mian (2008) focused on credit supply shocks, we extend this methodology to the context of extreme climate events and their impact on supply chains. Additionally, our multiperiod difference-in-differences design allows us to capture the temporal dynamics of these shocks, providing a more comprehensive analysis. This aligns with the methodologies used by Barrot and Sauvagnat (2016) and Carvalho et al. (2021), who also examined shock propagation within supply chains but did not specifically address climate-induced disruptions. Our study contributes to this literature by focusing on the specific effects of extreme climate events, offering new insights into the resilience and vulnerabilities of production networks.

[7]This approach ensures that control firms are always selected from regions unaffected by recent extreme climate events, allowing us to isolate firm-specific demand and supply shocks cleanly.

ural disasters related to extreme climate events based on their impacts on human and economic loss. Our analysis shows microregions in the North, Northeast, and Southeast experienced climate disasters with relatively high impact rankings during this period. We order the disasters by their impact ranking and select the thirty highest-ranked events for our empirical analysis. Among these top disasters, there is a prevalence of intense rains, with floods and flash floods also being well-represented.

Our empirical findings reveal significant disruptions in the supply chain due to extreme climate events, with affected suppliers receiving 4.3% less in payments compared to unaffected suppliers in the same industry. This disruption persists over time, consistent with theoretical predictions that climate events can impair production capabilities through infrastructure damage, raw material shortages, or labor constraints.[8] Affected suppliers in the agricultural sector[9] experience the largest payment reductions, with declines approaching 20%. Other sectors, including professional services, construction, transportation, and manufacturing, exhibit payment reductions in the range of 5% to 10%. Payments are predominantly reduced by outside customers in agriculture (approximately 10%), while accommodations & food services and administrative services perform reductions between 5% and 10%. Conversely, the information and communication sector benefits from the ability to operate digitally. These heterogeneous effects underscore the varying degrees of sectoral vulnerability and resilience to extreme climate events, highlighting the importance of tailored strategies to mitigate their adverse impacts (Huang et al., 2018; Piontek et al., 2014). We find upstream propagation is not economically significant. Our results indicate outside-the-affected-area suppliers respond to increased perceived risk by requiring more immediate payments.

We extend our analysis and examine the effects of acute extreme climate events on the financial conditions of affected firms, focusing on indebtedness to commercial banks. We utilize the Credit Information System (SCR) dataset, a proprietary granular database from the Central Bank of Brazil (BCB) containing identified borrower-lender credit relationships in Brazil. Our empirical strategy examines how outstanding credit issued by the same bank changes when comparing affected and unaffected borrowing firms. We control for unobserved time-varying sector-specific

[8] We also demonstrate this result remains consistent across varying numbers of disasters. We conduct 30 independent regressions, progressively including more climate events, and observe the coefficients converge to values around -4%.

[9] Agricultural suppliers are the most severely impacted due to their heavy reliance on environmental conditions.

supply shocks of each bank by analyzing the same bank's lending behavior to multiple firms within the same industry.

The theoretical prediction about how extreme climate events alter the financial conditions of affected firms is mixed. Directly affected suppliers and customers face disruptions impacting their cash flows, investment needs, and overall financial stability, often requiring additional liquidity to cope with operational challenges or rebuild infrastructure. Conversely, banks may perceive these firms as riskier borrowers, potentially tightening credit conditions due to increased uncertainty and the potential for future disruptions. Our study shows the dominant vector is the first component: firms in impacted areas experience increased indebtedness post-event. Affected suppliers (customers) increased 3.4% (1.7%) in outstanding credit compared to other unaffected firms of the same industry that borrow from the exact same banks. These findings suggest the importance of bank-firm relationships in facilitating financial resilience and adaptation to climate shocks, corroborating previous findings on the relevance of bank-firm relationships in times of distress (Beck et al., 2018; Höwer, 2016; Schäfer, 2019).

We also examine the effects of extreme climate events on individual loan types[10] to understand firms' financial strategies and banks' lending behaviors in response to climate shocks. Analyzing loan types separately is relevant for several reasons. Firstly, firms use different loan types to address specific financial needs. Secondly, banks may adjust lending conditions based on each loan type's perceived risk and repayment capacity. Finally, isolating effects by loan type ensures observed changes in outstanding credit reflect specific financial mechanisms rather than changes in the mixture between loan types. We find affected suppliers increase foreign trade, other credits, and working capital loans while outstanding credit in project financing decreases. Affected customers increase other credits and receivables operations, with a decrease in project financing. These results suggest affected firms raise their reliance on credit types suited to managing immediate liquidity needs arising from disruptions.

We also investigate how extreme climate events rearrange the supply chain structure outside affected areas. We analyze whether outside firms can replace firm counterparts located in affected areas with unaffected ones. We find no statistically significant change in total payments

[10] Foreign trade, working capital, receivables operations, investment, overdraft and guaranteed account, rural and agro-industrial, project financing, and other credits.

made by outside firms post-climate event, suggesting they can replace affected suppliers and customers with low economic frictions. However, while the total payments remain unchanged, the distribution between affected and unaffected firm counterparts shifts significantly (their sum equals total payments). For a one-standard-deviation increase in exposure to affected suppliers, outside customers reduce payments to affected suppliers by 11% and increase payments to unaffected suppliers by the same amount. Similar patterns are observed from the upstream perspective, reinforcing the supply chain's ability to renew itself by replacing affected entities with unaffected ones (Crosignani et al., 2023; Pankratz and Schiller, 2024).

The capacity of supply chains to substitute firm counterparts following extreme climate events plays a critical role in mitigating broader economic impacts. The inherent flexibility in reallocating production inputs and redistributing demand across unaffected firms enhances the resilience of the overall supply chain network. This adaptability ensures continuity in production and distribution processes, thereby averting potential disruptions that could cascade through the economy. However, this dynamic also has the unintended consequence of isolating firms in affected areas, exacerbating their economic distress. As outside firms increasingly rely on unaffected suppliers, the market share of firms in the impacted regions diminishes. This market share erosion can lead to prolonged financial instability for these firms, impeding their recovery and integration back into the supply chain.

Economically, this phenomenon underscores the duality of supply chain resilience: while the broader network exhibits robustness through adaptive reallocation, localized economic impacts can deepen, highlighting a need for targeted interventions. The displacement effect can lead to a concentration of economic activity in less vulnerable regions, creating spatial economic disparities. Moreover, firms in affected areas may face heightened liquidity constraints and diminished access to new orders, compounding the initial shock's adverse effects. In this context, the banking sector plays a crucial role by providing credit and financial support to firms in affected areas. By extending credit, restructuring existing loans, and offering tailored financial products, banks can help mitigate the liquidity constraints faced by these firms, enabling them to rebuild and reestablish their market positions.

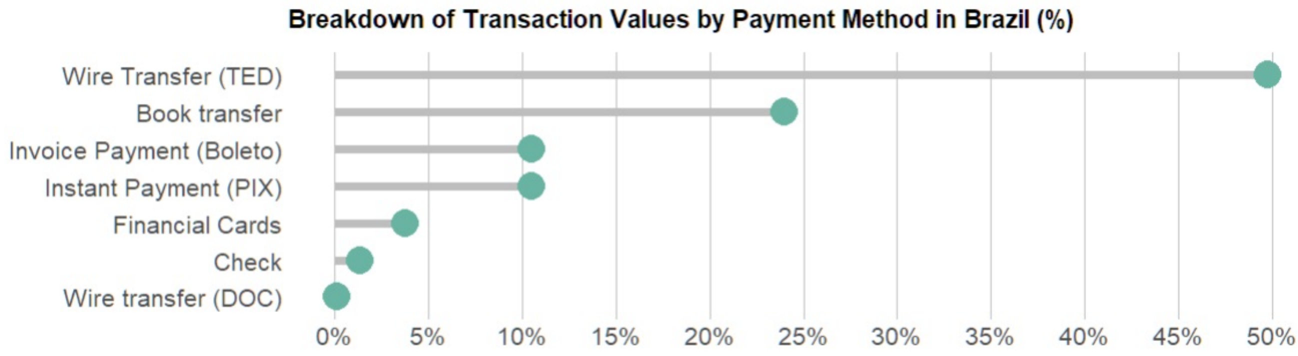



***Figure 1:*** *This figure shows the distribution of total transaction values (volume) across different payment streams in Brazil from 2020 to 2021. The payment streams include wire transfers, invoice payments, instant payments, financial cards, and checks.*

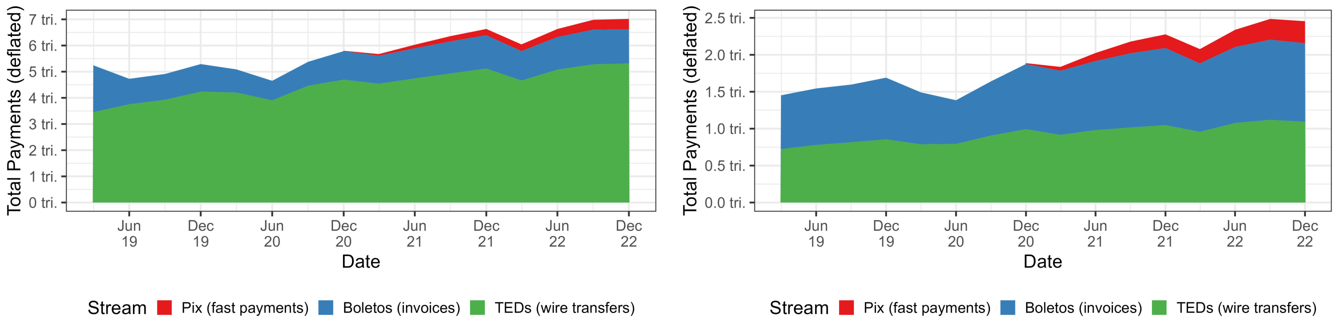
# 2 Data

## 2.1 Mapping Brazil's supply chain through inter-firm payments

Identifying a reliable proxy for the nation's production network is essential to estimate the impact of extreme physical events on the Brazilian supply chain. To this end, we focus on collecting inter-firm payments, which provide a comprehensive view of business transactions and relationships. We leverage a proprietary and high-frequency *Banco Central do Brasil* (BCB) database that includes three primary payment methods at the customer-supplier level: instant payments (Pix), invoices (boletos), and wire transfers (TEDs).

The BCB periodically publishes the Statistics on Payment Methods Bulletin, detailing the use of payment methods in Brazil. Figure 1 displays the breakdown of payment volumes by stream in 2020 and 2021. Four payment methods account for most of the payment volume. Wire transfers via TED represent the largest share at 49.7%. Book transfers are second at 24.9%, followed by invoice payments via Boletos at 10.5% and instant payments via Pix at 10.4%. Other methods, including financial cards, checks, and wire transfers via DOC, account for only 5.1% of the transaction values. Our inter-firm payment database includes three of the four most important methods of payment in Brazil according to Figure 1, serving as an excellent proxy for the structure of Brazil's supply chain.

Our dataset encompasses payment data from 2019 to 2022. Figure 2a illustrates the positive evolution of the total payment value over this period, increasing from approximately R$5 trillion at the beginning of 2019 to about R$7 trillion by the end of 2022. Wire transfers via TED dominate in volume, followed by invoice payments via Boletos and fast payments via Pix. All three payment streams display an overall positive trend in increasing financial volume (in real terms) throughout the period.




***(a)** Unfiltered database.*

***(b)** Filtered database.*

***Figure 2:** This figure depicts the evolution of total payments (financial value) in our database of inter-firm payments from the first quarter of 2019 to the fourth quarter of 2022, with values in Brazilian reais (R$) deflated using the IPCA index, based on the first quarter of 2019. The total payment values are categorized by the payment stream: fast payments via Pix (in red), invoices via Boletos (in blue), and wire transfers via TED (in green). Figure a) includes all payments in the database, while figure b) excludes payments involving financial institutions as either/both the customer or supplier, as well as payments between subsidiaries of the same firm.*

As we focus on payments related to business-to-business (B2B) transactions, we exclude payments involving the government or individuals as one of the parties. We also exclude payments involving financial institutions (as either the customer or supplier) and intra-firm payments between subsidiaries, which are usually for internal liquidity purposes. This ensures our data reflect transactions involving products and services. Figure 2b shows the evolution of payment volumes after these exclusions. We still observe a growing trend in real terms, with financial volumes rising from approximately R$1.5 trillion at the beginning of 2019 to around R$2.5 trillion by 2022. The most notable change is that invoice payments via Boletos now have much greater representation, comparable to wire transfers via TED. This indicates TEDs are typically used for intra-banking group transfers, while Boletos are used to settle business transactions with other parties. The increased representation of Boletos may also be because they can be used as receivables in banks, making them a versatile and preferred payment method for outside commercial transactions.

Figure 3 portrays an approximate input-output matrix using inter-firm payment data for 2022. We observe certain activities stand out with high transaction values: Manufacturing; Wholesale and retail trade; and Professional, scientific, and technical services. This result aligns with information from the 2021 Resource and Use Table published by the Brazilian Institute of Geography and Statistics (IBGE). Although IBGE uses a different sector classification, we find the activities with the most significant share in intermediate consumption in 2021 are similar: Manufacturing industry (47.4%), Service activities (9.8%), and Trade (7.9%). This reinforces that our inter-firm payment database is an excellent proxy for Brazil's supply chain structure.

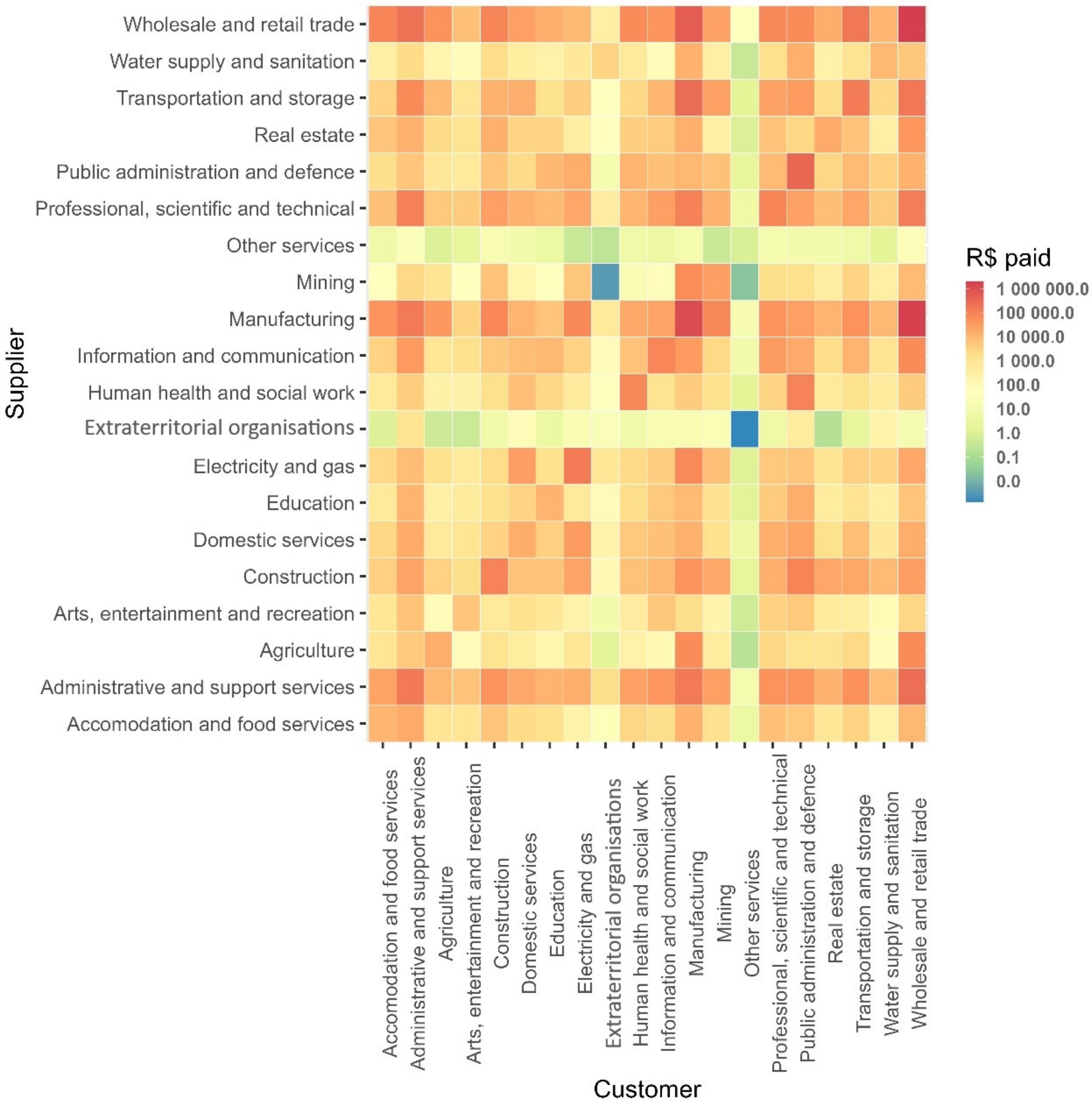


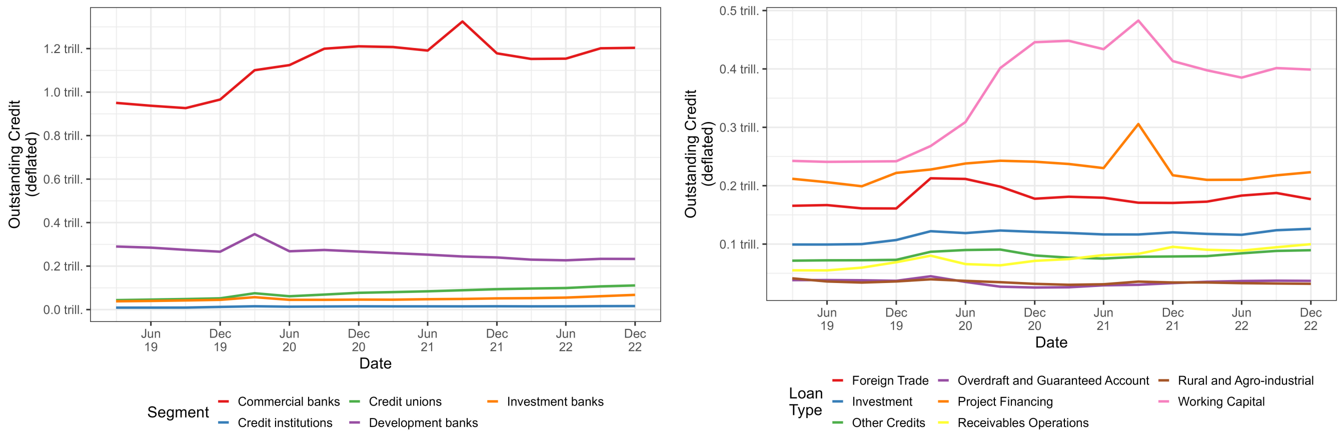

***Figure 3:*** *This heat map approximates the input-output matrix of the Brazilian economy using inter-firm payment data from 2022. The vertical axis lists economic activities as suppliers (sell products or services), and the horizontal axis lists economic activities as consumers (buy products and services), both classified according to the CNAE section level. The color scale ranges from blue (low transaction values) to yellow (intermediate values) to red (high transaction values). This visualization highlights the intensity and distribution of economic interactions across different sectors within Brazil's economy.*

In Appendix A, we present a more detailed explanatory analysis of our inter-firm payment data. This includes an overview of the evolution of the number of payments and the average payment ticket, categorized by payment stream. Additionally, we offer an analysis that segments the payment data by economic activity and examine them from both the customer and supplier perspectives.

## 2.2 Outstanding credit analysis by banking segment and loan type in Brazil

We use the *Sistema de Informações de Créditos* (SCR) database from the BCB to evaluate the financial conditions of firms post-climate events. Our dataset encompasses identified borrower-lender credit relationships from financial institutions in Brazil for the periods between 2019 and 2022. We focus on commercial banks, multiple banks with commercial portfolios, savings banks, and conglomerates composed of at least one institution of these types. We denominate this segment as the "commercial bank segment" for conciseness. We restrict our analysis to the commercial bank segment because these banks are the primary lending segment in Brazil in terms of outstanding credit and *clientele*. The other segments are less suitable for our methodology. Development banks provide specific infrastructure loans, large loans, and government policy-driven financing. Credit unions operate more locally, reducing the number of multiple clients across different locations, which is an important ingredient in our empirical strategy. Investment banks serve very specific niches, lacking significant representation in credit issuances.

Figures 4a and 4b illustrate the evolution of outstanding credit by bank segment and loan type. Commercial banks consistently hold the largest share of credit, growing from just under R$1.0 trillion in 2019 to R$1.2 trillion by 2022, while development banks show a declining trend from R$300 billion to R$200 billion. In terms of loan types, working capital loans lead in commercial banks, increasing from R$250 billion to R$400 billion, followed by project financing and foreign trade loans, both around R$200 billion, with investment loans remaining lower at R$100-150 billion.




***(a)** Outstanding credit by bank conglomerate.*

***(b)** Outstanding credit by loan type (commercial banks).*

***Figure 4:** This figure depicts the quarterly evolution from 2019 to 2022 of outstanding credit in two parts: (a) by segment or bank conglomerate according to BCB bank conglomerate classification, and (b) by loan type specifically for commercial banks. Both figures use the IPCA index to deflate values with a base date set as the first quarter of 2019.*

## 2.3 Ranking severe natural disasters based on human and economic impacts

We collect disaster information from the *Sistema Integrado de Informações sobre Desastres* (S2ID) database, managed by the Brazilian Ministry of National Integration. This comprehensive database serves as a centralized repository for disaster-related data at the municipality level, documenting both human and economic losses. Our initial dataset (before filtering) covers the period from 2013 to 2021.

We exclude disaster records that lack information on economic or human losses and remove all disasters not officially recognized by the Federal Executive Branch.[11] This ensures our sample includes only disasters with measurable impacts verified by the federal government. We note 19,274 disaster occurrences that meet these criteria. There are 41 categories of disasters, with six categories accounting for more than 90% of the occurrences.

The S2ID database comprises 46 variables detailing human damages and economic losses, offering substantial granularity. However, many of these variables contain a significant number of null values. To ensure data integrity, we select a subset of variables with a considerable proportion of non-null values and exclude the others. The variables measuring human damages include deaths, injuries, illnesses, displaced persons, evacuated persons, missing persons, and others

[11] Recognizing disasters involves an official assessment and validation by the Federal Executive Branch. This process ensures reported damages are accurately documented and verified. For more information, see the *Instrução Normativa* nº 2, December 20, 2016.

affected. We decided to exclude the variable "others affected" due to its questionable data quality, as our analysis indicates it often records the entire population of the municipality, thus exaggerating the disaster's impact. Economic variables in our study report private and public economic losses, measured in millions of reais.[12]

To assess the most severe natural disasters in Brazil, we apply additional treatment to our disaster dataset, considering restrictions on our inter-firm payment database and identification strategy. Due to these constraints, we exclude certain disasters from our sample. Given that our payment database covers the period from the end of 2018 to the end of 2022, we focus on disasters that occurred in 2020 and 2021 to ensure at least a twelve-month time window before and after each extreme climate event when analyzing inter-firm payment data. In line with our identification strategy, we exclude the following disaster categories: Dry Spell, Drought, and Viral Infectious Diseases.

The identification issue with Dry Spell and Drought categories arises from the difficulty in pinpointing the exact occurrence date, as they are chronic climate events. While most of the other disasters typically occur and cause damage within a relatively short time frame (acute extreme events), the damages from Dry Spell and Drought accumulate slowly. They are only reported when the situation becomes severe. Establishing the correct timing of the event is important in our empirical analysis. In the case of Viral Infectious Diseases, most records are related to the COVID-19 pandemic, which is unrelated to climate conditions and requires a specific identification strategy. After applying these exclusions, 1,369 disasters remain in our sample.

Given our focus on severe disasters, we aim to select the thirty most impactful events. To achieve this, we develop a ranking system for classifying natural disasters by their human and economic loss impact. First, we calculate the centile ranks for each damage variable representing human and economic losses.[13] The centile rank indicates the relative position of a disaster's impact compared to others. For example, a disaster in the 95th centile for deaths means it causes more fatalities than 95% of other disasters.

[12]Private economic loss variables measure losses across key sectors of private activity: agriculture, livestock, industry, commerce, and services. Public economic loss variables encompass losses related to essential public services and infrastructure: medical assistance, public health and emergency medical services, potable water supply, stormwater and sanitary sewer systems, urban cleaning and waste collection and disposal systems, habitat disinfestation/disinfection, pest and vector control, electricity generation and distribution, telecommunications, local, regional, and long-distance transport, fuel distribution (especially for domestic use), public security, and education.

[13]$\mathscr{V}$ represents the set of variables related to the disaster $i$.

Let $C_{i,j}$ represent the centile rank of disaster $i$ for damage variable $j$. We then average the centiles for all economic and human damage variables to obtain a composite score representing the overall severity of each disaster. This average centile score serves as the basis for our ranking system, with higher scores indicating more severe impacts.

$$S_i = \frac{1}{n} \sum_{j=1}^{n} C_{i,j}$$

where $S_i$ is the composite score for disaster $i$, $C_{i,j}$ is the centile rank of disaster $i$ for damage variable $j$, and $n$ is the total number of damage variables.[14]

In Figure 5, we present a map of Brazil divided into microregions, with each region color-coded to reflect the impact rank of its most significant disaster during 2020 and 2021. Notably, the microregions in the North, as well as some areas in the Northeast and Southeast, experienced disasters with relatively high impact ranks during this period. We order the disasters by their impact ranking and select the thirty highest-ranked events for our empirical analysis, which we present in Table 1. We observe a prevalence of the disaster category Intense Rains, with Floods and Flash Floods also represented. To exemplify the severity of these events, we provide references to journalistic reports on some of the events listed.

We now connect the largest identified climate-related disasters with public news reports. These reports confirm the significant disruptions in city activity, supporting the classification of these events as extreme climate disasters. The highest-ranked disaster occurred in the municipality of Medeiros Neto, classified under the category of Intense Rains. According to UOL, one of Brazil's largest digital news portals, "heavy rains in Bahia left Medeiros Neto almost entirely underwater." A municipal employee reported that "commerce is practically destroyed."[15] The second highest-ranked disaster occurred in the municipality of Alfredo Chaves, classified as a Flood. According to the news portal G1, more than 1,100 residents were displaced. The region, known for banana production, saw many lose their crops while others struggled to transport their produce due to the destruction of 17 bridges. The article notes that "a resident captured footage of rural workers carrying boxes of bananas across a river by hand because the bridge was no

[14] See Subsection 2.3 for details about damage variables.
[15] UOL News Link (Medeiros Neto).

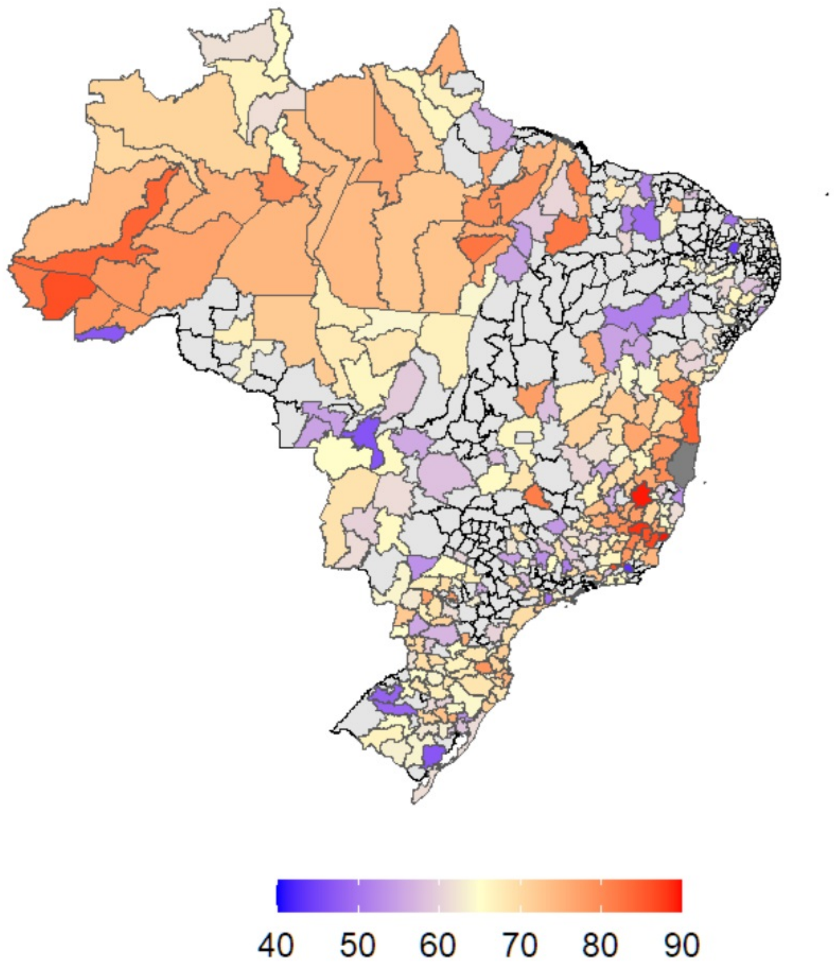



***Figure 5:*** *This figure presents a color-coded map of Brazil, divided into microregions, illustrating the impact rank of the most severe disaster in each microregion during 2020 and 2021. The colors represent the severity of the disaster's impact rank: blue for low values, light yellow for intermediate values, and red for high values. This visual highlights the geographical distribution of disaster severity across Brazil, identifying the areas most affected by severe disasters during the specified period.*

longer there."[16] The third most significant disaster on our list occurred in the municipality of Governador Valadares, classified as Intense Rains. According to G1, approximately 50,000 people were affected, with 15,000 displaced and 292 left homeless.[17]

# 3 Identification strategy

This section discusses the identification strategy employed to estimate the effects of extreme climate events on the supply chain. Identifying the causal effects of such events on economic agents is challenging. When an extreme climate event affects suppliers or customers, disentangling the effects of the climate shock on their operations from time-varying supply, demand,

[16] G1 News Link (Alfredo Chaves).
[17] G1 News Link (Governador Valadares).

***Table 1:*** *This table lists the thirty most severe natural disasters based on our ranking classification, including the rank position (1 to 30), rank score, municipality, state, microregion, date (year and quarter of occurrence), and category of disaster.*

| Position | Rank Value | Municipality | State | Microregion | Date | Disaster |
|---|---|---|---|---|---|---|
| 1 | 90.8 | Medeiros Neto | BA | Porto Seguro | 2021.4 | Intense Rains |
| 2 | 89.6 | Alfredo Chaves | ES | Guarapari | 2020.1 | Floods |
| 3 | 89.5 | Governador Valadares | MG | Governador Valadares | 2020.1 | Intense Rains |
| 4 | 89.3 | Vereda | BA | Porto Seguro | 2021.4 | Intense Rains |
| 5 | 88.5 | Manhuaçu | MG | Manhuaçu | 2020.1 | Intense Rains |
| 6 | 87.5 | Iconha | ES | Guarapari | 2020.1 | Floods |
| 7 | 87.1 | Jucuruçu | BA | Porto Seguro | 2021.4 | Floods |
| 8 | 87.1 | Vargem Alta | ES | Cachoeiro de Itapemirim | 2020.1 | Flash Floods |
| 9 | 86.3 | Três Rios | RJ | Três Rios | 2021.1 | Intense Rains |
| 10 | 86.3 | Tarauacá | AC | Tarauacá | 2021.1 | Floods |
| 11 | 86.1 | Iúna | ES | Alegre | 2020.1 | Intense Rains |
| 12 | 85.3 | Muniz Freire | ES | Alegre | 2020.1 | Intense Rains |
| 13 | 84.2 | Envira | AM | Juruá | 2021.1 | Floods |
| 14 | 84.0 | Floresta Azul | BA | Ilhéus-Itabuna | 2021.4 | Intense Rains |
| 15 | 82.8 | Ibitirama | ES | Alegre | 2020.1 | Intense Rains |
| 16 | 82.4 | Água Azul do Norte | PA | Parauapebas | 2021.1 | Intense Rains |
| 17 | 82.0 | Grajaú | MA | Alto Mearim e Grajaú | 2020.1 | Floods |
| 18 | 81.7 | Rodrigues Alves | AC | Cruzeiro do Sul | 2021.1 | Floods |
| 19 | 81.7 | Itapitanga | BA | Ilhéus-Itabuna | 2021.4 | Intense Rains |
| 20 | 81.5 | Coromandel | MG | Patrocínio | 2021.4 | Flash Floods |
| 21 | 81.3 | Espera Feliz | MG | Muriaé | 2021.1 | Intense Rains |
| 22 | 81.3 | Manhumirim | MG | Manhuaçu | 2020.1 | Intense Rains |
| 23 | 81.1 | Muriaé | MG | Muriaé | 2021.1 | Intense Rains |
| 24 | 81.0 | Valença | BA | Valença | 2021.4 | Intense Rains |
| 25 | 80.7 | Conceição do Lago-Açu | MA | Baixada Maranhense | 2021.1 | Floods |
| 26 | 80.4 | Raul Soares | MG | Ponte Nova | 2020.1 | Intense Rains |
| 27 | 80.0 | Machacalis | MG | Nanuque | 2021.4 | Intense Rains |
| 28 | 79.9 | Careiro da Várzea | AM | Manaus | 2021.2 | Floods |
| 29 | 79.8 | Carangola | MG | Muriaé | 2020.1 | Intense Rains |
| 30 | 79.6 | Feijó | AC | Tarauacá | 2021.1 | Floods |

and preference changes is difficult. In production networks, we only observe the final payments made by customers or received by suppliers, which are influenced by both observable and non-observable features of each firm.

Our empirical strategy to identify the effects of extreme climate events leverages the full production network in Brazil. This massive and time-varying firm-to-firm payments dataset allows us to control for many firm-specific and non-observable features, identifying how extreme climate events propagate through the supply chain. Using this network format dataset, which captures economic relationships between pairs of economic agents, we can effectively control for unobserved factors, such as time-varying demand shocks for customer firms and supply shocks for supplier firms, which may be unrelated to the climate shock. The seminal work by Khwaja and Mian (2008) pioneered the use of network data to control for firm-specific demand shocks, though in a different context (bank lending to the real sector) and for a different purpose (monetary policy transmission).

Figure 6 displays a schematic of our identification strategy. We analyze how extreme climate shocks propagate in the supply chain through two lenses: the downstream and the upstream perspectives. In the first perspective, the extreme climate event is interpreted as a supply shock (e.g., production shock) that hits suppliers in a specific geographical region (Affected Supplier A). This shock propagates downstream through the supply chain to the customers of the affected suppliers (Customer C). In the second perspective, the extreme climate event is interpreted as a demand shock (e.g., input consumption shock) that impacts customers in a specific geographical region (Affected Customer A). This shock propagates upstream through the supply chain to the suppliers of the affected customers (Supplier C).

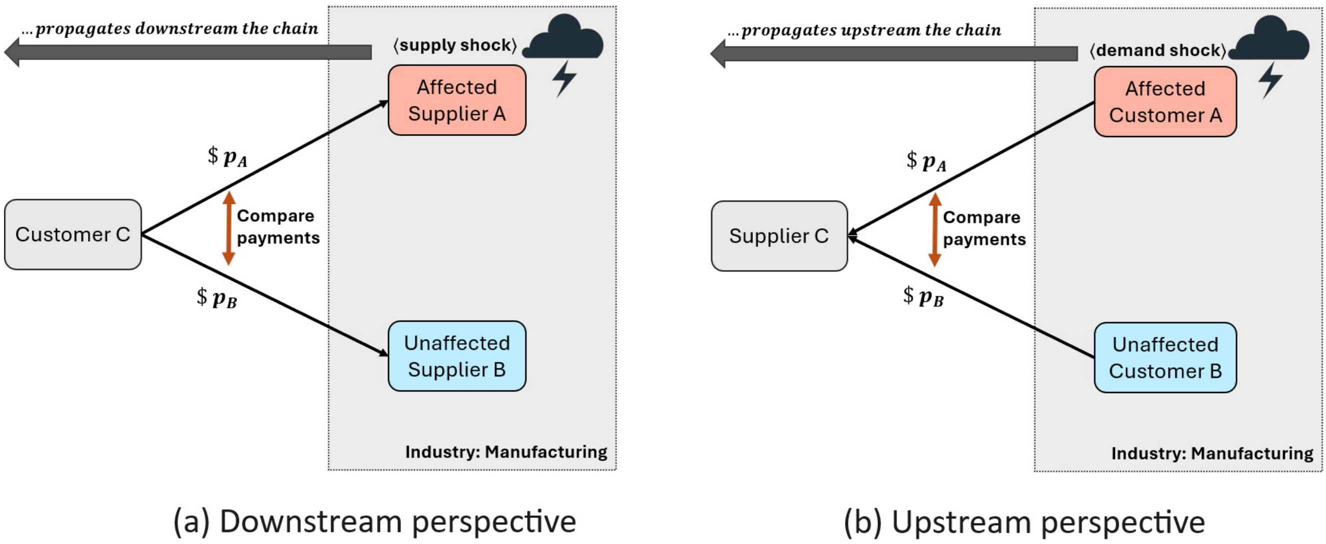



***Figure 6:*** *Schematic of the identification strategy for a single industry (manufacturing) for the (a) downstream and (b) upstream perspectives. (a) Downstream Perspective: the extreme climate event is interpreted as a supply shock (e.g., production shock) that hits suppliers in a specific geographical region (Affected Supplier A). This shock propagates downstream through the supply chain to the customers of the affected suppliers (Customer C). Our empirical strategy compares payments received from the same customer by affected suppliers (Supplier A) vis-à-vis unaffected suppliers (Supplier B) within the same industry. (b) Upstream Perspective: the extreme climate event is interpreted as a demand shock (e.g., input consumption shock) that impacts customers in a specific geographical region (Affected Customer A). This shock propagates upstream through the supply chain to the suppliers of the affected customers (Supplier C). Our empirical strategy here compares payments made to the same supplier by affected customers (Customer A) vis-à-vis unaffected customers (Customer B) within the same industry.*

Our identification strategy assumes that a specific extreme climate event directly affects an observable subset of firms only. This extreme event is well-delimited in geographical and temporal terms, such as a heavy rainfall episode affecting a specific Brazilian region during a week. Considering our schematic in Figure 6, it would affect firm A but not firm B because the former is located within the region impacted by the heavy rainfall while the latter is not.

Focusing on the downstream propagation, our identification strategy examines how payments received by the affected supplier (Supplier A) behave when compared to the unaffected supplier (Supplier B) from the *same* customer (Customer C) outside the affected region. Fixing the same outside customer effectively enables us to control for any customer-specific time-varying shocks unrelated to the climate event. Therefore, the changes observed in the payment pattern to affected vs. unaffected suppliers by the same customer should be due to the extreme climate event on the supplier side (and not the customer side), interpreted here as a supply shock. This identification assumption also presumes unaffected and affected suppliers are similar. We mitigate potential omitted variable biases across different suppliers by comparing sets of suppliers *within* the same industry and adding a comprehensive set of controls and fixed effects that we discuss later.

Economic rationale suggests we should expect a change in payments from outside customers to affected suppliers following an extreme climate event due to several factors. Firstly, such events can disrupt the production capabilities of suppliers by damaging infrastructure, limiting access to raw materials, or causing labor shortages, directly reducing the suppliers' ability to fulfill orders (Barrot and Sauvagnat, 2016; Boehm et al., 2019). Consequently, customers may delay or reduce payments as they wait for the resumption of regular supply or seek alternative sources, reflecting a temporary adjustment in cash flow (Carvalho et al., 2021; Cole et al., 2017). Secondly, the uncertainty induced by extreme climate events might lead customers to renegotiate payment terms to extend payment deadlines or adjust for increased transaction risk (Hoshi et al., 1990). Lastly, affected suppliers may request expedited payments to manage liquidity constraints and recover from the shock more swiftly, leading to variations in the timing and amount of payments (Berg et al., 2016). While we would observe a decrease in payments for the first two reasons, we should observe an increase for the last one. We will examine empirically which of these effects dominates in the aftermath of extreme climate events.

A similar reasoning applies when empirically evaluating upstream propagation in the supply chain by simply switching the customer and supplier roles. Such events can disrupt customer operations by damaging infrastructure, causing transportation delays, or impacting labor availability. This reduces input demand and decreases supplier payments as customers scale back orders (Barrot and Sauvagnat, 2016; Inoue and Todo, 2019). Additionally, affected customers might face liquidity constraints and delay or renegotiate payments to manage cash flow (Carvalho et al., 2021; Kim et al., 2015). Conversely, if customers prioritize securing their supply chains for rapid recovery, they may expedite payments to maintain favorable terms or compensate for future shipment delays (Berg et al., 2016). Suppliers might also request prepayments or reduce trade credit to mitigate their risks associated with customer instability (Hoshi et al., 1990). We will empirically examine which of these effects—decreased payments due to operational and financial stress or increased payments for supply chain stability—dominates in the aftermath of extreme climate events.

Our empirical strategy, which leverages firm-level data in a network format to control for unobserved heterogeneity, requires multiple customers per supplier or suppliers per customer to identify the extreme climate event accurately. However, many firms may have a limited number of trading partners, restricting the ability to isolate these effects. Moreover, focusing only on firms with multiple relationships may result in a sample not fully representative of the broader population, potentially skewing the analysis towards larger firms and overlooking smaller firms or those with a single trading relationship. To address these limitations, we also conduct supplementary analyses where we relax this multiple-supplier or customer requirement at the cost of introducing potential biases in our estimations. These additional tests will help verify the robustness of our findings, ensuring the specific structure of the empirical strategy does not drive the results.

# 4 Direct effects of extreme climate events

## 4.1 Effects of extreme climate events on the supply chain

This section empirically estimates the economic and financial effects of Brazil's 30 most significant acute extreme climate events from 2020 to 2021 on the supply chain from the downstream and upstream perspectives discussed in the previous section. Recall our geographical circumscription of an extreme event is a microregion and not a municipality since municipalities within a microregion tend to be strongly interconnected, and many of the extreme events we consider affect most of these municipalities. This strategy also prevents selecting firms within the same microregion as control units as they are likely strongly interconnected with firms in adjacent and affected municipalities.[18] In this situation, our identification strategy would not cleanly con-

[18] While a climate event may officially be declared within specific municipal boundaries, its impact often extends beyond those limits, affecting a larger region. Even if neighboring municipalities have not declared a state of emergency, they may still experience significant disruptions due to the climate event.

trol for the firm-specific demand when analyzing the downstream perspective and supply when analyzing the upstream perspective.

Our empirical framework relies on a multiperiod difference-in-differences approach. Since extreme events can occur at different moments, we stack different extreme event episodes into a pooled panel-data DiD analysis. We present in Table 2 summary statistics for the data considering the natural variation of each variable. In this setup, we uniquely identify firms by the firm identifier $\times$ shock, in which shock represents one of the top 30 acute extreme events. This approach enables us to classify the same firm as a control or treatment unit for different shocks. Moreover, our sample contains multiple occurrences of extreme climate events at adjacent periods within the same microregion. This could contaminate our estimates, especially when analyzing pre-trends after the first extreme event occurrence in a specific microregion. We consider the first extreme event in these multiple occurrence cases. We define the existence of numerous occurrences if there is another extreme event in a one-year window for each extreme event.

***Table 2:*** *Summary statistics for the data used to investigate the direct effects of extreme weather events on the supply chain. The dataset is replicated for each extreme event to display natural variation. Variables are as follows: Total Payment, Received Payments (ex-ante), and GDP per Capita are in thousands of R$. Population is in millions, and Firm Age is in years.*

| Statistic | N | Mean | St. Dev. | Min | Pctl(25) | Median | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|---|
| *Downstream - Customer-Supplier Level* | | | | | | | | |
| Total Payment | 76,449,721 | 38.998 | 2,246.559 | 0.00001 | 0.625 | 2.000 | 7.089 | 7,993,513.000 |
| Received Payments | 16,112,911 | 67.559 | 2,132.292 | 0.00001 | 1.343 | 4.466 | 16.330 | 1,663,690.000 |
| GDP per Capita | 16,112,911 | 35.886 | 26.601 | 4.924 | 20.877 | 32.727 | 44.186 | 591.101 |
| Population | 16,112,911 | 964.952 | 1,529.161 | 0.776 | 64.455 | 240.408 | 1,091.737 | 6,747.814 |
| *Upstream - Customer-Supplier Level* | | | | | | | | |
| Total Payment | 231,994,171 | 18.316 | 1,572.345 | 0.00001 | 0.563 | 1.714 | 5.308 | 11,288,406.000 |
| Firm Age | 54,960,631 | 13.626 | 10.989 | 1 | 5 | 10 | 19 | 131 |
| Received Payments | 54,960,631 | 9.346 | 355.681 | 0.00001 | 0.899 | 2.213 | 5.044 | 486,339.300 |
| GDP per Capita | 54,960,631 | 33.309 | 26.412 | 4.924 | 20.417 | 28.923 | 39.132 | 591.101 |
| Population | 54,960,631 | 807.370 | 1,393.613 | 0.776 | 38.103 | 150.658 | 699.097 | 6,747.814 |

The analysis uses the relative time to the extreme event rather than the absolute time to accommodate extreme events at different moments in our specification. We set $t = 0$ precisely at the extreme event's occurrence; $t > 0$ represents the relative time after its occurrence, and $t < 0$ indicates the relative time before. Therefore, our classic $Post$ variable in the DiD literature depends on the relative time and the considered shock. For every extreme event, we consider a one-year window before and after the event.

The treatment variable is specific for the firm and a particular shock. The treatment group for a given shock consists of firms in the microregion affected by that shock. The control group for that shock comprises firms outside this affected microregion, excluding those in other microregions affected by different extreme climate events within a one-year window relative to the analyzed shock. This approach ensures control firms are always selected from regions unaffected by recent extreme climate events, allowing us to isolate firm-specific demand and supply shocks cleanly.[19]

Including multiple extreme events in our empirical analysis provides a more robust and reliable picture of how such events impact the supply chain. By examining the effects of 30 distinct acute climate events over two years, we mitigate the risk of idiosyncratic shocks or unique characteristics of a single event disproportionately influencing our results. This approach enhances the external validity of our findings, ensuring our conclusions are not specific to a particular event's context or timing but are reflective of broader patterns. Additionally, the varied timing and geographical distribution of these events allow us to capture a range of responses and adaptations within the supply chain, providing a comprehensive understanding of the resilience and vulnerabilities inherent in different regions and sectors. By pooling data across multiple shocks, we also increase the statistical power of our analysis, enabling a more precise estimation of the economic and financial impacts of extreme climate events on the supply chain.

**Downstream perspective (shock: directly affected suppliers → customers)**: Our downstream perspective conceives the extreme climate event as a supply shock and examines how it propagates down the production network to the affected supplier's customers. We implement this empirical strategy with the following econometric specification:

$$\log(y_{x,c,s,t}) = \alpha_{x,c,sector(s),t} + \gamma_{x,s} + \beta \ \text{Post}_{x,t} \times \text{Affected}_{x,s} + \rho \ \text{Post}_{x,t} \times \text{Controls}_{x,s} + \varepsilon_{x,c,s,t} \qquad (1)$$

in which $x$, $c$, $s$, and $t$ index the extreme acute climate event (top 30), the outside customer firm, the affected or unaffected supplier firm, and time (quarterly), respectively. The dependent variable

[19] Let us consider a hypothetical country divided into four regions: Region A, Region B, Region C, and Region D. Suppose Region A experiences an extreme climate event in the first quarter of 2023. The treatment group consists of firms located within the microregion of Region A directly impacted by this event. For the control group, we include firms in Regions B, C, and D that were not affected by any extreme climate events within a one-year window relative to the event in Region A. For example, if Region C experienced an extreme climate event in the third quarter of 2022, firms in Region C are excluded from the control group. Similarly, if Region D experienced an extreme climate event in the first quarter of 2023, one month after Region A's event, firms in Region D are also excluded from the control group. Thus, the control group only includes firms from Region B, ensuring we isolate the effect of the climate event in Region A without contamination from other recent extreme events. This approach allows us to compare the outcomes of firms in Region A with those in unaffected regions, providing a clearer picture of the causal impact of the extreme climate event.

is the log of the sum of payments from outside customer $c$ to supplier $s$ during the relative time (quarter-year) $t$. The binary variable $\text{Post}_{x,t}$ equals 1 if the relative time is at or after the extreme climate event $x$, i.e., $t \geq 0$, and 0 otherwise. The binary variable $\text{Affected}_{x,s}$ equals 1 if supplier $s$ is located in the microregion affected by the extreme event $x$, and 0 otherwise. We also add the following set of time-invariant controls *ex-ante* to the extreme event $x$ and specific for supplier $s$: volume of received payments in the previous year to the extreme event, firm's age, the GDP per capita and population of the supplier's municipality. $\varepsilon_{x,c,s,t}$ is the error term. Following Abadie et al. (2023), we cluster errors at the extreme event $\times$ supplier's microregion dimension, which matches the level of variation of our binary treatment variable $\text{Affected}_{x,s}$.

The term $\alpha_{x,c,sector(s),t}$ denotes extreme event $\times$ outside customer $\times$ supplier's economic sector $\times$ time fixed effects. The matching of the affected and unaffected supplier's economic sectors considers the Brazilian CNAE economic sector classification at its most granular level (seven digits).[20] Introducing these fixed effects is key to implementing our identification strategy in Figure 6. It permits us to interpret our results as comparing payments from the *same* outside customer $c$ to affected and unaffected suppliers of the *same* economic sector for a given extreme event over time. Importantly, these fixed effects control for customer-level demand shocks or changes in the economic environment affecting the outside customer firm, ensuring payment variations are not driven by changes in the customer's financial health or demand. Additionally, it captures sector-specific trends, COVID-19 shocks,[21] technological changes, or regulatory impacts influencing supplier performance. Lastly, it controls for temporal changes like macroeconomic trends, seasonal effects, or other time-varying factors, ensuring our results are not confounded by broader economic cycles.

The term $\gamma_{x,s}$ represents extreme event $\times$ supplier fixed effects that further absorb any time-invariant supplier-specific factor that could influence payment patterns, such as average size, productivity, and managerial practices. It also accounts for inertial geographical and demographic

[20]CNAE (Classificação Nacional de Atividades Econômicas) is the Brazilian system for classifying economic activities, managed by the Brazilian Institute of Geography and Statistics (IBGE). It categorizes firms based on their primary economic activities, with classifications ranging from broad sectors to highly specific industries at the seven-digit level.

[21]The fixed effects help account for time-varying, sector-specific shocks such as those caused by the COVID-19 pandemic. Since the pandemic had heterogeneous impacts across sectors (e.g., a sharp decline in tourism versus growth in food delivery and streaming services), these fixed effects absorb the variation attributable to such industry-specific shocks. This ensures the effects of the extreme climate events are isolated from the disruptions caused by COVID-19.

characteristics of the supplier's location, including infrastructure quality, local economic conditions, and demographic factors, which could affect their vulnerability and response to extreme events.

Our coefficient of interest $\beta$ in Eq. (1) captures the percent change in payments to affected suppliers *vis-à-vis* unaffected suppliers of the same industry from the exact same outside customer firm. This is averaged across the extreme events after controlling for observable supplier-side variables introduced in our control set and time-invariant unobserved supplier-specific factors. Including these fixed effects and controls allows us to account for many potential confounders, including unobserved heterogeneity. This ensures our coefficient of interest, $\beta$, accurately captures the causal effect of the extreme climate event on payment patterns from outside customers to affected suppliers.

Spec. I of Table 3 reports the coefficient estimates of the downstream propagation estimation as defined in Eq. (1). We find affected suppliers receive 4.3% less than unaffected suppliers of the same industry from the exactly same outside customer. This result aligns with our theoretical predictions that extreme climate events disrupt suppliers' ability to fulfill orders, likely due to damaged infrastructure, limited access to raw materials, and labor shortages. Consequently, outside customers may delay or reduce their payments to these affected suppliers, reflecting a temporary adjustment in their cash flow management. The 4.3% reduction is economically significant for several reasons. First, it highlights the immediate financial stress that affected suppliers face, which can lead to liquidity issues and hinder their ability to recover quickly from the shock. Such financial strain may force suppliers to seek additional financing or cut back on operations, further exacerbating the disruption. Second, this reduction in payments can have a cascading effect on the broader supply chain. Suppliers struggling to manage their cash flow might delay payments to their own suppliers, amplifying the initial shock's impact throughout the network. This chain reaction underscores the theoretical prediction that supply chain disruptions can propagate shocks, causing broader economic impacts.

The fixed effects $\alpha_{x,c,sector(s),t}$ in Equation (1) only keep outside customer firms with multiple relationships with at least one affected and unaffected supplier of the same industry. This may restrict the sample to larger customer firms, which have many suppliers in the same industry to accommodate their substantial demand needs. We alleviate this restriction by dropping the requirement of comparisons within the same supplier's industry. Therefore, we replace $\alpha_{x,c,sector(s),t}$

with $\alpha_{x,c,t}$ in Equation (1). Spec. II in Table 3 shows the coefficient estimates of this alternate, less restrictive specification. We highlight the increase in the sample size: it increases from 65.6 million to 115.2 million observations. While the coefficient drops in magnitude, it is still statistically significant and has the same sign. This additional test shows our results are still valid when comparing suppliers of different industries.

***Table 3:*** *How do extreme climate events affect the supply chain?*

| *Dependent Variable*: | $\log(\text{Payments}_{x,c,s,t})$ | | | | | |
|---|---|---|---|---|---|---|
| *Perspective ($a$ dimension)*: | Downstream ($a$: supplier $s$ is affected) | | | Upstream ($a$: customer $c$ is affected) | | |
| *Model*: | (I) | (II) | (III) | (IV) | (V) | (VI) |
| *Variable of interest* | | | | | | |
| $\text{Post}_{x,t} \times \text{Affected}_{x,a}$ | -0.0430*** | -0.0207*** | -0.0319* | 0.0040 | 0.0049 | 0.0107* |
| | (0.0094) | (0.0074) | (0.0188) | (0.0031) | (0.0038) | (0.0055) |
| *Controls* | | | | | | |
| $\text{Post}_{x,t} \times \log(\text{Received Payments}_{x,a})$ | -0.1765*** | -0.1738*** | -0.1670*** | -0.0533*** | -0.0876*** | -0.0646*** |
| | (0.0027) | (0.0033) | (0.0036) | (0.0007) | (0.0016) | (0.0011) |
| $\text{Post}_{x,t} \times \log(\text{Firm's Age}_{x,a})$ | -0.0171*** | 0.0006 | 0.0163*** | 0.0048*** | 0.0010 | 0.0418*** |
| | (0.0031) | (0.0026) | (0.0029) | (0.0007) | (0.0009) | (0.0024) |
| $\text{Post}_{x,t} \times \log(\text{GDP Per Capita}_{x,a})$ | 0.0261*** | 0.0378*** | 0.0503*** | 0.0120*** | 0.0211*** | 0.0162*** |
| | (0.0037) | (0.0046) | (0.0068) | (0.0010) | (0.0011) | (0.0020) |
| $\text{Post}_{x,t} \times \log(\text{Population}_{x,a})$ | 0.0068*** | 0.0024* | 0.0034 | -0.0017*** | 0.0001 | -0.0072*** |
| | (0.0013) | (0.0013) | (0.0028) | (0.0006) | (0.0008) | (0.0012) |
| $\text{Affected}_{x,a}$ | | 0.1311*** | 0.0195 | | -0.0238*** | 0.0240*** |
| | | (0.0328) | (0.0369) | | (0.0054) | (0.0090) |
| $\log(\text{Received Payments}_{x,a})$ | | 0.6553*** | 0.7448*** | | 0.4623*** | 0.5912*** |
| | | (0.0024) | (0.0020) | | (0.0017) | (0.0024) |
| $\log(\text{Firm's Age}_{x,a})$ | | -0.0831*** | -0.1228*** | | 0.0125*** | -0.0392*** |
| | | (0.0069) | (0.0070) | | (0.0008) | (0.0015) |
| $\log(\text{GDP Per Capita}_{x,a})$ | | -0.0149* | -0.0188** | | 0.0194*** | -0.0647*** |
| | | (0.0076) | (0.0092) | | (0.0013) | (0.0030) |
| $\log(\text{Population}_{x,a})$ | | 0.0019 | -0.0097*** | | 0.0096*** | -0.0344*** |
| | | (0.0020) | (0.0019) | | (0.0007) | (0.0011) |
| *Fixed effects* | | | | | | |
| Extreme climate event × | | | | | | |
| × Time × Customer × Supplier's Sector | Yes | — | — | — | — | — |
| × Supplier | Yes | — | — | — | — | — |
| × Time × Customer | — | Yes | — | — | — | — |
| × Time × Supplier × Customer's Sector | — | — | — | Yes | — | — |
| × Customer | | — | — | Yes | — | — |
| × Time × Supplier | — | — | — | — | Yes | — |
| × Time | — | — | Yes | — | — | Yes |
| *Fit statistics* | | | | | | |
| Observations | 65,633,296 | 115,215,803 | 117,036,831 | 434,725,663 | 488,473,801 | 489,628,744 |
| $R^2$ | 0.7329 | 0.4755 | 0.3284 | 0.6671 | 0.5105 | 0.1954 |
| Within $R^2$ | 0.0073 | 0.2617 | 0.3258 | 0.0005 | 0.1425 | 0.1917 |

**Note:** This table reports coefficient estimates of variations of the specifications in Eqs. (1) (downstream perspective, Specs. I–III) and (2) (upstream perspective, Specs. IV–VI). Data are quarterly and correspond to a one-year window centered on each extreme climate event. The dependent variable is the log of the sum of payments from outside customer $c$ to supplier $s$ during the relative time (quarter-year) $t$. The binary variable $\text{Post}_{x,t}$ equals 1 if the relative time is at or after the extreme climate event $x$, i.e., $t \geq 0$, and 0 otherwise. The binary variable $\text{Affected}_{x,s}$ equals 1 if supplier $s$ is located in the microregion affected by the extreme event $x$, and 0 otherwise. We also add the following set of time-invariant controls *ex-ante* to the extreme event $x$ and specific for supplier $s$: volume of received payments in the previous year to the extreme event, firm's age, the GDP per capita and population of the supplier's municipality. $\varepsilon_{x,c,s,t}$ is the error term. Specs. I and IV introduce extreme climate event × outside customer × supplier's sector (7-digit CNAE code) × time and extreme climate event × supplier fixed effects. The first fixed effects keep outside customer firms with multiple relationships with at least one affected and unaffected supplier of the same industry only. Specs. II and V desaturates the previous regression by considering extreme climate event × outside customer fixed effects only. This still retains outside customer firms with multiple suppliers, but they need not be in the same industry. Specs. III and VI only maintain time fixed effects. This preserves in the sample outside customer firms with a single supplier. We cluster errors at the extreme climate event × supplier's microregion level. *, **, *** denote statistical significance of 10%, 5%, and 1%, respectively.

One could argue that restricting the sample to outside customers with multiple suppliers could still not reflect the national supply chain structure. We further alleviate this concern by replacing the $\alpha_{x,c,t}$ fixed effects with a simple $\alpha_{x,t}$, i.e., time fixed effects for each shock. We also drop the $\gamma_{x,s}$ fixed effects in Equation (1) to desaturate our model further. Spec. III of Table 3 shows the coefficient estimates of the resulting specification. The sample size does not expand substantially, increasing from 115.2 to 117.0 million observations. The slight increase may reflect the fact that small outside customers tend to interconnect mostly with geographically close suppliers. Due to identification matters, we only consider customers outside the affected area. We observe our qualitative conclusions still hold.

**Upstream perspective (shock: directly affected customers $\rightarrow$ suppliers)**: Our upstream perspective conceives the extreme climate event as a demand shock on customers and examines how it propagates up the production network to the affected customer's outside suppliers. The econometric specification is:

$$\log(y_{x,c,s,t}) = \alpha_{x,sector(c),s,t} + \gamma_{x,c} + \beta \text{ Post}_{x,t} \times \text{Affected}_{x,c} + \rho \text{ Post}_{x,t} \times \text{Controls}_{x,c} + \varepsilon_{x,c,s,t} \tag{2}$$

in which $x$, $c$, $s$, and $t$ index the extreme climate event (top 30), the affected or unaffected customer firm, the outside supplier firm, and time (quarterly), respectively. All the remainder of the empirical setup is analogous to the downstream case, except that we interchange the customer and supplier roles. Errors are clustered at the extreme event $\times$ customer's microregion dimension.

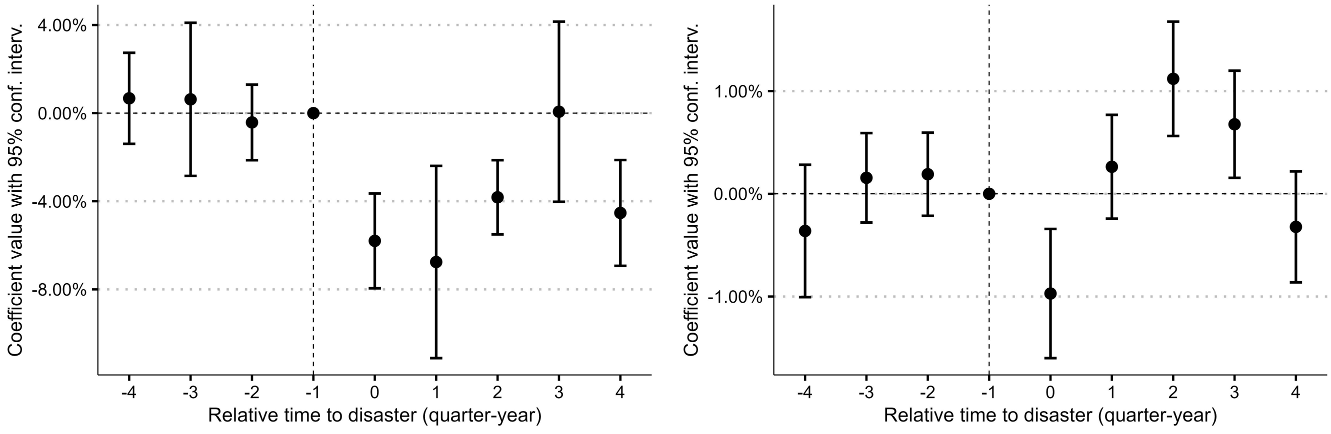
Spec. IV of Table 3 reports the coefficient estimates of the upstream propagation estimation as defined in Eq. (2). We find affected customers pay 0.4% more to their outside suppliers compared to unaffected customers, although this result is not statistically significant. This suggests outside suppliers may perceive affected customers as riskier and thus demand more liquidity or reduce trade credit. This behavior aligns with our theoretical prediction that outside suppliers might require quicker or larger payments from customers in distressed situations to mitigate the risk of non-payment or delayed payment.

We also drop the restriction that outside suppliers must have multiple customers in the same industry, replacing $\alpha_{x,sector(c),s,t}$ with $\alpha_{x,s,t}$ in Equation (2). Spec. V in Table 3 shows the sample size increases significantly from 434.7 million to 488.5 million observations, with the coefficient slightly increasing to 0.5% while remaining statistically insignificant. Finally, in Spec. VI, we further desaturate the model by replacing $\alpha_{x,s,t}$ with $\alpha_{x,t}$ and dropping $\gamma_{x,c}$, leading to a marginal increase in sample size to 489.6 million observations. The coefficient now increases to 1.07% and becomes statistically significant at the 10% level.

Overall, the average effect of the upstream propagation is not economically significant. The theoretical predictions suggested mixed outcomes: on the one hand, affected customers might delay payments due to their own liquidity constraints, while on the other hand, outside suppliers might demand quicker or larger payments to mitigate risk. Our empirical results lean towards the latter, indicating outside suppliers respond to increased perceived risk by requiring more immediate payments. This behavior can be attributed to outside suppliers' need to ensure financial stability and manage the risk of providing goods and services to customers affected by extreme climate events. Outside suppliers can safeguard their cash flow by demanding quicker payments and reducing the potential impact of delayed payments or defaults. This highlights the risk-averse strategies employed within supply chains during disruptions.

**Event study**: we also adapt our baseline specification for the downstream perspective in Eq. (1) and the upstream in Eq. (2) to an event study format to inspect for pre-trends and time-varying effects. We replace the step variable $\text{Post}_{x,t}$ with quarterly pulse dummies. Figure 7 displays the estimated $\beta$ coefficients for the downstream (a) and upstream (b) perspectives. Before the extreme climate event, there are no signs of pre-trends between payments from and to affected vs. unaffected units. Only after the extreme event occurred did we observe changes in payments to affected suppliers (downstream) and from customers (upstream).

From the downstream perspective, the supply shock imposed by the extreme climate event does not seem to dissipate over time despite the statistically insignificant coefficient exactly after three-quarters of the acute event. This persistence suggests the disruptions caused by extreme climate events, such as damaged infrastructure or persistent shortages in raw materials and labor, may have long-lasting effects on affected suppliers' ability to fulfill orders. The inability of the coefficient to revert to insignificance over time indicates recovery may be hampered by prolonged operational challenges or delayed adjustments in the supply chain. The sustained impact might also be compounded by outside customers' potential decisions to replace affected suppliers with alternative partners, causing affected firms to lose market share in the long term (Altay and Ramirez, 2010). The persistent nature of these disruptions reflects the complex and often slow




***(a)** Downstream propagation (directly affected suppliers → outside customers)*

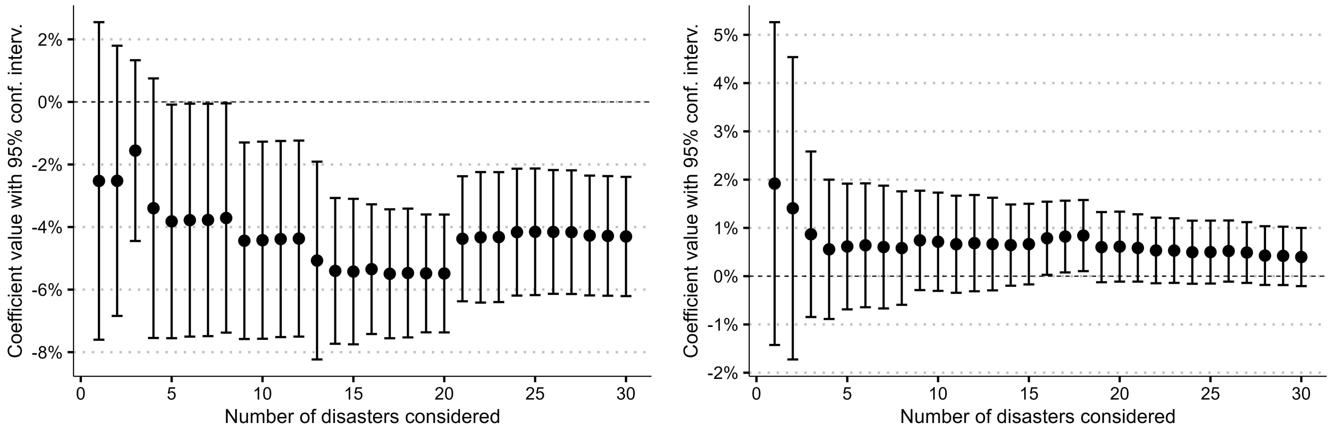
***(b)** Upstream propagation (directly affected customers → outside suppliers)*

***Figure 7:** Event study: pre-trend and time-varying effects check. We run (a) the downstream perspective specified in Eq. (1) and (b) the upstream perspective in Eq. (2), replacing the step variable $Post_{x,t}$ with quarterly pulse dummies. The figure displays the estimated $\beta$ coefficients for each quarter-year. Vertical bars denote the 95% confidence interval.*

recovery process of affected suppliers, who may face structural changes, financial distress, and a permanent shift in their market positioning.

From the upstream perspective, notable time-varying effects are observed. During the quarter of the extreme climate event, affected customers pay less to outside suppliers compared to unaffected customers of the same industry. Subsequently, affected customers pay relatively more until the third quarter after the event. Initially, this reduction in payments could be attributed to decreased demand or disruptions in production capabilities due to the shock. Following this period, the pattern likely reflects the increased risk perceived by outside suppliers dealing with affected customers, leading suppliers to demand higher prices or more stringent credit terms to compensate for added uncertainty and potential liquidity risks. This finding aligns with (McGuinness et al., 2018; Petersen and Rajan, 1997), who demonstrate firms adjust trade credit terms in response to perceived risks and creditworthiness of their partners following shocks. The increased payments by affected customers in subsequent quarters may reflect their efforts to secure supply stability and restore trust with outside suppliers. This observed pattern highlights the dynamic nature of supply chain adjustments and the ongoing negotiations between customers and suppliers in response to extreme climate events.

**Sensitiveness analysis of the number of extreme climate events considered**: our baseline results consider the average results from the top 30 extreme climate events. Figure 8 displays a sensitivity analysis of our results for (a) downstream and (b) upstream effects by varying the number of extreme climate events included. We conduct 30 independent regressions, progressively including the largest climate event, the two largest, the three largest, and up to the top 30 events cumulatively. The figure displays the estimated $\beta$ coefficients of Eq. (1) (downstream) and Eq. (2) (upstream) for each number of disasters considered.




***(a)*** *Downstream propagation (directly affected suppliers → outside customers)*

***(b)*** *Upstream propagation (directly affected customers → outside suppliers)*

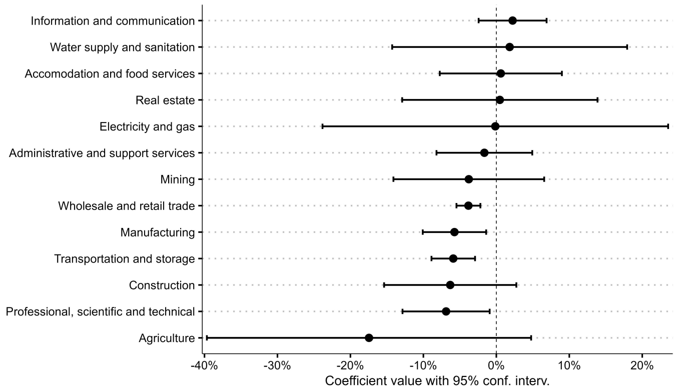
***Figure 8:*** *Sensitivity analysis of our results for (a) downstream and (b) upstream effects by varying the number of extreme climate events included. We conduct 30 independent regressions, progressively including the largest climate event, the two largest, the three largest, and up to the top 30 events cumulatively. The figure displays the estimated $\beta$ coefficients of Eq. (1) (downstream) and Eq. (2) (upstream) for each number of disasters considered. Vertical bars denote the 95% confidence interval.*

## 4.2 Extreme climate events and heterogeneous effects across industries

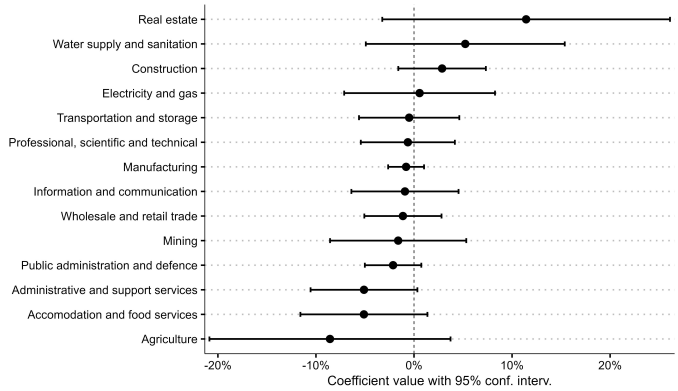
This section examines the heterogeneous effects of extreme climate events across industries from both downstream and upstream perspectives.

**Downstream perspective (shock: directly affected suppliers → customers)**: Figure 9 portrays the coefficient estimates of Eq. (1) when we run it with the following sub-samples independently: (a) suppliers of the same industry and (b) outside customers of the same industry with economic relationships with affected suppliers. This analysis provides a distilled view of the average effects of extreme climate events on economic transactions within the Brazilian supply chain by economic sectors. The estimates remain consistent for a wide range of disasters included, highlighting the robustness of our empirical findings.

Figure 9a illustrates agricultural suppliers are the most affected, despite a wide confidence interval. Our results demonstrate extreme climate events significantly disrupt agricultural supply chains, which rely heavily on weather conditions. This finding aligns with previous research on




***(a)** Average effect on payments received by directly affected suppliers*




***(b)** Average effect on payments made by outside customers*

***Figure 9:** Downstream perspective: heterogeneous effects of extreme climate events on (a) directly affected suppliers and (b) outside customers. We run Eq. (1) independently for each economic sector by splitting the sample as follows: (a) by the supplier's industry and (b) by the customer's industry. The dot is the $\beta$ coefficient in Eq. (1), and the horizontal bars denote the 95% confidence interval.*

agriculture's vulnerability to climate variability and extreme weather events (Lobell et al., 2011; Schlenker and Roberts, 2009).

In addition to agriculture, our results show negative impacts on other sectors, including suppliers in professional services, transportation, manufacturing, and trade. The professional services sector depends on stable economic conditions, and climate disruptions can cause project delays, reduced client engagement, and financial instability. The transportation and storage sector is similarly affected by infrastructure damage, leading to delays, higher costs, and logistical challenges, reducing efficiency and profitability (Hallegatte, 2009). Manufacturing firms face challenges from interruptions in raw materials, energy, and labor, causing production halts and increased costs (Hertel et al., 2010). Wholesale and retail trade also suffer from inventory shortages, higher prices, and decreased sales due to supply chain disruptions. Their dependence on timely deliveries and steady stock flows makes them particularly vulnerable to the cascading effects of climate shocks (Hertel et al., 2010).

Conversely, the information and communication sector seems to benefit from extreme climate events. Its resilience stems from its digital nature, allowing remote operations with less dependence on physical infrastructure. During such events, demand for digital communication tools and services rises as businesses and individuals seek to stay connected. This highlights the role of digital infrastructure in maintaining economic resilience during environmental disruptions.

In summary, the varying impacts across sectors reflect different levels of vulnerability and resilience in the economy. These results align with existing literature, highlighting the need for sector-specific strategies to mitigate climate shocks and strengthen economic resilience (Piontek et al., 2014).

Figure 9b illustrates that payments made by outside customers in the agriculture sector experience the most prominent negative variation despite a wide confidence interval. Outside customers in the accommodation and food services sector and the administrative and support services sector also exhibit negative variations in payments to suppliers affected by extreme weather events. Conversely, we observe outside customers in the real estate sector show substantial payment increases despite the wide confidence interval. Outside customers in the water supply and sanitation sector also increase their payments. These findings suggest that, from the perspective of an outside customer, the impact on payments to suppliers affected by extreme weather events can vary significantly across different sectors.

The previous analysis showed how affected industries of the supplier's viewpoint coped following acute extreme climate events by averaging across all outside customers' industries. We also conducted an analogous exercise considering specific outside customers' industries averaged across all affected suppliers' industries. We now distill both the customer and the supplier's industries simultaneously. Figure 10 displays a heatmap showing sector-to-sector payment dynamics between outside customers and suppliers impacted by extreme climate events in Brazil. Each cell shows the effect of climate events on the affected supplier compared to unaffected suppliers of the same industry, considering payments from the same outside customer. These correspond to the $\beta$ coefficient in Eq. (1) using paired subsamples of customer and supplier industries.

There are notable heterogeneities within sectors. Previously, we noted agriculture stands out negatively, with affected suppliers receiving fewer payments and outside customers reducing payments during extreme weather events. Figure 10 highlights an important intra-sector dynamic: when a supplier in agriculture is affected by a climate event, 82% of the payment reduction comes from customers within the same sector. This phenomenon highlights the high degree of interconnectivity within the agricultural supply chain. For example, consider a natural disaster affecting a region producing feed crops. Suppliers of these crops will experience a direct impact, but so too will poultry or dairy farms reliant on these feed supplies, even if they are located outside the disaster zone. These farms may reduce their payments to feed suppliers due to supply shortages,

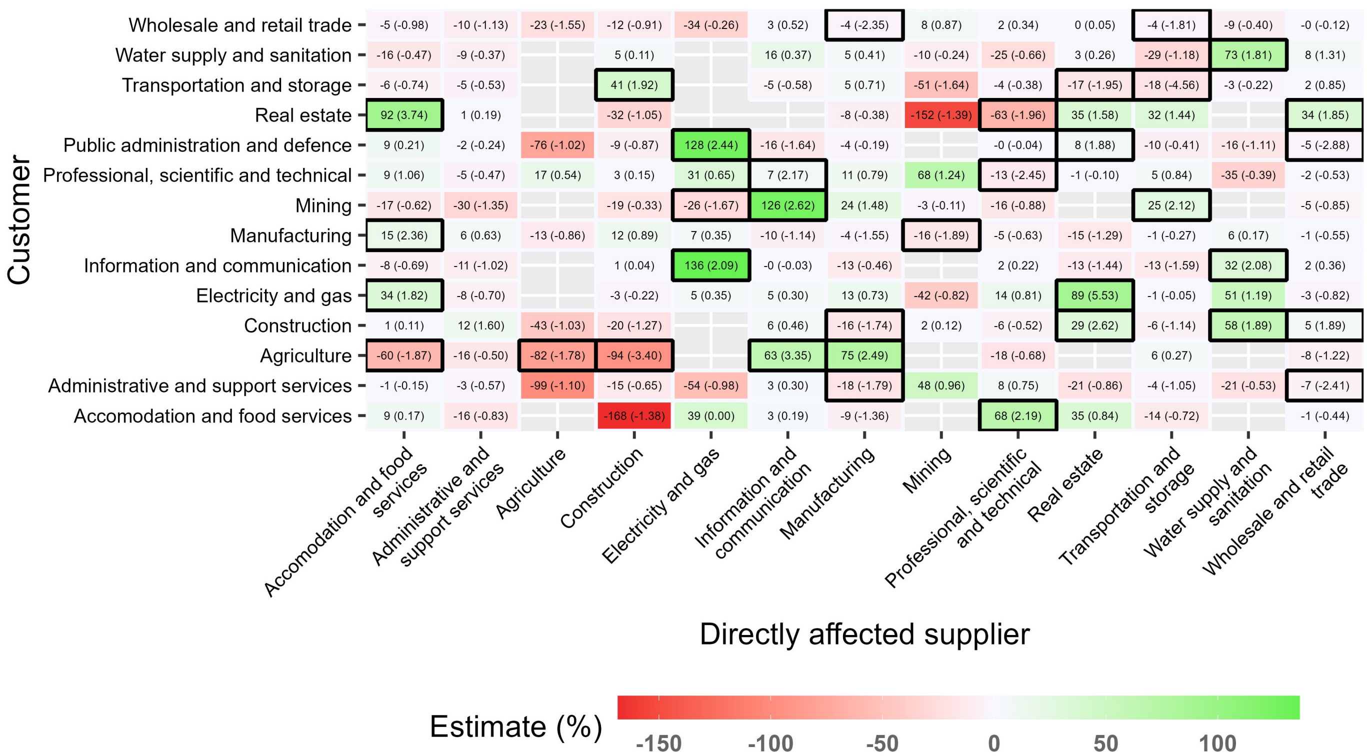


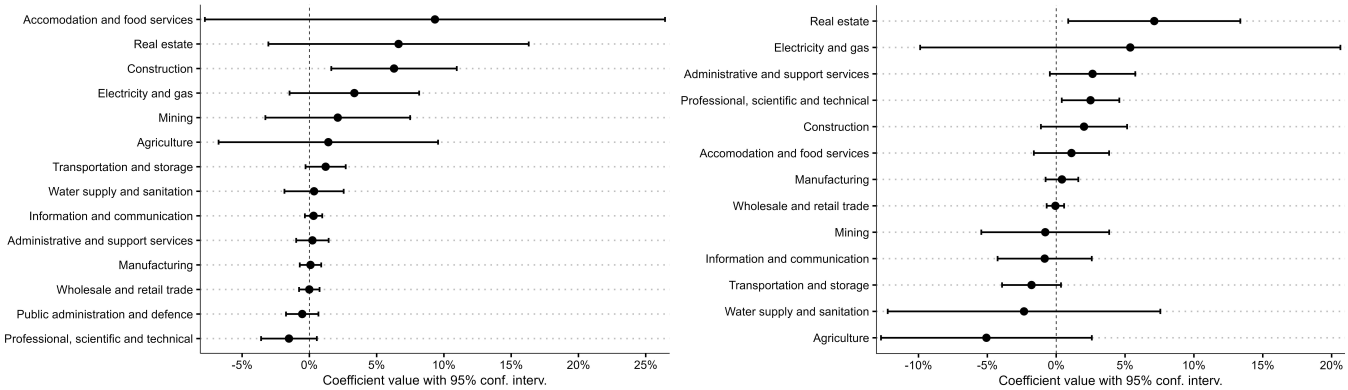

***Figure 10:*** *Heatmap showing sector-to-sector payment dynamics between outside customers and suppliers impacted by extreme climate events in Brazil. Each cell shows the effect of climate events on the affected supplier compared to unaffected suppliers of the same industry, considering payments from the same outside customer. These correspond to the $\beta$ coefficient in Eq. (1) using paired subsamples of customer and supplier industries. Cells are color-coded, with red indicating a decrease in payments and green an increase in payments. Each cell shows the percent change and the $t$-statistic in parentheses. Changes that are statistically significant at 10% are with a thick black border.*

leading to cascading financial strain.

Figure 10 shows that a significant portion of payment reductions for affected suppliers in professional services comes from outside real estate sector clients. During extreme weather events, outside real estate firms reduce payments to these suppliers by about 63%. This occurs due to several factors. For example, if a climate event disrupts engineering firms offering services like land surveying or consulting, outside real estate developers may delay or reduce payments due to project delays, uncertainty, or reassessment of project feasibility.

From the perspective of outside customers, as discussed above, real estate firms increase payments to affected suppliers during extreme weather events. Figure 10 indicates part of this increase is directed at affected suppliers in the accommodation and food services sector. This financial support likely arises from the symbiotic relationship between sectors, as real estate firms depend on hotels and restaurants for hosting clients, meetings, and accommodating out-of-town employees. When climate events disrupt these services, real estate firms may preemptively increase payments to ensure the continuity of these services. Additionally, real estate firms may consider such support an investment in maintaining the area's overall attractiveness and economic health, which, in turn, benefits property values and business prospects.

**Upstream perspective (shock: directly affected customers $\rightarrow$ suppliers)**: Figure 11 depicts the coefficient estimates of Equation (2) when applied to two distinct sub-samples: (a) outside suppliers within the same industry and (b) affected customers within the same industry. This analysis offers a clear perspective (upstream) on the average impacts of extreme climate events on economic transactions across different sectors within the Brazilian supply chain.




***(a)** Average effect on payments received by outside suppliers.*

***(b)** Average effect on payments made by directly affected customers.*

***Figure 11:** Upstream perspective: heterogeneous effects of extreme climate events on (a) outside suppliers and (b) directly affected customers. We run Eq. (2) independently for each economic sector by splitting the sample as follows: (a) by the supplier's industry and (b) by the customer's industry. The dot is the $\beta$ coefficient in Eq. 2, and the horizontal bars denote the 95% confidence interval.*

Figure 11 shows real estate customers are the most affected by increased payments to outside suppliers during extreme weather events. This can be attributed to their focus on rapid recovery and maintaining project timelines, leading to higher payments for prioritized delivery of essential goods and services. In addition, these payments can be seen as an investment in quality and reliability, ensuring repairs and rebuilds are performed to high standards to prevent future vulnerabilities. On the other hand, customers in the agriculture sector experience the most significant reduction in payments to outside suppliers. This decrease is due to the vulnerabilities of agricultural operations. Extreme events such as floods or heavy rains cause significant damage to crops, livestock, and infrastructure, leading to financial distress. As revenues fall from reduced yields or livestock losses, businesses face liquidity constraints, which delay payments to suppliers. Additionally, tight margins in agriculture mean unexpected disruptions severely strain cash flows, forcing farmers to prioritize survival and operational needs over supplier payments.

Figure 11 shows outside suppliers in the accommodation and food services sector see the largest increase in payments received during extreme climate events. This rise can be attributed to the immediate demand for accommodation and food services during disruptions. Businesses and communities increase spending on catering and food delivery to ensure access to meals when supply chains are disrupted. Additionally, suppliers in these sectors may raise prices due to higher demand, as hotels, for example, increase rates to accommodate evacuees and emergency teams. For example, a hotel might raise rates due to increased occupancy, leading affected customers to spend more to secure the necessary services.

Similarly to our analysis from the downstream perspective, we now aim to distill the dynamics of both customer and supplier industries simultaneously, but from the upstream perspective. Figure 12 presents a heatmap illustrating sector-to-sector payment dynamics between outside suppliers and customers affected by extreme climate events in Brazil. Each cell represents the effect of climate events on the affected customer compared to unaffected customers within the same industry, considering payments received by the same outside supplier. These values correspond to the $\beta$ coefficient in Equation (2) using paired subsamples of customer and supplier industries.

We identify notable heterogeneities within these sectors. Previously, we showed outside real estate suppliers received the second largest increase in payments from affected customers. Figure 12 reveals a substantial portion of this increase originates from affected customers within the real estate sector, with a 33% increase in payments, indicating an important intra-sector pattern. This occurs because extreme weather events force real estate firms to engage in extensive repairs, leading to increased collaboration with outside suppliers. This also aligns with a 19% increase in payments from real estate to construction suppliers, although the latter lacks statistical significance. Our analysis also shows affected customers in the electricity and gas sector are the second most impacted by increased payments to outside suppliers. A significant portion of these payments goes to suppliers in the administrative and support services sector (+22%). This can be attributed to the need for rapid infrastructure repairs, which require logistical coordination and large-scale operations. Administrative services, such as disaster recovery planning and temporary staffing, are essential in this process. Additionally, enhanced customer communication during outages leads to increased payments to external call centers.

Previously, we demonstrated affected customers in the transportation and storage sector

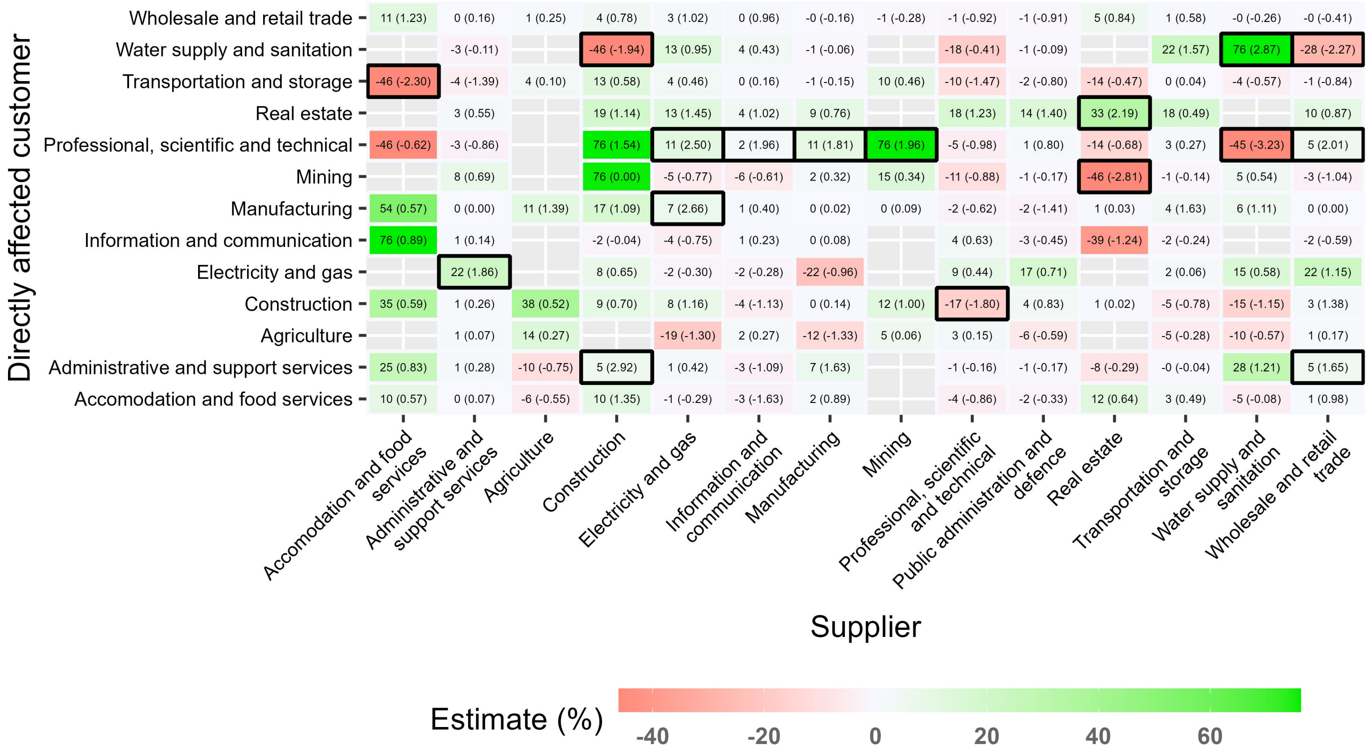



***Figure 12:*** *Heatmap showing sector-to-sector payment dynamics between outside suppliers and customers impacted by extreme climate events in Brazil. Each cell shows the effect of climate events on the affected customer compared to unaffected customers of the same industry, considering payments received by the same outside supplier. These correspond to the $\beta$ coefficient in Eq. (2) using paired subsamples of customer and supplier industries. Cells are color-coded, with red indicating a decrease in payments and green an increase in payments. Each cell shows the percent change and the $t$-statistic in parentheses. Changes that are statistically significant at 10% are with a thick black border.*

tend to reduce payments to outside suppliers when impacted by extreme weather events. Figure 12 illustrates a significant portion of this reduction is directed towards payments to outside suppliers in the accommodation and food services sector (-46%). This pattern underscores the specific nature of operations in the transportation and storage sector. While extreme weather events lead some sectors to increase their demand for accommodation and food services, these events often disrupt transportation and storage operations. These disruptions result in fewer employees and contractors traveling or requiring accommodation and food services.

## 4.3 Effects of extreme climate events on corporate financial conditions

This section analyzes the financial conditions of suppliers and customers affected by acute extreme climate events. This investigation complements our previous findings on economic customer-supplier conditions in the supply chain.

**Baseline**: we focus on the indebtedness of affected firms to commercial banks. Since the sets of supplier and customer firms directly affected by extreme climate events differ (downstream vs. upstream perspectives), we examine their financial conditions separately. From the downstream perspective, we consider the directly affected suppliers of Brazil's top 30 acute extreme climate events from 2020 to 2021. Analogously, we look at the directly affected customers from the upstream perspective.

As with our economic analysis of the supply chain, extracting the causal effect of extreme climate events on bank-firm credit relationships is challenging. One requires granular data to disentangle the extreme climate effects on borrowers from unrelated and time-varying supply conditions of lenders. We use the SCR dataset, a proprietary granular database from the BCB containing identified borrower-lender credit relationships from all banking institutions in Brazil. Our empirical strategy examines how outstanding credit issued by the *same* bank alters when comparing affected and unaffected borrowing firms in the surroundings of the extreme climate event. Table 4 presents summary statistics for outstanding credit data. We control for unobserved time-varying sector-specific supply shocks of each bank by analyzing the same bank's lending behavior to multiple firms of the same industry. By controlling for the bank's supply conditions within each industry, we can empirically identify changes in the credit relationship originating from extreme climate events.

We use the following econometric model:

$$\log\left(y_{x,b,f,t}\right) = \alpha_{x,b,sector(f),t} + \gamma_{x,f} + \beta \text{ Post}_{x,t} \times \text{Affected}_{x,f} + \rho \text{ Post}_{x,t} \times \text{Controls}_{x,f} + \varepsilon_{x,b,f,t} \tag{3}$$

in which $x$, $b$, $f$, $t$ index the extreme climate event (top 30), the commercial bank, the firm, and relative time to extreme event (quarterly), respectively. The dependent variable $y_{x,b,f,t}$ is the outstanding credit (plus one) from bank $b$ to firm $f$ at time $t$. The fixed effects of extreme event–bank–firm's sector (7-digit CNAE code)–time, $\alpha_{x,b,sector(f),t}$, permit us to interpret our results as percent changes on the total amount borrowed by affected firms compared to unaffected firms of the same industry from exactly the *same* bank. For comparability with the results of the previous section, we run two types of regressions. In the first analysis, the index $f$ represents the firms acting as suppliers in the production network (similar to the downstream perspective). The second investigation encompasses firms in the role of customers (downstream perspective). Firms are in the treatment group when they are located in microregions affected by one of the disasters. Otherwise, they compose the control group. The remaining variables and error clustering strategy are similar to those in Eqs. (1) and (2).

***Table 4:*** *Summary statistics for outstanding credit data, with values expressed in thousands of R$. The top section presents data from the downstream perspective, while the bottom section presents data from the upstream perspective. For each perspective, information is provided for both aggregated and separate loan types.*

| Statistic | N | Mean | St. Dev. | Min | Pctl(25) | Median | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|---|
| *Downstream* | | | | | | | | |
| Aggregated | | | | | | | | |
| Outs. Credit | 9,064,753 | 1,012.746 | 35,018.330 | 0.00001 | 2.933 | 20.369 | 102.140 | 18,622,031.000 |
| Separated | | | | | | | | |
| Outs. Credit | 14,445,562 | 635.381 | 23,141.580 | 0.00001 | 1.813 | 10.105 | 56.910 | 11,256,094.000 |
| *Upstream* | | | | | | | | |
| Aggregated | | | | | | | | |
| Outs. Credit | 18,978,973 | 690.810 | 26,563.770 | 0.00001 | 2.263 | 14.019 | 72.586 | 18,622,031.000 |
| Separated | | | | | | | | |
| Outs. Credit | 29,545,633 | 443.525 | 18,207.120 | 0.00001 | 1.432 | 7.402 | 41.575 | 11,256,094.000 |

The theoretical prediction about how extreme climate events alter the financial conditions of affected firms is mixed ($\beta$ coefficient in (3)). On the one hand, directly affected suppliers and customers face disruptions that impact their cash flows, investment needs,[22] and overall financial stability. These disruptions often necessitate additional liquidity to cope with operational challenges or rebuild damaged infrastructure, increasing credit demand. For instance, affected suppliers might experience reduced production capacity and sales, as we observed in our previous empirical results, leading to lower revenues and heightened liquidity needs. This scenario prompts them to seek additional credit to maintain operations, invest in recovery efforts, or perform precautionary hoarding. Analogously, affected customers may require additional liquidity to secure alternative supplies or adapt to new operational and contractual conditions.

On the other hand, banks may perceive these firms as riskier borrowers due to increased uncertainty and potential for future disruptions, aligning with findings that banks adjust lending behavior based on changes in the borrower's perceived risk and creditworthiness (Berger and Udell, 1992). Consequently, banks might tighten credit conditions, reflecting concerns about affected firms' repayment capacity (Petersen and Rajan, 1997). Our financial analysis will indicate the most preponderant element. This empirical exercise complements the payment behavior investigation by underscoring how affected firms' credit terms adjust in response to shocks.

[22] Rao et al. (2022) demonstrate firms sensitive to rainfall tend to significantly increase their investments after experiencing excess rainfall and decrease their investments following a rainfall deficit.

*Table 5:* *How do extreme climate events affect corporate financial conditions (outstanding credit)?*

| *Dependent Variable*: | $\log\left(\text{Outstanding Credit}_{x,f,t}\right)$ | | | |
|---|---|---|---|---|
| *Perspective ($f$ dimension)*: | Downstream ($f$: affected supplier) | | Upstream ($f$: affected customer) | |
| *Model*: | (I) | (II) | (III) | (IV) |
| *Variable of interest* | | | | |
| $\text{Post}_{x,t} \times \text{Affected}_{x,f}$ | 0.0336*** | 0.0257** | 0.0171** | 0.0178** |
| | (0.0113) | (0.0105) | (0.0083) | (0.0090) |
| *Controls* | | | | |
| $\text{Post}_{x,t} \times \log\left(\text{Received Payments}_{x,a}\right)$ | -0.0007 | -0.0008 | 0.0215*** | 0.0214*** |
| | (0.0007) | (0.0006) | (0.0008) | (0.0009) |
| $\text{Post}_{x,t} \times \log\left(\text{Firm's Age}_{x,a}\right)$ | -0.1472*** | -0.1599*** | -0.1501*** | -0.1506*** |
| | (0.0069) | (0.0074) | (0.0031) | (0.0030) |
| $\text{Post}_{x,t} \times \log\left(\text{GDP Per Capita}_{x,a}\right)$ | 0.0034 | 0.0024 | 0.0031 | 0.0042* |
| | (0.0035) | (0.0031) | (0.0020) | (0.0022) |
| $\text{Post}_{x,t} \times \log\left(\text{Population}_{x,a}\right)$ | -0.0021 | -0.0026** | 0.0007 | 0.0038*** |
| | (0.0013) | (0.0012) | (0.0009) | (0.0010) |
| *Fixed effects* | | | | |
| Extreme climate event × Firm | Yes | Yes | Yes | Yes |
| Extreme climate event × Time × Bank × Firm's Sector | Yes | — | Yes | — |
| Extreme climate event × Time × Bank | — | Yes | — | Yes |
| Extreme climate event × Time × Firm's Sector | — | Yes | — | Yes |
| *Fit statistics* | | | | |
| Observations | 5,325,619 | 6,702,320 | 50,735,819 | 53,866,996 |
| $R^2$ | 0.75493 | 0.66524 | 0.77264 | 0.70309 |
| Within $R^2$ | 0.00081 | 0.00073 | 0.00101 | 0.00085 |

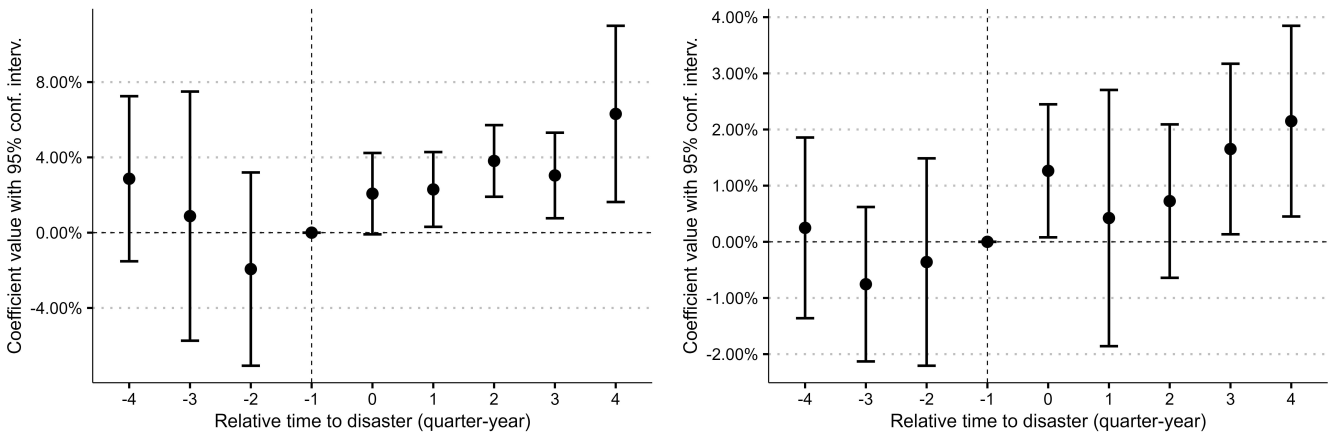
**Note:** This table reports coefficient estimates of variations of Eq. (3) for firms acting as suppliers (Specs. I and II, similar to the downstream perspective in the previous section) and as customers (Specs. III and IV, upstream perspective). Data are quarterly and correspond to a one-year window centered on each extreme climate event. The dependent variable is the log of the outstanding credit from the commercial bank $b$ to firm $f$ at the relative time $t$. The binary variable $\text{Post}_{x,t}$ equals 1 if the relative time is at or after the extreme climate event $x$, i.e., $t \geq 0$, and 0 otherwise. The binary variable $\text{Affected}_{x,s}$ equals 1 if firm $f$ (supplier in Specs. I and II, and customer in Specs. III and IV) is located in the microregion affected by the extreme event $x$, and 0 otherwise. We also add the following set of time-invariant controls *ex-ante* to the extreme event $x$ and specific for firm $f$: volume of received payments in the previous year to the extreme event, firm's age, the GDP per capita and population of the firm's municipality. $\varepsilon_{x,b,f,t}$ is the error term. Specs. I and III include extreme climate event × bank × firm's sector (7-digit CNAE code) × time and extreme climate event × firm fixed effects. The first fixed effects keep banks with multiple relationships with at least one affected and unaffected firm of the same industry only. Specs. II and IV desaturate the previous regression by considering extreme climate event × bank × time and extreme climate event × firm's sector × time only. This setup retains banks that lend to multiple firms irrespective of their industries. We cluster errors at the extreme climate event × firm's microregion level. *, **, *** denote statistical significance of 10%, 5%, and 1%, respectively.

Specs. I and III of Table 5 reports coefficient estimates of Eq. (3) for firms acting as suppliers (similar to the downstream perspective in the previous section) and as customers (upstream perspective). Our results are consistent regardless of the firm's role in the supply chain: affected suppliers (Spec. I) and customers (Spec. III) increase bank debt following the extreme climate event by 3.4% and 1.7%, respectively, compared to unaffected firm counterparts of the same industry that borrow from the exactly same commercial bank. This increase in bank debt for both affected suppliers and customers aligns with the theoretical expectation that these firms, facing disruptions and heightened liquidity needs, would seek additional credit. This finding also corroborates existing literature, which indicates firms experiencing losses due to extreme weather events have a greater need for bank credit (Benincasa et al., 2024). These results underscore the necessity for affected firms to secure additional liquidity to manage operational challenges, invest in recovery, and ensure continuity. However, the magnitude of the increase also suggests banks' perceptions of increased risk and potential tightening of credit conditions may not be as constraining as anticipated, allowing affected firms to access the needed funds despite the heightened uncertainty.

Specs. II and IV of Table 5 provide further insights by desaturating the model in Eq. (3) to consider extreme climate event $\times$ bank $\times$ time and extreme climate event $\times$ firm's sector $\times$ time interactions, thereby allowing a broader range of banks with multiple firm relationships irrespective of the borrowers' industry. The consistent positive coefficients across all specifications reinforce our theoretical prediction that affected firms increase their credit demand in response to extreme climate events, underscoring the robustness of our findings. Together, these analyses highlight the critical role of bank-firm relationships in facilitating financial resilience and adaptation to climate shocks.

**Event study**: we also adapt our baseline specification in Eq. (3) to an event study format for the set of firms acting as (a) suppliers and (b) customers in the production network. We replace the step variable Post$_{x,t}$ with quarterly pulse dummies. Figure 7 displays the estimated $\beta$ coefficients for the (a) downstream and (b) upstream perspectives. Before the extreme climate event, there were no signs of pre-trends between the outstanding credit of affected and unaffected suppliers and customer firms. The upward trend in bank indebtedness over time, especially for affected suppliers, underscores the prolonged financial strain and ongoing need for liquidity support. This is consistent with evidence from Cortés and Strahan (2017), which shows bank lending increases significantly in the months following natural disasters, with the peak increase occurring approximately six months after the event. This sustained credit demand suggests affected firms continue to rely on bank loans as a critical mechanism to navigate the aftermath of extreme climate events, highlighting the essential role of financial institutions in supporting corporate resilience and adaptation to climate-related shocks.

**Outstanding credit by loan type**: while previous analyses considered the total outstanding credit aggregated across all loan types, examining the effects of extreme climate events on individual loan types may uncover insights into firms' financial strategies and banks' lending behaviors in response to these shocks. We follow the BCB's Financial Stability Report loan type classification and divide them into foreign trade, working capital, receivables operations, investment, overdraft and guaranteed account, rural and agro-industrial, project financing, and other credits. They serve




***(a)** Directly affected suppliers by extreme climate events*   ***(b)** Directly affected customers by extreme climate events*

***Figure 13:** Event study (pre-trend and time-varying effects check). We adapt Eq. (3) for the set of firms acting as (a) suppliers and (b) customers in the production network by replacing the step variable $Post_{x,t}$ with quarterly pulse dummies. The figure displays the estimated $\beta$ coefficients for each relative quarter-year of the extreme event. Vertical bars denote the 95% confidence interval.*

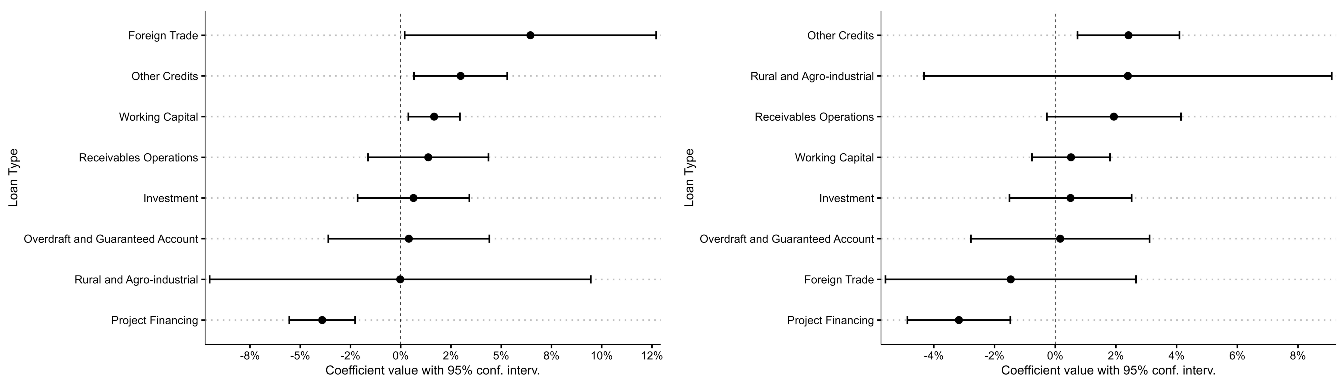
distinct purposes and have varying risk profiles. Therefore, the impact of extreme climate events on outstanding credit is likely to differ across these categories.

Analyzing loan types separately is relevant for several reasons. Firstly, firms utilize different loan types to address specific financial needs. For instance, working capital loans and receivables operations help manage immediate liquidity needs due to cash flow disruptions caused by climate events. In contrast, investment loans reflect long-term adjustments or delays in planned expansions and capital expenditures. Secondly, banks may adjust lending conditions based on each loan type's perceived risk and repayment capacity. For example, working capital loans might be tightened due to immediate cash flow concerns, while investment loans may be more flexible based on long-term recovery expectations. Finally, isolating effects by loan type ensures that observed changes in outstanding credit reflect specific financial mechanisms rather than aggregate trends, thereby verifying the robustness and specificity of our results.

We run one regression for each loan type according to Eq. (3). By fixing the same loan type in each regression, we are effectively comparing the percent change in credit of a *specific* type issued by the exact same bank to affected and unaffected firms of the same industry. Figure 14 displays the coefficient estimates for firms acting as (a) suppliers and (b) customers. Our analysis by loan type reveals distinct patterns in the financial responses of affected suppliers and customers to extreme climate events. For affected suppliers, we find that foreign trade, other credits, and working capital loans increase while project financing decreases. The remaining loan types—

receivables operations, investment, overdraft and guaranteed account, rural and agro-industrial—do not show significant changes. For affected customers, other credits and receivables operations increase while project financing decreases. The other loan types—foreign trade, working capital, investment, overdraft and guaranteed account, rural and agro-industrial—do not exhibit significant changes.

These results suggest both affected suppliers and customers increase their reliance on types of credit that are more related to managing immediate liquidity needs arising from disruptions. Decreased project financing may indicate a postponement or reduction in long-term investments due to heightened uncertainty. The unchanged categories highlight areas where climate events do not significantly alter borrowing behavior, possibly due to stable risk assessments or less immediate financial impact.




***(a)** Loans by directly affected suppliers*

***(b)** Loans by directly affected customers*

***Figure 14:** Coefficient estimates of Eq. (3) for firms acting as (a) suppliers and (b) customers by loan type (one regression is run independently for each loan type). The figure displays the estimated $\beta$ coefficients for each relative quarter-year of the extreme event. Vertical bars denote the 95% confidence interval.*

# 5 Indirect effects of extreme climate events

This section complements the previous analysis by exploring how acute extreme climate events rearrange the supply chain structure outside the affected area. We found climate events disrupt the payment chains of affected firms. Our focus now is on understanding the behavior of payments from outside firms—customers from the downstream perspective and suppliers from the upstream perspective.

**Baseline**: we exemplify our empirical exercise considering the downstream perspective, in which the extreme event is seen as a supply shock affecting suppliers. We found outside customers pay less to affected suppliers compared to other suppliers of the same industry. A natural question is whether these outside customers can fully replace these affected suppliers with other unaffected ones. If they experience any sort of economic friction with this substitution, we would expect a change in their payments. For instance, substitution would not be perfect if contractual terms are not similar to those engaged with affected suppliers that no longer can fulfill the outside customer's input needs. In this case, the extreme event's economic consequences would spill over outside the affected area. In contrast, if outside customers can fully replace suppliers from the affected region, then the shock does not spill over outside the affected area. We would then not observe any changes in the outside customer's payment patterns. This section aims at testing this replacement behavior by outside firms.

To estimate firm-level outcomes, our empirical exercises now consider a firm-level dataset rather than customer-supplier relationships. We present in Table 6 summary statistics for the data. From the downstream perspective, we only take customers from outside affected areas. We evaluate their degree of exposure to each of the top 30 acute extreme climate events by considering how reliant they are with respect to payments to affected suppliers relative to all suppliers (affected and unaffected). We consider unaffected suppliers those outside the area where the extreme event occurred. Mathematically, we evaluate the outside customer's exposure—and, analogously, the outside supplier's exposure by simply swapping the customer and supplier roles—as follows:

$$\begin{aligned}\text{Outside Customer's Exposure}_{x,c} &= \frac{\sum_{s \in \mathscr{S}_{x,c}^{(\text{affected})}} p_{c \to s}}{\sum_{s \in \mathscr{S}_{x,c}} p_{c \to s}}, \\ \text{Outside Supplier's Exposure}_{x,s} &= \frac{\sum_{c \in \mathscr{C}_{x,s}^{(\text{affected})}} p_{c \to s}}{\sum_{c \in \mathscr{C}_{x,s}} p_{c \to s}},\end{aligned} \tag{4}$$

in which $x$ and $c$ ($s$) index the extreme climate event (top 30) and the outside-the-affected-area customer (supplier) with at least one connection with affected suppliers (customers). $\mathscr{S}_{x,c}$ ($\mathscr{C}_{x,s}$) is the set of customer $c$'s supplier firms (supplier $s$'s customer firms) observed during twelve months before the occurrence of the extreme climate event $x$. $\mathscr{S}_{x,c}^{(\text{affected})} \subset \mathscr{S}_{x,c}$ ($\mathscr{C}_{x,s}^{(\text{affected})} \subset \mathscr{C}_{x,s}$) is the subset of those supplier (customer) firms that are located in the extreme climate event's microregion. $p_{c \to s}$ is the total payments from the customer $c$ to supplier $s$ during the twelve months before the climate event occurrence. The first part of Figure 15 exhibits a schematic of how the exposure is evaluated for the downstream case (outside customers).

***Table 6:*** *Summary statistics for the data used to investigate the indirect effects of extreme weather events on the supply chain. The table is divided into two sections: the top shows data from the downstream perspective, and the bottom shows data from the upstream perspective. Total Payments are expressed in thousands of R$. Payments Paid (Received) refers to the amount in thousands of R$ for transactions made to (received from) suppliers (customers) affected or unaffected before the event. Exposure measures the dependency of outside customers (suppliers) on affected suppliers (customers) as a percentage.*

| Statistic | N | Mean | St. Dev. | Min | Pctl(25) | Median | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|---|
| *Downstream (Outside Customer)* | | | | | | | | |
| Total Payments | 6,524,241 | 742.935 | 21,702.530 | 0.00001 | 3.578 | 16.301 | 77.646 | 15,331,697.000 |
| Payments Paid (Af.) | 6,524,241 | 11.643 | 368.523 | 0.000 | 0.000 | 0.000 | 1.784 | 231,768.700 |
| Payments Paid (Un.) | 6,524,241 | 731.292 | 21,653.610 | 0.000 | 1.970 | 13.300 | 71.608 | 15,306,026.000 |
| Exposure | 853,398 | 25.041 | 37.846 | 0.000 | 0.000 | 2.017 | 37.893 | 100.000 |
| *Upstream (Outside Supplier)* | | | | | | | | |
| Total Payments | 4,825,722 | 1,696.857 | 37,037.830 | 0.00001 | 7.269 | 43.734 | 254.477 | 23,480,387.000 |
| Payments Received (Af.) | 4,825,722 | 26.483 | 709.033 | 0.000 | 0.000 | 0.000 | 2.500 | 418,004.700 |
| Payments Received (Un.) | 4,825,722 | 1,670.374 | 36,829.040 | 0.000 | 5.270 | 39.059 | 242.466 | 23,480,147.000 |
| Exposure | 614,283 | 18.079 | 33.551 | 0.000 | 0.000 | 0.887 | 12.700 | 100.000 |

Our identification strategy is depicted in the right-most part of Figure 15. From the downstream perspective, it compares payment patterns of outside customers of the same industry located exactly in the same municipality. The only observable difference is that some of them are more reliant on affected suppliers while others are not. We gauge this dependence degree using Equation (4). Mathematically, we run the following econometric specification:

$$\log(y_{x,f,t}) = \alpha_{x,\text{sector}(f),\text{municipality}(f),t} + \gamma_{x,f} + \beta \ \text{Post}_{x,t} \times \text{Exposure}_{x,f} + \varepsilon_{x,f,t}, \tag{5}$$

in which $x$, $f$, and $t$ index the extreme climate event (top 30), the outside-the-affected-area firm (customer in the downstream and supplier in the upstream perspective), and the relative time to extreme event (quarterly), respectively. The term $\alpha_{x,\text{sector}(f),\text{municipality}(f),t}$ represents extreme climate event–firm's sector (7-digit CNAE)–firm's municipality-time dynamic fixed effects, allowing us to interpret our results as comparisons among firms with different exposures to the climate event within the same industry and municipality. The term $\gamma_{x,f}$ is extreme climate event–firm fixed effects that absorb time-invariant firm-specific features. We standardize the numeric variable $\text{Exposure}_{x,f}$, as defined in Equation (4). We cluster errors at the extreme event-firm level, the same variation of $\text{Exposure}_{x,f}$.

Comparing customers within the same municipality and industry helps mitigate omitted variable bias by ensuring the firms being compared share similar local economic conditions, regu-

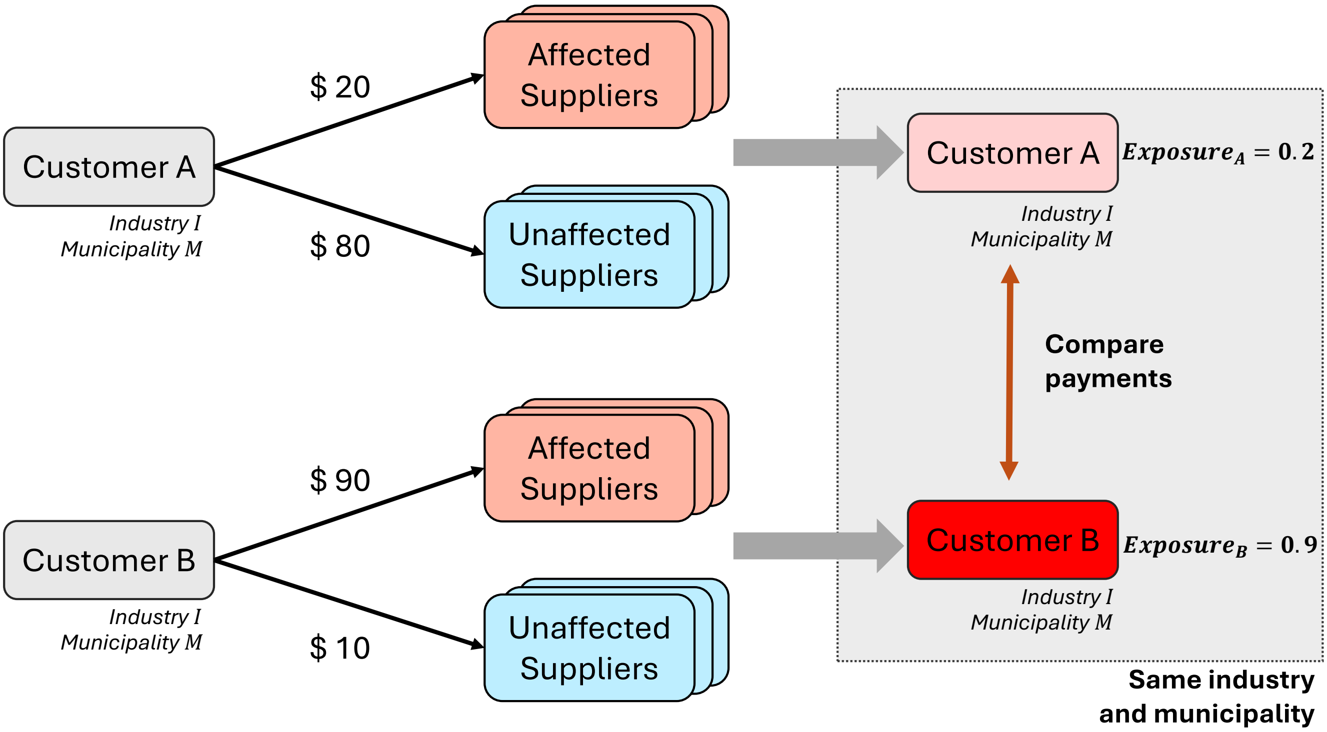



***Figure 15:*** *Schematic of the identification strategy to evaluate indirect effects of acute extreme climate events for the downstream perspective. We first aggregate payments from outside-the-affected-area customers into those to affected and unaffected suppliers. We then evaluate their exposure intensity level by considering the share of payments to affected suppliers relative to total payments as defined in Equation (4). In the figure, Customer A pays $20 to suppliers in affected areas and $80 to suppliers outside affected areas. Then, their exposure level is* $\frac{80}{100} = 0.2$. *Similarly, Customer B's exposure level is* $\frac{90}{100} = 0.9$. *Our identification strategy compares outside customers within the same industry and municipality with different intensity levels to affected suppliers.*

latory environments, and market dynamics. This geographic and sectoral control reduces the influence of unobserved heterogeneity that could confound the analysis. For example, firms in the same municipality are subject to the same local infrastructure, labor market, and municipal policies, which can significantly impact their operational capabilities and economic behavior. Similarly, firms within the same industry face analogous demand patterns, competitive pressures, and sector-specific shocks. Additionally, firms within the same municipality and industry tend to have comparable opportunities regarding potential suppliers, which is crucial for our quasi-experimental design. After controlling for their idiosyncratic features, they will likely have access to the same pool of suppliers, face similar logistical constraints, and share equivalent information about alternative sourcing options. This commonality in supplier opportunities means any heterogeneity observed in their payment patterns is fairly exogenous.

The upper section of Table 7 reports coefficient estimates of Equation (5). The dimension $f$ in Specs. I—III (our downstream perspective) represents outside customers with at least one connection with suppliers located in microregions affected by extreme climate events. Analogously, it

*Table 7: How do extreme climate events rearrange the supply chain outside affected areas?*

| *Perspective ($f$ dimension)*: | Outside customers ($f = c$, downstream) | | | Outside suppliers ($f = s$, upstream) | | |
|---|---|---|---|---|---|---|
| *Dependent Variable*: | $\log(\text{Payments}_{x,c,t})$ | | | $\log(\text{Received Payments}_{x,s,t})$ | | |
| | Total | Affected | Unaffected | Total | Affected | Unaffected |
| *Model*: | (I) | (II) | (III) | (IV) | (V) | (VI) |
| *Variable of interest* | | | | | | |
| $\text{Post}_{x,t}$ × Outside Firm's $\text{Exposure}_{x,f}$ | -0.0044 | -0.1107*** | 0.1096*** | -0.0003 | -0.0658*** | 0.0938*** |
| | (0.0144) | (0.0131) | (0.0272) | (0.0060) | (0.0110) | (0.0117) |
| *Fixed effects* | | | | | | |
| Extreme climate event × | | | | | | |
| × Time × Firm's Sector × Firm's Municipality | Yes | Yes | Yes | Yes | Yes | Yes |
| × Firm | Yes | Yes | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | | | |
| Observations | 4,831,233 | 4,831,233 | 4,831,233 | 3,393,784 | 3,393,784 | 3,393,784 |
| $R^2$ | 0.9924 | 0.9901 | 0.9924 | 0.9963 | 0.9922 | 0.9963 |
| Within $R^2$ | 0.0001 | 0.0035 | 0.0002 | 0.0001 | 0.0022 | 0.0003 |
| Robustness test (removing same municipality constraint): | | | | | | |
| *Variable of interest* | | | | | | |
| $\text{Post}_{x,t}$ × Outside Firm's $\text{Exposure}_{x,f}$ | -0.0035 | -0.0600*** | 0.1039*** | 0.0035 | -0.0476*** | 0.0837*** |
| | (0.0099) | (0.0141) | (0.0171) | (0.0055) | (0.0053) | (0.0097) |
| *Fixed effects* | | | | | | |
| Extreme climate event × | | | | | | |
| × Time × Firm's Sector | Yes | Yes | Yes | Yes | Yes | Yes |
| × Firm | Yes | Yes | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | | | |
| Observations | 6,797,829 | 6,797,829 | 6,797,829 | 5,371,979 | 5,371,979 | 5,371,979 |
| $R^2$ | 0.9878 | 0.9793 | 0.9878 | 0.9917 | 0.9839 | 0.9918 |
| Within $R^2$ | 0.0001 | 0.0019 | 0.0003 | 0.0001 | 0.0018 | 0.0003 |

**Note:** The upper section of this table reports the coefficient estimates from Eq. (5). The lower section presents robustness tests by re-running the same empirical specification as in the upper section, but without the constraint of comparing against firm counterparts within the same municipality. The dimension $f$ in Specs. I—III (our downstream perspective) represents outside customers with at least one connection with suppliers located in microregions affected by extreme climate events. Analogously, it indicates in Specs. IV—VI (our upstream perspective) outside suppliers receiving payments from at least one affected customer. The dependent variables correspond to payments aggregated at the firm level (either customer or supplier) into three different forms: total payments (Specs. I and IV), payments made to/received from affected firm counterparts (Specs. II and V), and payments made to/received from unaffected firm counterparts (Specs. III and VI). Data are quarterly and correspond to a one-year window centered on each extreme climate event. The binary variable $\text{Post}_{x,t}$ equals 1 if the relative time is at or after the extreme climate event $x$, i.e., $t \geq 0$, and 0 otherwise. The continuous variable $\text{Exposure}_{x,f}$ follows Eq. (4). All specifications contain extreme climate event–firm's sector (7-digit CNAE)–firm's municipality-time and extreme climate event–firm fixed effects. We cluster errors at the extreme climate event × outside firm level. *, **, *** denote statistical significance of 10%, 5%, and 1%, respectively.

indicates in Specs. IV—VI (our upstream perspective) outside suppliers receiving payments from at least one affected customer. The dependent variables correspond to payments aggregated at the firm level (either customer or supplier) into three different forms: total payments (Specs. I and IV), payments made to/received from affected firm counterparts (Specs. II and V), and payments made to/received from unaffected firm counterparts (Specs. III and VI).

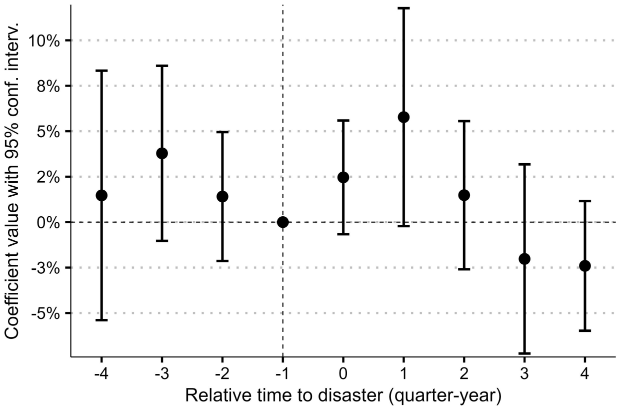
Total payments made by outside customers (Spec. I) and received by outside suppliers (Spec. IV) do not exhibit statistically significant changes in response to extreme climate events compared to firm counterparts of the same industry located in the same municipality but with lower exposures to the climate event. This finding suggests that, on aggregate, outside firms can replace affected suppliers or customers with relatively no friction, maintaining stable payment levels. However, when we disaggregate the payments into those made to affected versus unaffected firms, distinct dynamics emerge.

From the downstream perspective, outside customers significantly reduce their payments to affected suppliers: for a one-standard-deviation increase in the exposure to the climate events, outside customers reduce by 11% their payments compared to other less exposed customers of the same industry located in the same municipality (Spec. II). Simultaneously, they increase payments to unaffected suppliers (Spec. III) by the same amount for each one-standard-deviation increase in their exposure to the climate event. This shift indicates outside customers actively substitute away from affected suppliers for unaffected ones to maintain their supply chain continuity.

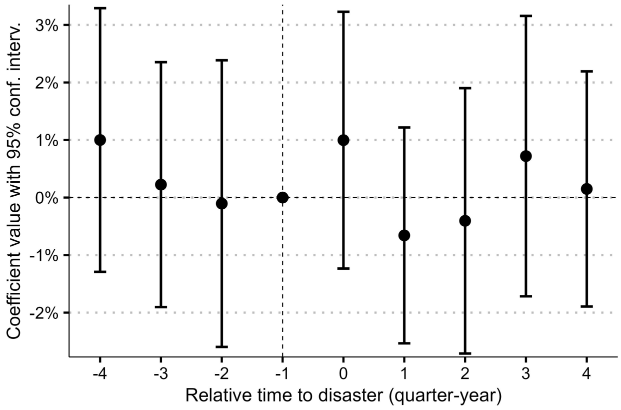
Similarly, in the upstream perspective, outside suppliers receive significantly fewer payments from affected customers: they decrease by 7% for each one-standard-deviation increase in the supplier's exposure (Spec. V). However, outside suppliers experience increased payments from unaffected customers by 9% for each one-standard-deviation increase in their exposure to the climate event (Spec. VI). This pattern reflects a substitution effect where outside suppliers adjust their customer base in response to the disruptions caused by the climate event.

In Table 7, we also present robustness tests by re-running the same empirical specification as in the upper section, this time without the constraint of comparing firms within the same municipality. We find that our main results remain qualitatively consistent. These results underscore the resilience of the supply chain, highlighting how firms outside affected areas adapt by shifting their business to unaffected counterparts. This ability to reconfigure supply chains demonstrates a form of economic flexibility that mitigates the broader impact of extreme climate events. Our findings corroborate evidence provided by existing literature that customers replace suppliers exposed to floods and heat (Pankratz and Schiller, 2024). This adaptive behavior ensures that while individual relationships within the supply chain are disrupted, the overall network remains functional by reallocating economic activities to unaffected nodes.

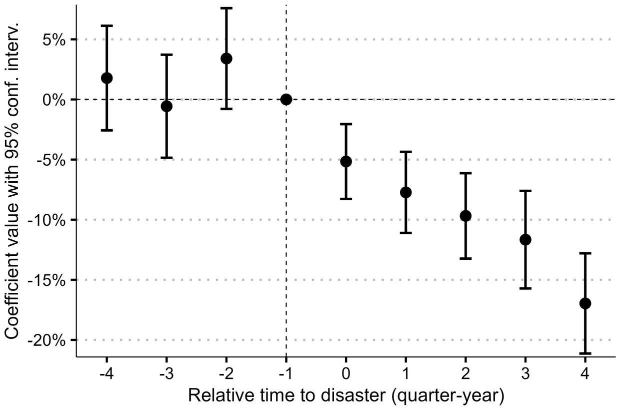
**Event study**: similar to our previous empirical designs, we also adapt our baseline specification in Equation (5) for outside customers (our downstream perspective) and outside suppliers (our upstream perspective) to an event study format to inspect for pre-trends and time-varying effects. We



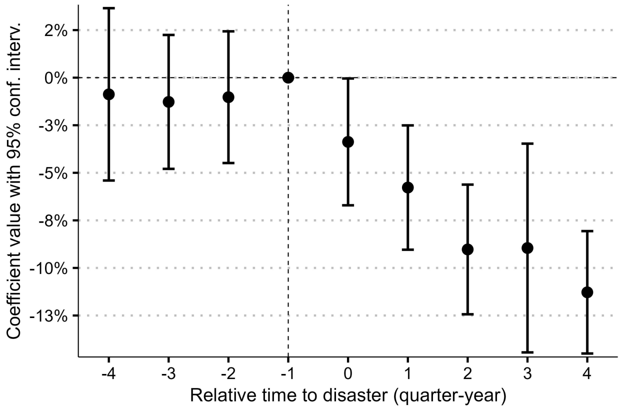

***(a)** Downstream – Outside customer's total payments*



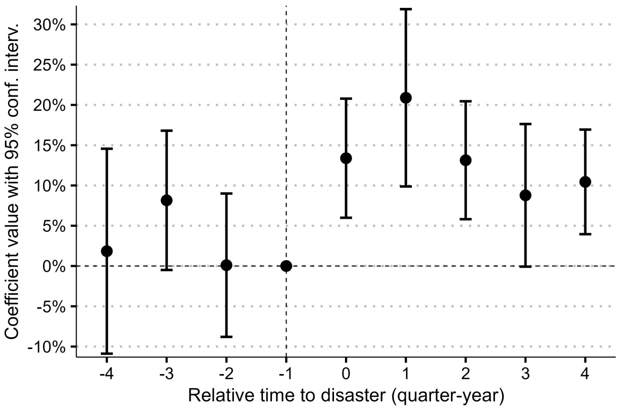

***(b)** Upstream – Outside supplier's total payments*



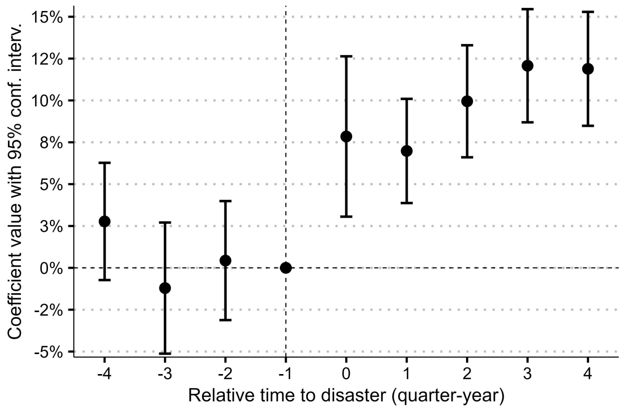

***(c)** Downstream – Outside customer's payments to affected suppliers*




***(d)** Upstream – Outside supplier's received payments from affected customers*




***(e)** Downstream – Outside customer's payments to unaffected suppliers*



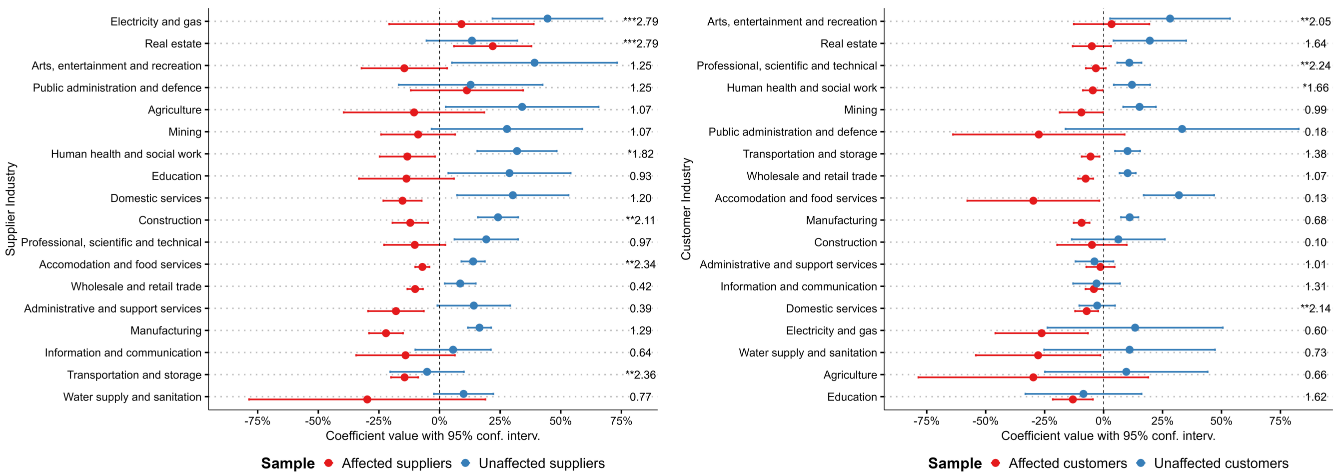

***(f)** Upstream – Outside supplier's received payments from unaffected customers*

***Figure 16:** Event study (pre-trend and time-varying effects check). We adapt Eq. (5) by replacing the step variable $Post_{x,t}$ with quarterly pulse dummies. We consider the sample of outside customers with affected suppliers in the left panel (our downstream perspective) and outside suppliers with affected customers (our upstream perspective). We use three dependent variables: (a) and (b) total payments, (c) and (d) payments made to/received from affected firm counterparts, and (e) and (f) payments made to/received from unaffected firm counterparts. The figure displays the estimated $\beta$ coefficients for each relative quarter-year of the extreme event (top 30). Vertical bars denote the 95% confidence interval.*

replace the step variable $\text{Post}_{x,t}$ with quarterly pulse dummies. Figure 16 displays the estimated $\beta$ coefficients for outside customers (left panel) and outside suppliers (right panel) perspectives for the three analyzed dependent variables. Before the extreme climate events, there were no signs of pre-trends between more and less exposed outside firms. Only after the extreme events did we observe changes in the dependent variables, consistent with our previous conclusions.

We highlight the persistent effect of the extreme climate events on affected firms and the economic consequences in the supply chain through their immediate outside suppliers and customers located outside affected areas. The rearrangement of connected outside firms away from affected firm counterparts grows stronger over time (see (c) and (d) in Figure 16). This suggests sudden changes in firm relationships have long-lasting effects on affected firms.

**Substitution Frictions Across Industries**: our previous results indicate generally low friction in substituting affected firm counterparts across when considering all economic sectors. We now examine the degree of substitutability for each economic sector. Figure 17 displays the coefficient estimates from Eq. (5) for (a) outside customers and (b) outside suppliers by their respective industries (with one independent regression for each industry). It includes t-statistics on the right side comparing coefficients regarding payments to affected versus unaffected firms, with the rejection of the null hypothesis indicating significant friction in substitution. We consider two dependent variables: the volume of payments to affected and unaffected firm counterparts in each perspective.




***(a)** Downstream – effects on the suppliers of outside customers*

***(b)** Upstream – effects on the customers of outside suppliers*

***Figure 17:** Coefficient estimates of Eq. (5) for (a) outside customers and (b) outside suppliers by their corresponding industry (one independent regression for each industry and dependent variable). Panel (a) shows the coefficients for outside customers' aggregate payments to suppliers in affected areas (red) versus those in unaffected areas (blue). Panel (b) swaps the roles of supplier and customer. The figure presents $\beta$ coefficients for each quarter-year relative to the extreme climate event, with 95% confidence intervals denoted by horizontal bars. The numbers on the right are t-statistics comparing whether the negative coefficient for affected firms is statistically equal to the coefficient for unaffected firms given the same industry. The test assesses whether substituting affected firms with unaffected ones involves significant friction. Rejection of the null hypothesis (equal coefficients) suggests substitution is not frictionless. *, **, *** denote statistical significance of 10%, 5%, and 1%, respectively.*

Consistent with our previous empirical results, most economic sectors can reallocate payments from affected to unaffected firm counterparts without altering their total payments, suggesting low economic frictions. Most t-statistics (12 of 18 downstream, 14 of 18 upstream) do not reject the null hypothesis of frictionless substitution. However, there are notable exceptions. From the downstream perspective, sectors such as construction and accommodation and food services exhibit a pattern in which payments to unaffected suppliers rise more than the decrease in payments to affected ones. Several factors may contribute to this pattern.

Using the construction sector as an example, the increased demand for substitute suppliers often gives these suppliers greater market power. For instance, if a natural disaster affects a local concrete supplier, construction firms might need to source concrete from suppliers farther away, which may raise their prices due to the sudden increase in demand. Construction projects often have strict deadlines, so firms may be willing to pay a premium to ensure timely delivery from new suppliers. Lastly, logistic and transportation challenges can also increase costs. Sourcing materials from distant suppliers can result in higher transportation expenses, particularly if the new suppliers are located far from the construction site.

Different patterns emerge for outside customers in sectors such as electricity and gas. While we observe a substantial increase in payments to unaffected suppliers, payments to affected suppliers remain relatively stable. This pattern highlights that, for some sectors, reducing payments to affected suppliers can be challenging. Outside customers in electricity and gas may have long-standing contractual obligations with affected suppliers, requiring them to maintain payments even during disruptions. By maintaining payments, outside customers help ensure these suppliers can recover and remain viable partners. This stability is crucial in sectors where infrastructure and service continuity are essential. Furthermore, the dual approach[23] of simultaneously maintaining payments to affected suppliers and increasing payments to unaffected suppliers can be understood as a strategic balancing act, ensuring both immediate and long-term operational stability.

From the upstream perspective, a distinctive pattern emerges in sectors such as domestic services. While there is a reduction in payments received from affected customers, payments

[23] Continuity and Recovery: Affected suppliers are financially supported to recover and continue to provide services, preserving long-term relationships and supply chain stability. Diverse and Reliable Supply: Unaffected suppliers are leveraged to ensure immediate continuity and reliability, even at increased costs, reflecting a strategic investment in resilience and risk mitigation.

from unaffected customers remain relatively stable. This pattern underscores the difficulty some outside suppliers face in replacing affected customers with unaffected ones. Domestic services often operate within specific geographic areas and are limited by logistical constraints, which restrict their ability to reach new, unaffected customers quickly. Additionally, these services rely heavily on established relationships and trust, and building similar relationships with new customers requires time and effort. Furthermore, non-affected customers may already have established relationships with local service providers, making them less likely to switch to a new supplier.

In summary, our findings confirm supply chains generally exhibit a strong ability to adapt to supply or demand shocks, with most sectors showing high substitutability and low friction. However, some sectors encounter significant challenges in replacing affected business partners with unaffected ones due to the nature of their operations. In such cases, different types of frictions can emerge. These challenges may stem from an inability to reduce obligations with existing relationships or difficulties establishing new partnerships. Additionally, even when outside firms manage to form new business relationships, market dynamics can impose a significant price premium.

# 6 Conclusions

This paper examines the causal impact of extreme climate events on a national supply chain. To explore this topic, we combine proprietary granular data on inter-firm payments and borrower-lender credit relationships from all banking institutions in Brazil with natural disaster records. We report three main findings.

First, affected suppliers experience payment reductions from outside customers, by up to 8% in the immediate aftermath of a disaster, compared to unaffected suppliers within the same industry (downstream perspective). We observe significant heterogeneities, with some affected suppliers in agriculture facing payment reductions near 20%, five times greater than the average. Second, affected firms experience increased indebtedness post-event, with a documented increase in reliance on credit types suited to managing immediate liquidity needs arising from disruptions. Third, outside firms are generally able to replace firm counterparts located in affected areas with unaffected ones. However, some sectors, such as construction, encounter substitution frictions near 10 p.p., leading to indirect effects that amplify the total impact of extreme climate events on the supply chain.

Despite the adverse effects of extreme climate events, the Brazilian supply chain generally demonstrates resilience by quickly adapting to supply and demand shocks through the establishment of new suppliers and customers. Although affected firms can secure emergency liquidity from banks, they face a potential permanent loss of market share. Based on our findings, we offer two key takeaways for policymakers. First, they should design strategies to support affected firms and prevent loss of competitiveness or economic dynamism in impacted areas, which could lead to increased poverty or loss of wealth among the population. Second, they can formulate plans to reduce frictions in industries that struggle to replace economic partners.

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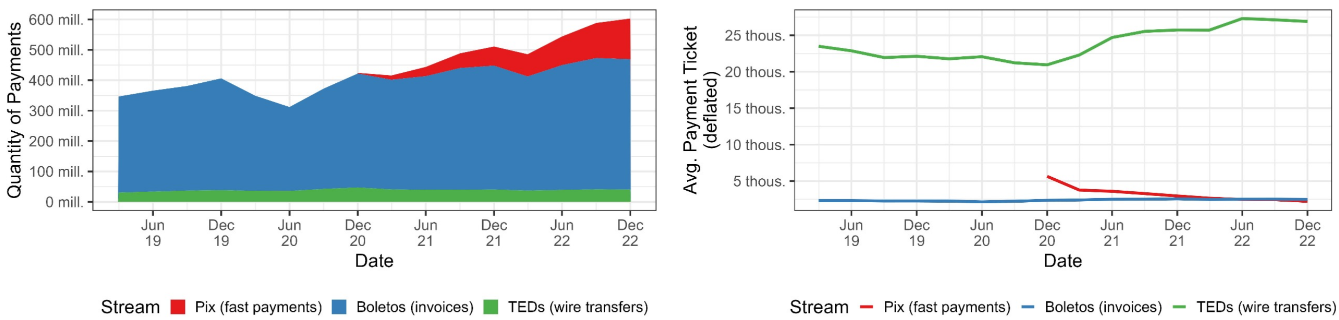
# A Analysis of inter-firm payments by stream and economic activity

Our filtered dataset encompasses 1,736,469,169 inter-firm quarterly payments, considering customer-supplier pairs and the payment stream (invoice, wire transfer, fast payment) made between 2019 and 2022. Figure A1a illustrates the quarterly evolution of the quantity of payments aggregated by stream. Most transactions are conducted via invoices through Boletos, totaling approximately 1,242,068,140 (about 71.5% of the total). Fast payments via Pix come in second with around 289,394,474 transactions (about 16.8%), while wire transfers via TED are third, with approximately 205,006,555 transactions (around 11.8%). Overall, the number of payments increases over time. Notably, fast payments via Pix, introduced at the end of 2020, grew rapidly, soon surpassing the number of wire transfers. Despite the rapid adoption of Pix, invoice payments via Boletos continue to grow in the corporate environment, highlighting the preference of Brazilian firms for this payment method.



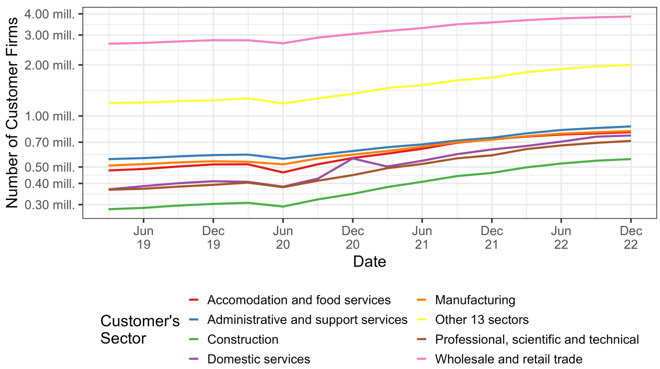

***(a)** Evolution of quantity of payments.*

***(b)** Evolution of average payment ticket.*

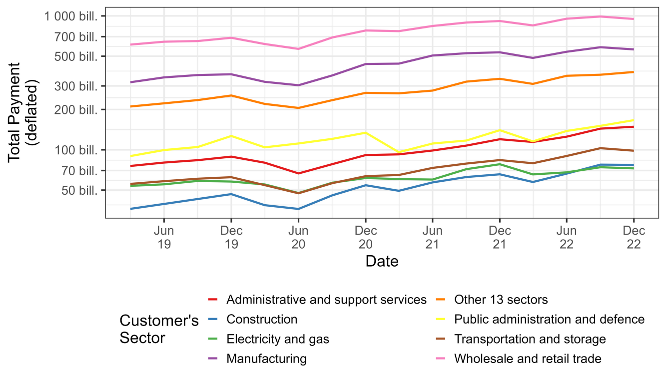
***Figure A1:** This figure depicts the evolution of (a) the quantity of payments and (b) the average payment ticket from 2019 to 2022, categorized by payment stream: fast payments via Pix (in red), invoices via Boletos (in blue), and wire transfers via TED (in green). The average payment ticket, presented in Brazilian reais (R$), is deflated using the IPCA index, with the base period set to the first quarter of 2019.*

Figure A1b illustrates the evolution of the average transaction value by payment stream over the period. Wire transfers via TED stand out with an average transaction value of around R$25,000. These values are significantly higher than the average transaction values of invoice payments via Boleto and fast payments via Pix, both of which are below R$5,000. This indicates a preference among Brazilian firms for using wire transfers for higher-value payments.

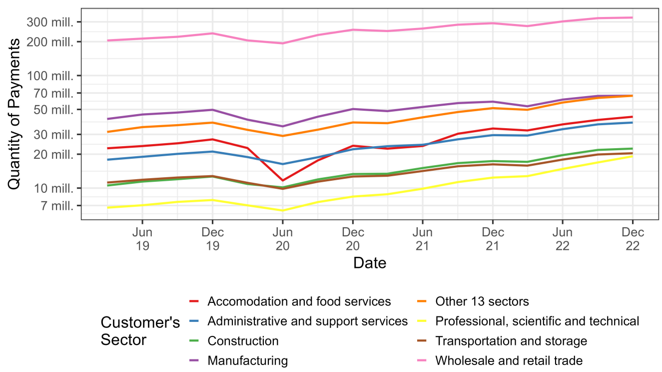
We now segment the payment data based on economic activity and the customer/supplier perspective. Figure A2a shows the evolution of the number of unique customers. By the end of 2022, there were 10,379,668 unique customers in our dataset. Throughout the period, we observed an increasing trend in the number of unique customers. The wholesale & retail trade sector stands out with the number of unique customers ranging between 3 and 4 million, significantly surpassing the second sector with the most unique customers, administrative & support services, which has slightly fewer than 1 million unique customers.



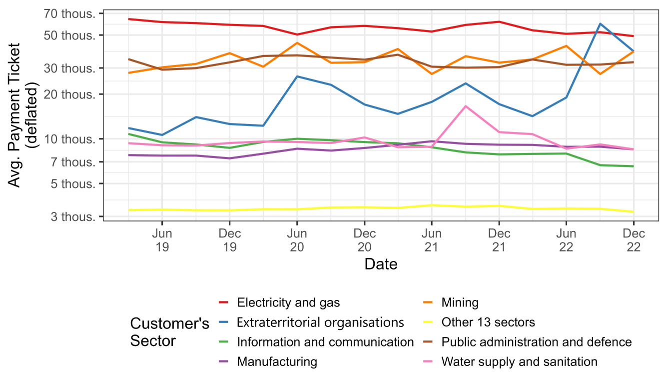

***(a)** Number of customer firms.*




***(b)** Total payment.*




***(c)** Quantity of payments.*




***(d)** Average payment ticket.*

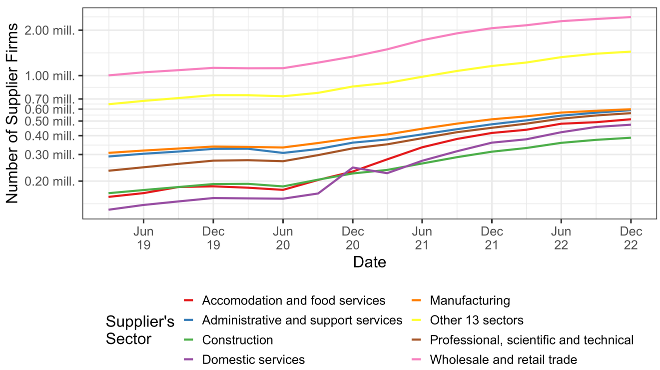
***Figure A2:** This figure depicts, from a customer perspective, the evolution of various metrics grouped by sectors (CNAE sections) in our database, aggregated quarterly between 2019 and 2022. The metrics include a) the number of firms, b) the total payment, c) the quantity of payments, and d) the average payment ticket. Data in b) and d) are deflated using the IPCA index with the base period set to the first quarter of 2019. For readability, the vertical axis is on a log scale.*

Figure A2b shows that customers in the wholesale & retail trade and manufacturing sectors stand out, registering the highest financial volumes of payments. Customers in these two sectors also lead in the number of transactions. Figure A2c shows wholesale & retail trade significantly outpacing the others in terms of transaction count. The large number of payments made by customers in the wholesale & retail trade sector results in a low average transaction value, as indicated by Figure A2d. In contrast, customers in the electricity & gas sector stand out with the highest average transaction value, around R$60,000. Other notable sectors include mining and public administration & defense, both registering average transaction values around R$35,000.

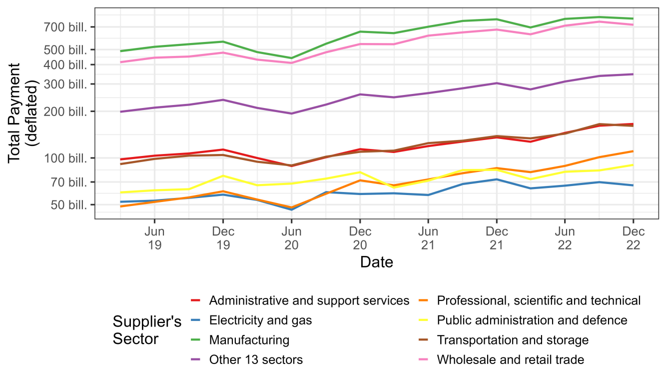
Additionally, the extraterritorial organisations sector shows remarkable growth in its average transaction value, more than tripling over the period and positioning itself among the sectors with the highest average transaction values by the end of 2022.

We now analyze the data from the supplier's perspective. Figure A3a shows the evolution of the number of unique suppliers in our dataset, revealing a growing trend over the period, reaching 7,011,672 by the end of 2022. Similar to our observations from the customers' perspective, the wholesale & retail trade sector stands out with over 2 million unique suppliers at the end of the period, significantly surpassing the manufacturing sector, which has nearly 600,000 unique suppliers. Figure A3b shows the evolution of the financial volume of payments received by suppliers by economic activity. We observe that suppliers in the manufacturing and wholesale & retail trade sectors are prominent, each receiving about R$700 billion in the last quarter of 2022. These amounts are nearly three times those of the next leading sectors: administrative & support services and transportation & storage, each receiving about R$150 billion in the final quarter of 2022.

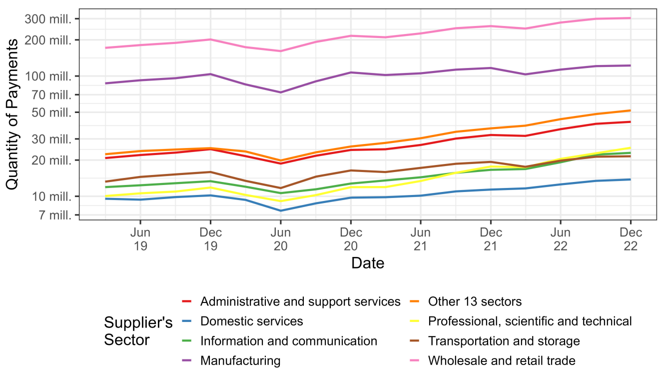
Figure A3c shows the number of payments received by suppliers. Again, the wholesale & retail trade and manufacturing sectors stand out, receiving approximately 300,000 and nearly 150,000 payments in the last quarter of 2022, respectively. These numbers significantly surpass the third place, suppliers in the administrative & support services sector, who received about 50,000 payments in the last quarter of 2022. As observed for the average transaction value paid by customers, suppliers in the wholesale & retail trade and manufacturing sectors, due to their high number of payments received, record low average payment values received, as shown in Figure A3d. Suppliers in the extraterritorial organisations sector stand out with an average transaction value received of about R$70,000 in the last quarter of 2022. Suppliers in the mining and agriculture sectors follow in second and third positions, with an average transaction value received of about R$22,000 in the period.



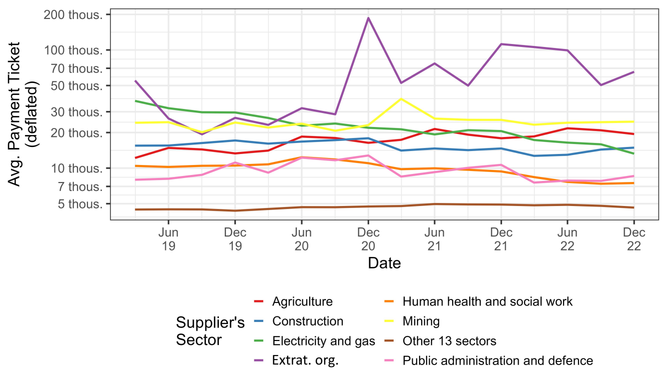

***(a)*** *Number of supplier firms.*




***(b)*** *Total payment.*




***(c)*** *Quantity of payments.*




***(d)*** *Average payment ticket.*

***Figure A3:*** *This figure depicts, from a supplier perspective, the evolution of various metrics grouped by sectors (CNAE sections) in our database, aggregated quarterly between 2019 and 2022. The metrics include a) the number of firms, b) the total payment, c) the quantity of payments, and d) the average payment ticket. Data in b) and d) are deflated using the IPCA index with the base period set to March 2019. For readability, the vertical axis is on a log scale.*