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# Natural disasters and financial technology adoption[☆]

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ABSTRACT

This paper investigates the impact of natural disasters on the adoption of PIX payments in Brazilian municipalities. Using data from multiple sources, including the Ministry of Integration and Regional Development of Brazil, the Central Bank of Brazil, and the Monthly Banking Statistics by Municipality database, we employ the Differences-in-Differences method to measure the effect of disasters on PIX adoption. Our findings reveal a significant and positive impact of natural disasters on the utilization of PIX among households. Additionally, we observe that the intensity of the disasters influences PIX adoption, with more severe disasters exerting a greater impact.

## 1. Introduction

Natural disasters occur more often, affecting the economy in different ways, such as changing migration trends, risk aversion, housing demand, energy consumption and innovation (Bourdeau-Brien and Kryzanowski, 2020; Boustan et al., 2020; Lee et al., 2021; Zhao et al., 2022). This paper contributes to this literature by measuring the effect of natural disasters on adopting new payment technology.

In November 2020, the Central Bank of Brazil (BCB) launched PIX, an instant payment system that revolutionized financial transactions by promoting financial inclusion and enhancing transaction speed. Unlike previous payment alternatives, PIX allows for instant inter-bank transfers without intermediaries and at no cost to individuals. Users only need access to a bank or payment institution account and a registered key, such as a social security number, phone number, or email. Duarte et al. (2022) document how PIX quickly replaced traditional payment methods in Brazil.[1]

This study investigates the effect of natural disasters on PIX adoption across Brazilian municipalities comprising 5570 cities. We combine monthly data from the Ministry of Integration and Regional Development's Integrated Information System on Disasters and PIX payment data from the BCB, covering November 2020 to October 2022, during which 1295 municipalities suffered a natural disaster. Employing the Differences-in-Differences (DID) method by Callaway and Sant'Anna (2021), we consider different types and intensities of natural disasters and measure the impact of these disasters on PIX adoption.

Our findings indicate a positive and statistically significant impact of natural disasters on PIX utilization. The effect varies with the intensity of the disasters, measured by monetary losses, with more severe disasters leading to higher PIX adoption. However, we find no significant impact on traditional financial transactions such as savings and credit operations, suggesting that natural disasters push individuals towards fintech solutions like PIX due to disruptions in transportation and communication infrastructure.

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[1] Fintech's exponential growth has made PIX significantly cheaper and more accessible to a larger population, further promoting financial inclusion in Brazil (Ferrarine, 2021).

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Our findings indicate a positive and statistically significant cumulative impact of natural disasters on the utilization of PIX among households. Additionally, our analysis reveals that the cumulative effect of these disasters varies depending on their intensity. Specifically, we observe that more severe disasters, as measured by the associated monetary losses, exert a greater influence on the local populace's adoption of PIX. These effects are discernible in both incoming and outgoing PIX transactions.

This paper contributes to two strands of literature: the adoption of new payment technologies (Wright et al., 2017; Riley, 2018; Chodorow-Reich et al., 2020; Agarwal et al., 2020; Mariani et al., 2023; Crouzet et al., 2023) and the economic impacts of natural disasters (Kirchberger, 2017; Karbownik and Wray, 2019; Henry et al., 2020; Hoang et al., 2020; Czura and Klonner, 2023; Friedt and Toner-Rodgers, 2022). By examining how shocks influence financial technology adoption, this study highlights the critical role of shock intensity and the importance of fintech in enhancing financial resilience in disaster-prone areas. To the best of our knowledge, this is the first study to examine the impact of natural disasters on financial technology adoption.

The rest of this paper is structured as follows. Section 2 provides an overview of our data. Section 3 outlines our empirical approach for assessing the impact of natural disasters on PIX adoption. Section 4 presents the results. Finally, Section 5 concludes.

## 2. Data

We gathered information on credit movements by consulting the Monthly Banking Statistics by Municipality, provided by the Central Bank of Brazil. This database details monthly changes in commercial banks' balance sheets, focusing on Credit Operations, Loans and Securities, and Saving Deposits. For data on the number of PIX transactions, we accessed the Central Bank's SPI[2] dataset, which includes all PIX transactions of households, both incoming and outgoing, organized by municipality and month. The distinction between outgoing and incoming PIX transfers is critical, as these do not always mirror each other due to the involvement of both businesses and individuals.

The incidence of natural disasters, and the intensity of the disaster proxy, measured by the total monetary loss per capita caused by the disasters, are provided by the Ministry of Integration and Regional Development of Brazil (Brasil - MDIR - Secretaria de Proteção e Defesa Civil, 2023), through the Integrated Information System on Disasters. The natural disasters dataset contains the following disaster groups: (i) Climatological, defined by drought and dry spells, forest fires, cold and heat waves, and low humidity; (ii) Hydrological, which are flash floods, floods, waterlogging, mass movement, and heavy rains; (iii) Meteorological, which are gales and cyclones, hail, tornados, and cold waves; and (iv) Others, given by erosion, infectious diseases, dam break/collapse, and others not typified. Descriptive statistics show that most natural disasters in Brazil are climatological, followed by hydrological and meteorological events. As additional control variables in our econometric exercises, we used population, longitude, latitude, altitude, and biomes, which were collected from the Brazilian Institute of Geography and Statistics (IBGE); while for the Koppen Index control, a climate classification system based on temperature and rainfall used in geography and climatology studies, we used the data made available by Alvares et al. (2013).[3]

## 3. Empirical strategy

We apply an Event Study Difference-in-Differences approach to estimate the effects of natural disasters on financial technology adoption, as in the following:

$$Y_{mt} = \alpha_m + \gamma_t + \sum_{j=-8}^{+8} \beta_j + X'_{mt}\Theta + \epsilon_{mt}. \tag{1}$$

where $Y_{mt}$ represents the outcome of interest, which in our main specification is given by the number of PIX transactions *per capita* at the municipality $m$ and time $t$ (year-month).[4] The variable $D_{mj}$ is an indicator variable for whether unit $m$ has been treated and observed $j$ months apart from the event/calamity, i.e., indicates 1 (one) for each time after/before which we observe the first calamity in municipality $m$, and zero otherwise. By doing so, the $\beta_j$ coefficient captures the average differences in $Y_{mt}$ in municipalities $j$ months before/after the calamity, relative to the baseline at one month after the calamity $j = -1$, which is omitted from the model as the reference category. Thus, the event study specification allows us to test not only for the persistence of the calamity shocks, by allowing their effects to vary by time, but also to determine whether pre-treatment trends were similar before the calamities.[5] The coefficients $\alpha_m$ control for municipality-specific (time-invariant) heterogeneities at the municipality level while the $\gamma_t$ controls for aggregate shocks over time. The vector $X_{mt}$ includes a set of control variables relevant to the analysis, such as the natural log of population, latitude, longitude, altitude, biome dummies, and Koppen's climate classification dummies. Finally, the term $\epsilon_{mt}$ represents idiosyncratic error to which we assume the classical assumptions.

Considering the staggered treatment and considering municipalities with only one natural disaster as treated, we adopt the developed estimator of Callaway and Sant'Anna (2021), which accounts for variation in treatment timing and adequately assesses the impact of the staggered calamity events.[6] Let $G_m$ be the period when unit $m$ becomes treated (often groups are defined by the period when a unit becomes treated; hence, the G notation) and let $C_m$ be an indicator variable for whether unit $m$ is in a never-treated group. Based on these "never-treated units", we have that, for all $t \geq g$, the parameter of interest can be measured by group-time average treatment effects:

$$ATT(g,t) = E[Y_t - Y_{g-1}|G = g] - E[Y_t - Y_{g-1}|C = 1]. \tag{2}$$

Following Callaway and Sant'Anna (2021), we aggregate the group-time average treatment effect to highlight treatment effect dynamics as follows:

$$\theta_D(e) := \sum_{g=2}^{\mathcal{T}} \mathbf{1}\{g + e \leq \mathcal{T}\} ATT(g, g+e) P(G = g|G + e \leq \mathcal{T}). \tag{3}$$

The parameter $\theta_D(e)$ measures the average effect of experiencing the calamity for the group of municipalities exposed to the treatment for exactly $e$ periods.

## 4. Results

This section begins by presenting the main findings on the effects of natural disasters on household use of PIX. The analysis uses the "always treated" approach from Callaway and Sant'Anna (2021). It focuses on the first disaster occurring during the period, with the treated group consisting of municipalities that experienced only one disaster within this timeframe. Fig. 1(a) illustrates that high-severity disasters significantly boost PIX adoption over time, as indicated by the increase in the number of PIX transactions sent. In contrast, low-severity disasters have a smaller impact on PIX adoption. Unlike the

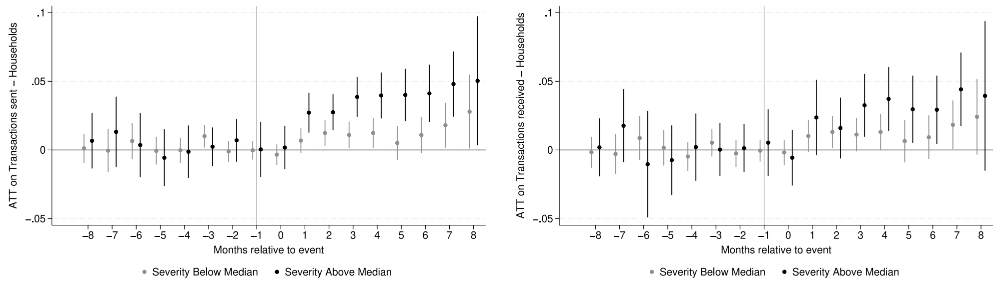
[2] Estatísticas do Sistema de Pagamentos Instantâneos (SPI) - Instant Payment System Statistics.

[3] See our Online Appendix for descriptive statistics of our data.

[4] We also use other outcomes of interest, such as credit operation, savings deposits, loans, and securities, in our analysis.

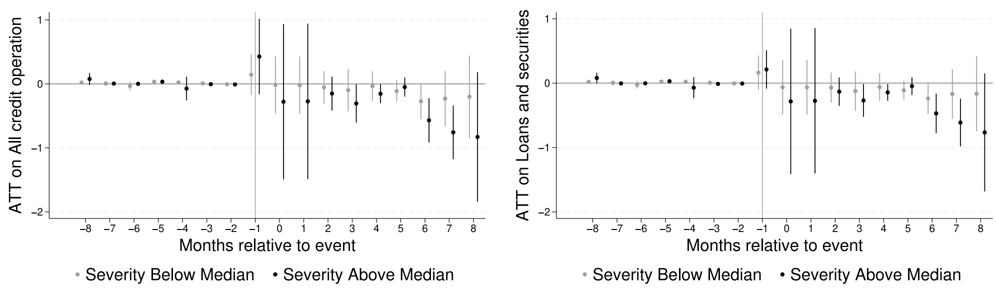
[5] In particular, we expect the estimated $\beta_j$'s for the prior months to be statistically indistinguishable from zero to validate our empirical strategy.

[6] See our Online Appendix for a series of robustness checks, where we consider different controls and treatment. We also report the results separately, considering the different types of natural disasters.

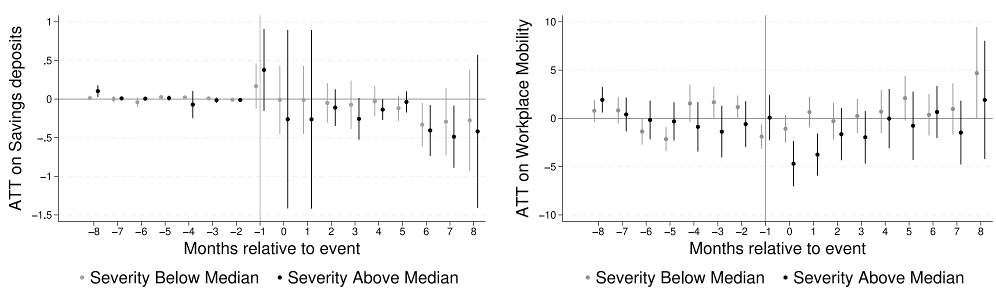



(a) Transfers sent　　　　(b) Transfers received

**Fig. 1.** The impact of natural disasters on the number of transactions using PIX.
*Note:* We apply the Callaway and Sant'Anna (2021) method to estimate the impact of natural disasters for high and low severity on financial technology adoption. We split our dataset into (i) transfers sent by household 1(a) and (ii) transfers received by household 1(b). In the regression, we employ the fixed effect of time and municipality and the following covariates: natural log. of population, latitude, longitude, altitude, biome dummies, Koppen's climate classification dummies, and state dummies.




(a) All credit operation　　　　(b) Loans and Securities




(c) Savings deposits　　　　(d) Workplace Google Mobility index

**Fig. 2.** The impact of natural disasters on the credit side and workplace Google Mobility index.
*Note:* In this figure, we apply the Callaway and Sant'Anna (2021) method to estimate the impact of natural disasters for high and low severity on credit operations and on the Google Mobility related to workplace. Panel 2(a) presents the results for all credit operations, Panel 2(b) for loans and securities operations, Panel 2(c) for savings deposits, and Panel 2(d) for workplace Google Mobility. In the regressions, we employ the fixed effect of time and municipality and the following covariates: natural log. of population, latitude, longitude, altitude, biome dummies, Koppen's climate classification dummies, and state dummies.

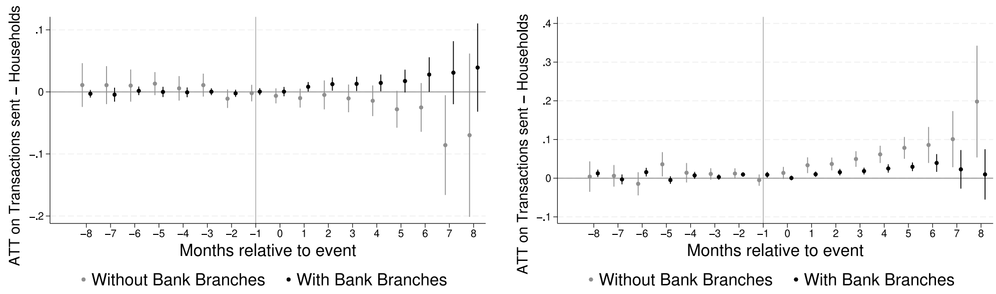
persistent effect observed for PIX sent, Fig. 1(b) reveals a short-lived effect for PIX received, becoming statistically insignificant by the eighth month for both high- and low-severity disasters.

Fig. 2 shows that natural disasters have a negative effect on credit operations in the first months but no statistical effect after eight months, highlighting that the increase in PIX adoption is not linked to a broader expansion of credit within the financial system. This suggests that while natural disasters drive the adoption of instant payment technologies like PIX, they do not positively impact other traditional financial system variables. Furthermore, the long-run effect of this negative shock on PIX adoption is not related to mobility constraints due to the natural disaster. For example, more people may turn to remote work and online shopping, which often require instantaneous payment methods. In Fig. 2(d) we present the impact of natural disasters on Google Mobility related to the workplace. For high-severity disasters, there is only a short-run negative effect on people attending the workplace.

In Fig. 3, Panels 3(a) and 3(b) show estimations for PIX transfers, dividing the sample by municipalities with varying numbers of bank branches. The results suggest that disasters have a stronger impact on areas without bank branches, likely due to limited access to banking infrastructure. Coupled with reduced mobility, this finding implies that people increase PIX transfers when physical access to banks is constrained, whereas areas with unaffected mobility show no effect.

## 5. Final remarks

Our research highlights the significant impact of PIX, an instant payment system launched by the Central Bank of Brazil in November 2020, swiftly replacing traditional payment methods and enhancing financial inclusion. Using a comprehensive dataset that includes records of natural disasters and PIX transactions across Brazilian municipalities, we employed the Differences-in-Differences (DID) method to explore




(a) Low-Severity Disasters (b) High-Severity Disasters

**Fig. 3.** The impact of natural disasters for different numbers of bank branches.
*Note:* In this figure, we apply the Callaway and Sant'Anna (2021) method to estimate the impact of natural disasters for high and low severity on financial technology adoption considering municipalities with different numbers of bank branches. The panel 3(a) presents the results for municipalities where disasters are below the median and the panel 3(b) presents the results for municipalities where disasters are above the median. In the regressions, we employ the fixed effect of time and municipality and the following covariates: natural log. of population, latitude, longitude, altitude, biome dummies, Koppen's climate classification dummies, and state dummies.

the link between disaster exposure and PIX adoption. The findings reveal a statistically significant increase in PIX usage in areas affected by severe natural disasters, emphasizing the role of disaster intensity in driving financial technology adoption.

Future research could delve into the broader economic impacts of such technology adoption, particularly discussing the potential spillover effects from households to businesses and shedding light on how different market sides interact and amplify natural disaster shock, such as in Higgins (2024).

## Declaration of generative AI

In the process of preparing this article, the author(s) used ChatGPT to ensure that there were no grammatical or typographical errors. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

## Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.econlet.2024.112092.

## Data availability

Data will be made available on request.

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# Online Appendix: Natural Disasters and Financial Technology Adoption

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**Abstract**

This online appendix provides additional details and analyses to support the findings in our main paper, "Natural Disasters and Financial Technology Adoption." It includes comprehensive descriptive statistics, distinguishing between affected and unaffected municipalities, and explores the differential impacts of various disaster types on PIX adoption. We also conduct robustness checks using alternative control groups, late treatments, and matched sample analyses. Additionally, we investigate the role of local banking infrastructure, showing that disaster impacts on PIX adoption are more pronounced in municipalities with fewer bank branches. Together, these supplementary materials reinforce the robustness of our main results.

# 1 Descriptive statistics

Table 1 presents the financial and geographical characteristics of municipalities that remained unaffected by disaster events during the study period, forming the 'never treated' control group. These municipalities serve as a baseline to assess typical levels of PIX transactions, credit activities, and demographic and geographic features in areas that were not exposed to natural disasters.

Table 1: Municipalities without disasters

| Variable | Obs | Mean | Std. dev | Min | Max |
|---|---|---|---|---|---|
| Transactions Sent per capita | 60,214 | 2.46 | 1.97 | 0.0015 | 20.33 |
| Transactions Received per capita | 60,214 | 2.12 | 1.63 | 0.004 | 16.51 |
| All credit operation (R$ per capita) | 60,214 | 3,829.53 | 14,244.74 | 0 | 766,845.41 |
| Loans and Securities (R$ per capita) | 60,214 | 1,220.36 | 5,939.72 | 0 | 343,487 |
| Saving deposits (R$ per capita) | 60,214 | 1,885.32 | 2,551.06 | 0 | 19,680.08 |
| Population (1000) | 60,214 | 43.71 | 296.07 | 0.77 | 12,396.37 |
| Longitude | 60,214 | -46.83 | 5.32 | -72.79 | -32.43 |
| Latitude | 60,214 | -15.92 | 7.72 | -33.68 | 3.22 |
| Elevation (100 m) | 60,214 | 4.29 | 2.96 | 0 | 16.39 |

Tables 2 and 3 summarize the characteristics of municipalities affected by natural disasters, classified into 'below median severity' and 'above median severity' based on per capita damages in reais (R$). The median is calculated using the full dataset before any municipalities are excluded. For instance, municipalities experiencing more than one disaster are excluded in the revised sample.[1]

[1] In the full dataset, the median damage is R$285 per capita. After excluding certain municipalities, the median shifts to R$508 per capita.

Table 2: Municipalities with disasters – Damage below median

| Variable | Obs | Mean | Std. dev | Min | Max |
|---|---|---|---|---|---|
| Disaster damage (R$ per capita) | 9,031 | 92.46 | 81.79 | 0.23 | 285.46 |
| Transactions Sent per capita | 9,031 | 3.03 | 2.10 | 0.022 | 39.46 |
| Transactions Received per capita | 9,031 | 2.67 | 1.82 | 0.022 | 36.91 |
| All credit operation (R$ per capita) | 9,031 | 3,612.08 | 5,882.97 | 0 | 68,032.9 |
| Loans and Securities (R$ per capita) | 9,031 | 1,196.51 | 1,668.51 | 0 | 21,263.54 |
| Saving deposits (R$ per capita) | 9,031 | 2,060.23 | 2,727.25 | 0 | 27,688.13 |
| Population (1000) | 9,031 | 52.63 | 178.91 | 1.74 | 2,900.31 |
| Longitude | 9031 | -43.48 | 5.85 | -72.73 | -34.88 |
| Latitude | 9,031 | -14.79 | 7.33 | -31.62 | 4.23 |
| Elevation (100m) | 9,031 | 3.99 | 3.00 | 0.02 | 12.47 |

Table 3: Municipalities with disasters – Damage above median

| Variable | Obs | Mean | Std. dev | Min | Max |
|---|---|---|---|---|---|
| Disaster damage (R$ per capita) | 12,729 | 6,705.08 | 121,11.19 | 288.05 | 131,631.2 |
| Transactions Sent per capita | 12,729 | 2.26 | 1.45 | 0.01 | 12.61 |
| Transactions Received per capita | 12,729 | 1.85 | 1.20 | 0.01 | 11.27 |
| All credit operation (R$ per capita) | 12,729 | 4,050.02 | 7,155.96 | 0 | 59,847.04 |
| Loans and Securities (R$ per capita) | 12,729 | 1,042.70 | 1,484.00 | 0 | 9,866.72 |
| Saving deposits (R$ per capita) | 12,729 | 1,718.13 | 2,701.85 | 0 | 18,608.86 |
| Population (1000) | 12,729 | 15.16 | 25.63 | 1.08 | 393.73 |
| Longitude | 12,729 | -47.12 | 6.83 | -62.87 | -34.82 |
| Latitude | 12,729 | -20.10 | 8.74 | -33.28 | -1.98 |
| Elevation (100m) | 12,729 | 4.35 | 2.49 | 0.065 | 14.75 |

Table 4, 5, and 6 present descriptive statistics based on the specific type of disaster encountered.

Table 4: Climatological disasters

| Variable | Obs | Mean | Std. dev | Min | Max |
|---|---|---|---|---|---|
| Disaster damage (R$ per capita) | 11,404 | 6,574.07 | 11,721.09 | 0.023 | 125,090.4 |
| Transactions Sent per capita | 11,404 | 2.13 | 1.44 | 0.01 | 17.93 |
| Transactions Received per capita | 11,404 | 1.76 | 1.22 | 0.01 | 17.75 |
| All credit operation (R$ per capita) | 11,404 | 4,140.23 | 7,416.80 | 0 | 68,032.9 |
| Loans and Securities (R$ per capita) | 11,404 | 1,125.91 | 1699.76 | 0 | 21,263.54 |
| Saving deposits (R$ per capita) | 11,404 | 1,679.69 | 2,759.62 | 0 | 27,688.13 |
| Population (1000) | 11,404 | 17.91 | 63.67 | 1.084 | 1,492.53 |
| Longitude | 11,404 | -46.74 | 7.30 | -57.83 | -35.29 |
| Latitude | 11,404 | -18.99 | 9.95 | -33.28 | -3.14 |
| Elevation (100m) | 11,404 | 4.17 | 2.29 | 0.07 | 11.62 |

Table 5: Hydrological disasters

| Variable | Obs | Mean | Std. dev | Min | Max |
|---|---|---|---|---|---|
| Disaster damage (R$ per capita) | 8,933 | 683.94 | 2096.02 | 0.25 | 26,300.61 |
| Transactions Sent per capita | 8,933 | 3.06 | 1.99 | 0.027 | 39.46 |
| Transactions Received per capita | 8,933 | 2.67 | 1.71 | 0.029 | 36.91 |
| All credit operation (R$ per capita) | 8,933 | 3,071.19 | 4,934.35 | 0 | 40,807.99 |
| Loans and Securities (R$ per capita) | 8,933 | 970.01 | 1,294.81 | 0 | 8,244.66 |
| Saving deposits (R$ per capita) | 8,933 | 1,967.45 | 2,643.22 | 0 | 14,200.4 |
| Population (1000) | 8,933 | 41.85 | 157.88 | 1.39 | 2,900.31 |
| Longitude | 8,933 | -43.61 | 5.20 | -71.95 | -34.82 |
| Latitude | 8,933 | -15.99 | 6.14 | -31.19 | 4.23 |
| Elevation (100m) | 8,933 | 4.31 | 3.15 | 0.02 | 14.75 |

Table 6: Meteorological disasters

| Variable | Obs | Mean | Std. dev | Min | Max |
|---|---|---|---|---|---|
| Disaster damage (R$ per capita) | 1,068 | 4,434.29 | 17,108.5 | 1.32 | 131,631.2 |
| Transactions Sent per capita | 1,068 | 2.98 | 1.81 | 0.05 | 9.67 |
| Transactions Received per capita | 1,068 | 2.45 | 1.47 | 0.05 | 7.98 |
| All credit operation (R$ per capita) | 1,068 | 6,854.20 | 8,783.84 | 0 | 51,953.62 |
| Loans and Securities (R$ per capita) | 1,068 | 1,799.57 | 1,738.81 | 0 | 7,021.25 |
| Saving deposits (R$ per capita) | 1,068 | 2701.59 | 2711.36 | 0 | 9875.16 |
| Population (1,000) | 1,068 | 35.45 | 65.11 | 1.34 | 349.72 |
| Longitude | 1068 | -50.33 | 5.57 | -72.73 | -34.98 |
| Latitude | 1068 | -23.00 | 6.16 | -30.13 | 3.54 |
| Elevation (100m) | 1068 | 4.03 | 2.86 | 0.11 | 11.19 |

Table 7 provides a breakdown of municipalities by treatment groups, detailing the timing of disaster occurrences and categorizing them based on disaster severity and type. This table clarifies the temporal spread and diversity of the treatment group, illustrating the distribution of municipalities affected across different time periods (e.g., starting from September 2021 through October 2022) and disaster characteristics. The table also highlights the presence of three main types of disasters—hydrological, climatological, and meteorological—alongside severity levels, with municipalities further divided by whether their disaster damages fall above or below the median. By showing how municipalities were grouped and treated over time, Table 7 shows the composition of the treatment groups and how these differ from the ”never treated” control group, which is consistently disaster-free throughout the study period. It is worth noting that, while municipalities began being treated in September 2021, our dataset starts in November 2020. We excluded municipalities that were treated between November 2020 and September 2021 to ensure that PIX technology was well-established at the time of the disaster.

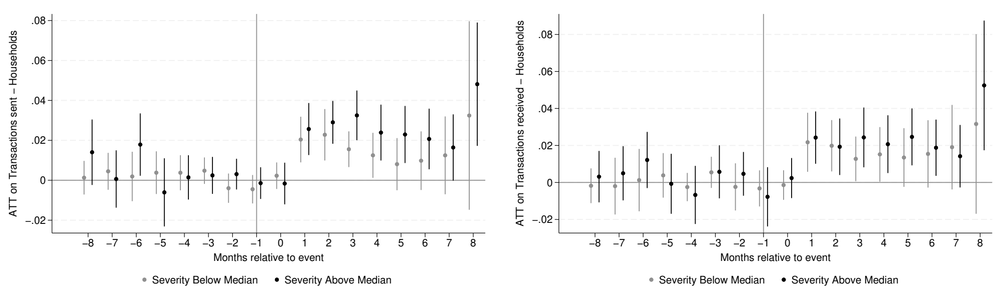
Table 7: Municipalities per Treatment Groups

| Treatment Groups | Total Disasters | Below Median | Above Median | Hydro. | Climat. | Meteo. |
|---|---|---|---|---|---|---|
| Never Treated | 2737 | 2737 | 2737 | 2737 | 2737 | 2737 |
| T = 9/2021 | 28 | 11 | 17 | 2 | 25 | 1 |
| T = 10/2021 | 39 | 18 | 21 | 1 | 38 | 0 |
| T = 11/2021 | 39 | 27 | 12 | 3 | 31 | 5 |
| T = 12/2021 | 69 | 35 | 34 | 9 | 39 | 16 |
| T = 1/2022 | 135 | 32 | 103 | 11 | 120 | 4 |
| T = 2/2022 | 274 | 133 | 141 | 146 | 116 | 7 |
| T = 3/2022 | 471 | 134 | 337 | 215 | 245 | 9 |
| T = 4/2022 | 67 | 42 | 25 | 37 | 23 | 5 |
| T = 5/2022 | 27 | 20 | 7 | 20 | 4 | 2 |
| T = 6/2022 | 23 | 15 | 8 | 15 | 6 | 2 |
| T = 7/2022 | 63 | 40 | 23 | 52 | 1 | 7 |
| T = 8/2022 | 6 | 5 | 1 | 3 | 0 | 1 |
| T = 9/2022 | 39 | 24 | 15 | 30 | 7 | 1 |
| T = 10/2022 | 15 | 13 | 2 | 4 | 2 | 7 |

# 2 Different types of disasters

This section analyzes the diverse impacts of hydrological, climatological, and meteorological disasters on PIX transactions. Figures 1, 2, and 3 illustrate transaction trends over time according to disaster severity and type of disaster. The most pronounced effects on PIX transactions are from hydrological and climatological disasters. Indeed, meteorological disasters differ from hydrological and climatological disasters due to their typically short-term and less sustained disruptions. While hydrological and climatological events often cause prolonged damage to infrastructure and services, necessitating extended reliance on digital payments, meteorological disasters tend to result in quicker recoveries, reducing the need for lasting behavioral change.

Figure 1: Heterogeneity by Type of Disaster: Hydrological

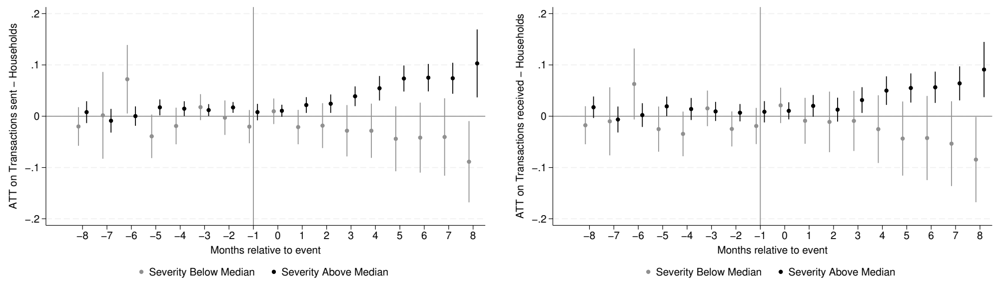



(a) Transfers Sent

(b) Transfers received

*Note:* We apply the Callaway and Sant'Anna (2021) method to estimate the impact of hydrological natural disasters for low and high severity on financial technology adoption. We split our dataset into (i) transfers sent by household (1a) and (ii) transfers received by household (1b). In the regression, we employ the fixed effect of time and municipality and the following covariates: natural log. of population, latitude, longitude, altitude, biome dummies, and Koppen's climate classification dummies.

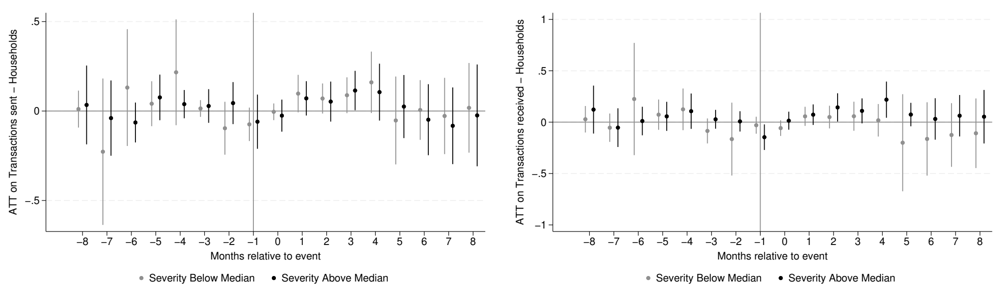
Figure 2: Heterogeneity by Type of Disaster: Climatological




(a) Transfers Sent (b) Transfers received

*Note:* We apply the Callaway and Sant'Anna (2021) method to estimate the impact of climatological natural disasters for low and high severity on financial technology adoption. We split our dataset into (i) transfers sent by household (2a) and (ii) transfers received by household (2b). In the regression, we employ the fixed effect of time and municipality and the following covariates: natural log. of population, latitude, longitude, altitude, biome dummies, and Koppen's climate classification dummies.

Figure 3: Heterogeneity by Type of Disaster: Meteorological




(a) Transfers Sent (b) Transfers received

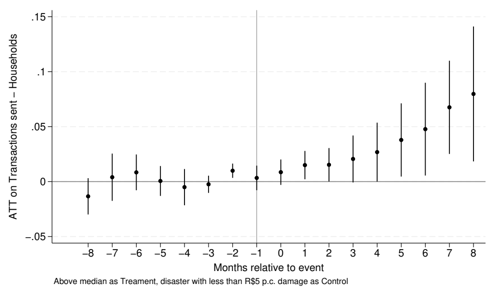
*Note:* We apply the Callaway and Sant'Anna (2021) method to estimate the impact of meteorological natural disasters for low and high severity on financial technology adoption. We split our dataset into (i) transfers sent by household (3a) and (ii) transfers received by household (3b). In the regression, we employ the fixed effect of time and municipality and the following covariates: natural log. of population, latitude, longitude, altitude, biome dummies, and Koppen's climate classification dummies.

# 3 Robustness checks

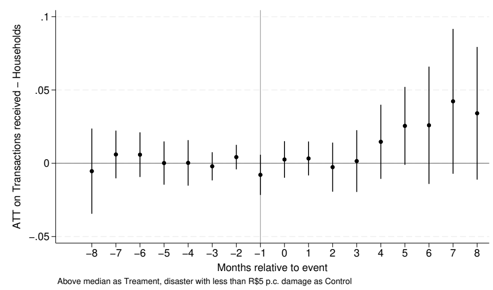
## 3.1 Municipalities with minimal disaster impact

Figure 4 assesses the robustness of the findings by redefining the control group to include municipalities with minimal disaster impact (less than R$5 per capita in damages). This minimal damage threshold enhances confidence that incidental factors do not influence the observed effects on PIX adoption in areas with only slight disaster exposure.

Figure 4: Alternative Controls – Municipalities with minimal disaster impact




(a) Transfers sent



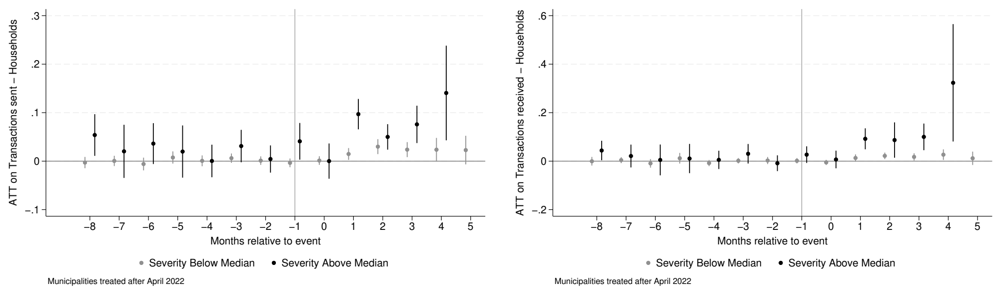

(b) Transfers received

*Note:* We apply the Callaway and Sant'Anna (2021) method to estimate the impact of natural disasters for high severity (above the median) on financial technology adoption, with the control group being the municipalities with disasters with less than R$5 per capita. We split our dataset into (i) transfers sent by household (4a) and (ii) transfers received by household (4b). In the regression, we employ the fixed effect of time and municipality and the following covariates: natural log. of population, latitude, longitude, altitude, biome dummies, and Koppen's climate classification dummies.

## 3.2 Late treatements

Figure 5 focuses on municipalities affected after April 2022, isolating the effects of natural disasters while excluding early PIX adopters. The patterns observed in these late-treated groups reinforce the main findings, demonstrating that natural disasters consistently drive increased PIX adoption even among later adopters.

Figure 5: Late Treatments - Treatment after April 2022




(a) Transfers sent

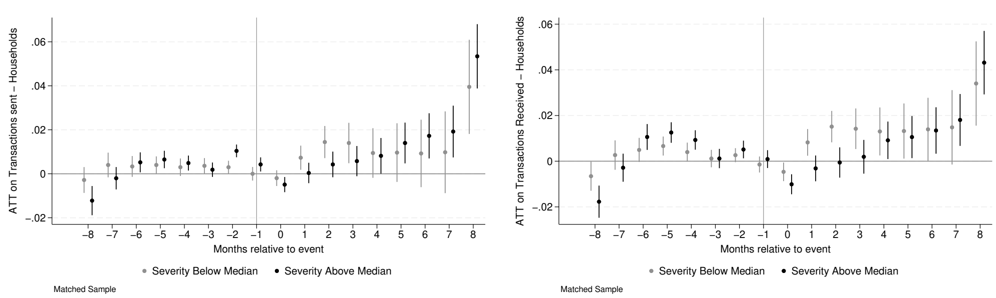
(b) Transfers received

*Note:* We apply the Callaway and Sant'Anna (2021) method to estimate the impact of natural disasters for high and low severity on financial technology adoption for late treatments (after April/2022). We split our dataset into (i) transfers sent by household (5a) and (ii) transfers received by household (5b). We employ the fixed effect of time and municipality and the following covariates: natural log. of population, latitude, longitude, altitude, biome dummies, and Koppen's climate classification dummies.

## 3.3 Matched sample

Here, a matched sample of municipalities based on observable characteristics is used to validate the results. Matching on variables like population size and geographical location minimizes confounding factors, and the consistent results further validate the study's conclusions on the relationship between disaster events and PIX adoption.

Figure 6: Matched Sample




(a) Transfers sent

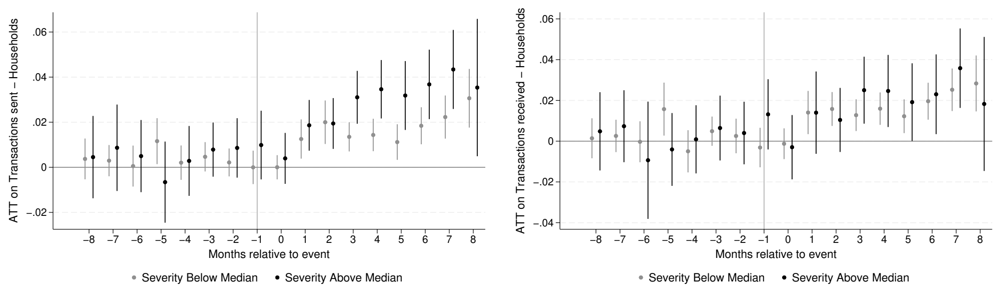
(b) Transfers received

*Note:* In the regression, we matched the sample on the natural log. of population, Latitude, Longitude, altitude, biome dummies, Koppen's climate classification dummies, and state dummies. Results were estimated with Callaway and Sant'Anna (2021) without covariates. We split our dataset into (i) transfers sent by household (6a) and (ii) transfers received by household (6b).

## 3.4 One or more disasters as treatment

Figure 7 captures the cumulative impact of natural disasters on both incoming and outgoing PIX transactions, focusing on municipalities that experienced one or more disaster events. High-severity disasters show a pronounced increase in PIX transactions post-event, indicating that severe disruptions lead to more sustained fintech usage among households.

Figure 7: The impact of natural disasters on the number of transactions using PIX




(a) Transfers sent

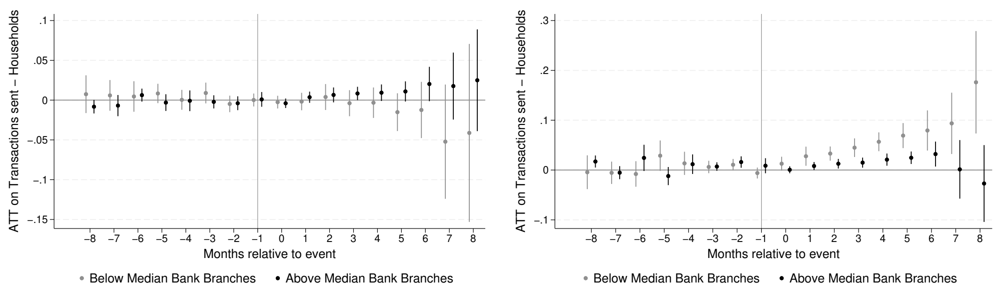
(b) Transfers received

*Note:* We apply the Callaway and Sant'Anna (2021) method to estimate the impact of natural disasters for high and low severity on financial technology adoption. We split our dataset into (i) transfers sent by household (7a) and (ii) transfers received by household (7b). In the regression, we employ the fixed effect of time and municipality and the following covariates: natural log. of population, latitude, longitude, altitude, biome dummies, Koppen's climate classification dummies, and state dummies.

## 3.5 Heterogeneity by Bank Branches

Here, we can analyze the impact of disasters not only across varying disaster intensities but also in relation to the presence of bank branches. Figure 8 shows a stronger impact of disasters on PIX adoption in areas with below-median bank branches, suggesting that limited access to physical banking services amplifies the shift to digital payments.

Figure 8: Heterogeneity by Bank Branches




(a) Low-Severity Disasters (b) High-Severity Disasters

*Note:* We apply the Callaway and Sant'Anna (2021) method to estimate the impact of natural disasters for high and low severity on financial technology adoption. We split our dataset into (i) disasters with severity below the median (8a) and (ii) above the median (8b), with heterogeneity within each exercise for municipalities above and below the median of the number of bank branches per capita. In the regression, we employ the fixed effect of time and municipality and the following covariates: natural log. of population, latitude, longitude, altitude, biome dummies, Koppen's climate classification dummies, and state dummies.

# References


**Callaway, Brantly and Pedro HC Sant'Anna**, "Difference-in-differences with multiple time periods," *Journal of Econometrics*, 2021, *225* (2), 200–230.