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# EFFECT OF A POSITIVE CONSTRUCTION SECTOR DEMAND SHOCK ON BANKRUPTCY: EVIDENCE FROM NATURAL DISASTERS IN FRANCE

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# Effect of a positive construction sector demand shock on bankruptcy: evidence from natural disasters in France

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**Abstract**

In this thesis,[1] I use data on insolvency proceedings at the "département"[2] level, a decree dataset of natural disasters (GASPAR) as well as meteorological observations on precipitations to provide a first evidence on how natural disasters may be generating demand shocks to the construction sector and affecting firms' insolvency. A Generalized-Difference-in-Difference model is set up and suggests that propensity for insolvency in the construction sector is reduced after the issuance of a natural disaster decree while it is not the case for other sectors. It reduces liquidation filings by 0.109 percentage points from an average of 0.316 while having no effect on reorganization and safeguard proceedings. Moreover, the effect seems to be lasting only one quarter, having no spillover effect onto neighboring "départements", nor changing employment features. However, parallel trends seem to be valid only for some disasters and once I use actual rainfall as a measure of natural disasters, I find that there is a weaker correlation between rainfall and bankruptcy although still in the same direction. This suggests that establishing a decree, while correlated with meteorological factors, may be partially endogenous to the condition of the construction sector. Nevertheless, natural disasters do appear to provide some positive boost to the construction sector that diminishes their reliance on bankruptcy.

[1] I thank deeply my thesis directors at the microeconomics commission professor Jeanne Lafortune and Eugenio Bobenrieth for the guidance and help they provided me all semester long while working on the subject. I want also to thank professor Anne Epaulard for suggesting me the subject and providing me the BODACC dataset, as well as Shirley Redroban for her proofreading.

[2] In the administrative divisions of France, the "département" is one of the three levels of government division under the national level, between the administrative regions and the communes (municipalities). There are 96 metropolitan and 5 overseas "départements".

# 1 Introduction

When either a firm or a strategic sector faces economic struggles, it is quite common for local or even national politicians to provide public contracts to reduce the hardships they face with the goal of allowing companies to survive the crisis. More broadly, public contracts policies can be perceived as demand subsidies, especially in the construction sector. The vision underlying this type of policy is that both the State and firms benefit from those contracts. Indeed, while public goods or services are obtained from that market, these contracts can also be a demand channel from which private firms can draw some benefits. They can be anticipated by firms for setting their investment, production or decision to enter a local market, leading to an equilibrium resulting of firms' behaviors although this aspect is not addressed in this thesis. However, demand shocks may also allow industries to reduce financial distress, affect firms' exit decisions (Kumar & Zhang, 2019) or improve local economic conditions by increasing level of output, employment and inflation in the short-run (Lorenzoni, 2009).

To the best of my knowledge, this type of strategy may not always be efficient. In particular, if the companies' difficulties stem from insufficient profitability or inadequate supply, these new contracts are unlikely to have any effect on firms' long-term chances of survival. On the contrary, while companies may have entered the market when it was thriving, the economic shifts occurring meanwhile may have led to lowering demand in the sector and deteriorating firms' financial conditions. In those cases, when firms either have hired too many workers and cannot reduce their workforce or have invested in physical capital but cannot sell it, demand subsidies may permit survival. However, public contracts are endogenous: their use may respond to economic downturns. Since the economic situation may be affected by these policies as well, it would not be possible to identify its effects due to a simultaneity bias. To solve that issue, one way to test the effect of demand shocks on firms' survival is to observe how these firms respond to a local temporary exogenous demand shock. In order to find a demand shock exogenous to the area's economic conditions, I focus on climate shocks and on the construction industry. Doing so resolves the endogeneity bias since natural disasters are independent of local economic conditions. Therefore, assessing whether firms of the affected "départements" have a lower probability of entering insolvency proceedings after a positive demand shock should allow to understand if natural shocks reduce financial distress for firms in the construction sector. Indeed, the destruction of buildings and individual properties should increase demand for work in the construction sector, leading to better financial conditions only in that industry.

In general, natural disaster shocks randomly affect very specific areas, chosen here to be “départements”, and studied through decree issuance data and meteorological observations in that thesis. To my knowledge, this study is the first using the “Base nationale de Gestion ASsistée des Procédures Administratives relatives aux Risques” (GASPAR) database[3] for economic research purpose. The national agency has been compiling natural disaster decrees on French territory since 1982, and meteorological observations can be combined with these data since disasters in France are mainly floods. This register is thus completed with the SYNOP dataset[4] issued by Meteo France which records wind speed and precipitations of 51 french meteorological stations on a daily basis since 2000. It is then possible to define that a natural disaster has occurred in a given “département” when meteorological stations record large amounts of rain during a short period or when a majority of the municipalities has been decreed as affected by a natural catastrophe. I then analyze how spatial and time heterogeneity within natural disasters influences the local economy.[5] These data are merged with a dataset on insolvency proceedings and trial judgments that occurred from 2008 to 2018 (BODACC). This enables me to compute statistics on insolvency by sectors to study how the different industries affected by the demand shock react to it, and whether the insolvency prevalence is decreased in the construction sector when natural shocks occur.

I measure the effect of decree issuance and rain shocks through a Generalized-Difference-in-Difference econometric model saturated with “département” and year fixed effects. The specification includes controls for each “département” such as changes in the number of firms, the share of the sector in the local economy, as well as the share of each category of firms. Results suggest that when a decree is issued in more than half of the municipalities of the “département”, it induces a reduction of insolvency within the period of disaster. I find that this reduction in propensity to bankruptcy only occurs in the construction sector while other sectors are not affected at all by those events. However, I neither find further evidence that it affects insolvency in neighboring “départements”, nor that these effects are lasting. The higher the share of municipalities affected is, the stronger the effect on insolvency is. This suggests that negative effects of the largest disasters such as depicted by Strobl (2011) do not exist in the French case. It may be because the effect of hurricanes is not comparable to that of floods, storms and mudslides occurring generally in Eu-

[3] It is a public dataset, updated every month, and available at: http://www.georisques.gouv.fr/dossiers/telechargement/gaspar

[4] https://donneespubliques.meteofrance.fr/

[5] The scope includes only the metropolitan areas because french overseas territories face very different economic and natural conditions from the metropolitan area. Any reference to France in the rest of the paper must be understood as the metropolitan area.

rope. Indeed, the latter disasters imply smaller destruction magnitude and no lasting after-effects aftermaths as it is the case for tropical events in some developing countries or in the US.

Nevertheless, while I show that decrees are associated with reduced insolvency, rain shocks do not have the same impact magnitude despite the fact that it significantly influences decree issuance. The effect of heavy precipitations is weaker although it goes in the same direction. Indeed, since decree issuance is asked by the local authorities, it may be that political reasons such as bad results in the construction sector lead the local politicians to be more prone to ask for the recognition of the natural disaster state than in areas where the construction industry is thriving. Another possibility is that the natural disaster recognition process is better-known in "départements" where natural disasters often occur than in other areas. This would lead local authorities of municipalities that are often struck by natural catastrophes to ask for a decree issuance with higher probability at a same level of damage. The partial endogeneity of decree issuance may explain why decree and rain correlation with bankruptcy is of different magnitude. Nevertheless, natural disasters do appear to affect positively the construction sector through the reduction they operate on bankruptcy.

First, I present in Section 2 the state of art regarding natural disasters studies and the use of such events as an instrument for demand shocks. In Section 3, the interest of such a study is underlined by explaining what are the existing conditions in France concerning natural disasters, how the debt contract settings may affect insolvency and how the differences in disaster occurrence probability are taken into account in the econometric model. Then in Section 4, all the data and information used is explained while the identification methodology is detailed further along with the model in Section 5. Eventually, all the results are presented in Section 6 while robustness checks and possible endogeneity of decree measurement of disaster are discussed in Section 7.

## 2 Literature

The study of natural disasters and their impact on economies have been discussed in a wide theoretical economic literature. Broad themes have been raised by researchers but one of the main questions has been to know whether natural events lead the economy toward a lower equilibrium associated with lower growth (Long, 1978), has a very moderate effect on output (Albala-Bertrand, 1993), or force a capital update leading to the process known as creative destruction (Skidmore & Toya, 2002; Crespo Cuaresma et al., 2008). Those various ends can be reached through different channels. Negative impact on growth can be identified whenever available capital has been destroyed or disaster damage exceed reconstruction capacity (Hallegatte & Dumas, 2009). However, not only capital loss is unlikely to have an important effect on growth, but it is likely that very moderate response may be sufficient to prevent growth from falling (Albala-Bertrand, 1993) or foster recovery (De Mel et al., 2012). It is also emphasized that natural disasters can have a negative effect on migration, or housing price without hurting the economy (Boustan et al., 2020), and that local output may be affected without any effect on the national growth rate (Strobl, 2011). The rationale behind such an idea is that the response of the various sectors may be very different depending on the characteristics of the sector: capital-intensity (industry for instance), dependence on meteorological conditions (agriculture), new demand opportunities (construction)... Moreover, natural disasters can lead to improvements in total factor productivity thanks to updates in capital stock and new technologies (Hallegatte & Dumas, 2009), accelerated replacement of capital and assets (Crespo Cuaresma et al., 2008; Gignoux & Menéndez, 2016), or aid provision stimulating public infrastructure improvements (De Mel et al., 2012; Gignoux & Menéndez, 2016). Another reason pointed out in the literature is that higher frequency of natural disasters implies higher rates of human capital accumulation because of the substitution from physical capital to human capital caused by the event generating increased return to human capital, and reduced return to physical capital (Skidmore & Toya, 2002).

Natural disasters also have already been used in prior work to instrument for various phenomena: school displacement (Imberman et al., 2012), temporary shocks to local labor markets (Belasen & Polachek, 2009), changes in uncertainty (Baker et al., 2014), propagation of shocks to the suppliers network (Barrot & Sauvagnat, 2020) and changes in risk perception and pricing (Dessaint & Matray, 2017; Kruttli et al., 2020). However, to my knowledge, no papers use those quasi-random experiences as a demand shock in the construction sector. If many authors have studied how local economies are affected by natural events, few of them differentiate the effect by sector (Kirchberger, 2017; Loayza et al., 2012). Impact on agriculture is often emphasized in studies about developing economies since it is often one of the major employment sectors and that work from that sector is what allows fragile households to survive, and because weather is a good instrument for agricultural production (Blakeslee & Fishman, 2018). In particular, rainfall have been used in the literature to instrument phenomena such as migration (Munshi, 2003; Chalfin, 2014) or agricultural output (Mahajan, 2017). Some research suggests that in low-income countries post-disaster labor markets observe significant wage changes across sectors (Belasen & Polachek, 2009; Kirchberger, 2017; Mueller & Quisumbing, 2011) while there is fewer evidence of an overall influence on employment. Eventually, Loayza et al. (2012) find that natural disasters affect economic growth not always negatively but differently across events and economic sectors. However, they do not consider the construction sector growth in the study. To my knowledge, few works have been carried by focusing on the impact of natural disasters on firms' survival (Cole et al., 2013), but none on bankruptcy in the construction sector. I propose to study this phenomenon in detail in that thesis.

In addition, another difficulty is to model the demand shock. Away from extreme events such as hurricanes (Strobl, 2011), earthquakes (Uchida et al., 2013) or storms undergone in the US or in developing countries, France is generally hit either by floods or by droughts. Thus, there is no official scale as the Saffir-Simpson, or Richter scale to account for the intensity of the natural phenomena. Thus, a crucial topic to infer on the demand shock is how to measure or find a proxy for the damage caused by the natural disaster on the local economies. As so, understanding what the main drivers of the demand shock are is crucial. While some studies have been carried on using the number of deaths to measure the disaster intensity (Boustan et al., 2020; Aceto et al., 2016; Vinet et al., 2011; Noy, 2009), it may not be a good proxy for the damage. Indeed, as explained in Vinet et al. (2011), people may die because of information default due to ageing, or being the wrong time at the wrong place without meaning that damage on property is elevated.

In contrast, other features such as human-related or event-related characteristics may be better to understand the magnitude of the demand shock. First ones such as affected people (Cavallo et al., 2013; Noy, 2009; Loayza et al., 2012), home and property prices (Boustan et al., 2020), or monetary direct damage estimates (De Mel et al., 2012; Noy & Nualsri, 2011; Crespo Cuaresma et al., 2008) are mainly met in the economic literature. Second ones such as precipitations (Faridzad et al., 2018; E. H. Lee & Kim, 2018; Iadanza et al., 2016); inundation depth (Mueller & Quisumbing, 2011; E. H. Lee & Kim, 2018; Van Verseveld et al., 2015), duration (E. H. Lee & Kim, 2018; Strobl, 2011; Aceto et al., 2016; Iadanza et al., 2016), wind speed (Cavallo et al., 2013; Noy, 2009; Strobl, 2012) and also land area (Mueller & Quisumbing, 2011; Aceto et al., 2016) are different indicators existing in economic and engineering literature. Since the scope of this study only covers flood aftermaths, I both propose a meteorological approach based on precipitation ratios, and official decrees to account for disaster occurrences.

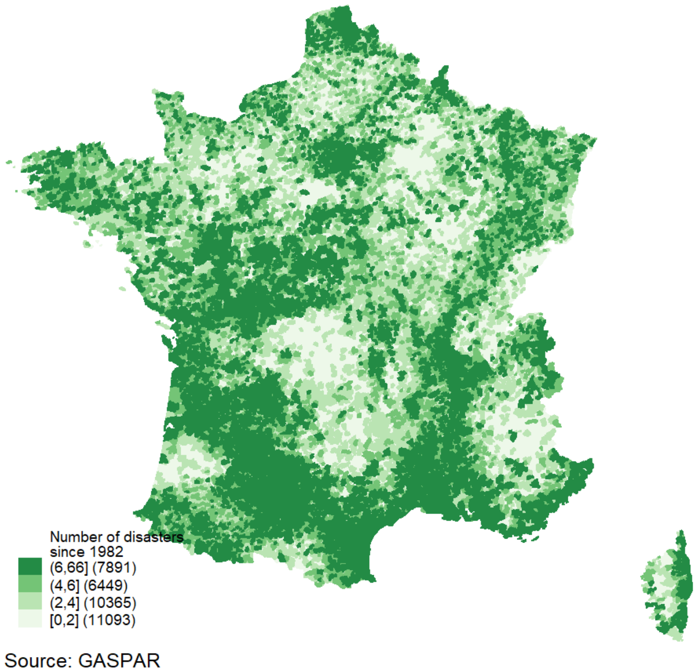
In some countries, natural disasters follow a quasi-random spatial and temporal distribution that allow the authors to consider the natural disasters as being quasi-exogeneous (Gignoux & Menéndez, 2016; Cavallo et al., 2013). In the case of France, temporal distribution of disasters seems to be quasi-random as yearly intensity is very heterogeneous and not cyclical, while its spatial distribution is not. Therefore, one could be concerned with the endogeneity of natural disaster localization in the sense that "départements" with more frequent occurrence of natural disasters would influence firms' expectations. I discuss that issue in next section by proposing to use fixed effect to take into account optimal settings in debt contracts that could vary due to differences in disaster probabilities across the areas.

# 3 The probability of disaster occurrence issue

## 3.1 Natural disasters in France

Although different kinds of risks exist (hydrological, geological, wind-related coastal risk (CCR, 2019)), two types of natural disasters in France occur with a higher frequency and level of damage: floods and droughts. However, mainly floods have an impact on the construction sector through the damages it causes. Spatial distribution of disaster occurrence is heterogeneous (Figure 1): some regions experience more disasters than others. For instance, floods mostly occur around main rivers such as the Garonne, Rhône and Seine and the seaside because of massive precipitation or storms and lead to important damages on housing and individual properties. Areas that are disaster-free are mostly the mountainous regions such as the Alps, Pyrenees and the Massif Central. Indeed, even if those areas are subject to intense rainy sessions, the elevation and slope allow to carry the water along the main rivers leading generally to floods downstream.

Figure 1: Number of disasters by municipality (1982-2020)




However, heterogeneity in disaster occurrence may make identification of the demand shock harder. Indeed, as well as households' decisions (Campbell & Cocco, 2015; Mitman, 2016), firms' bankruptcy decisions are endogenous (White, 1989; Von Thadden et al., 2010). Therefore, if the probability of a demand shock is increasing, even under financial difficulties, firms may wait to see if their financial conditions improve and only then decide if they file for bankruptcy or not. These differences across areas may either delay shock aftermaths, reduce propensity for bankruptcy in areas often subject to demand shock by giving firms the incentive to avoid bankruptcy, or to set its debt in a different manner (Leland, 1994; Leland & Toft, 1996; Fan & Sundaresan, 2000). Also, it may also influence the way those firms decide to finance their activity. Indeed, if a natural disaster is expected by the companies, it may reduce their risk perception at the moment of financing their activity. Natural disasters may affect these strategic behaviors in the same way public demand shocks do. So, if the possibility for public demand increase is taken into account by firms and that it leads to a reduction of the number of failures, it is an effect that should not be ignored.

Of course, changes in the outcome variable are one of the results of those strategic decisions, which may actually come from differences in non-observable factors. If these unobservable factors vary at the same time a natural disaster occurs, the effect could be attributed to natural disaster occurrence while the actual determinants of the outcome variable are not included into the model. However, this issue is only partially taken into account in this thesis. Fixed effects are set in the econometric analysis to control for the differences in characteristics due to the disaster probability gap among "départements", assuming two hypothesis.

First is that accounting for the disaster probability and some observable characteristics in the model will be sufficient to capture firms' behaviors. We are aware this cannot always be the case and that unobservable factors (like local changes in risk aversion, or local financial distress) may affect firms' behaviors. One way to take such changes into account would be to include control variables related to it, to avoid the omitted variable bias. We further give some insights of literature on debt contracts negotiation, on what could be the observable characteristics that may be included in the model and why we mainly rely on fixed effects and a few area's characteristics to solve the issue depicted above. The second hypothesis is that the disaster probability is not changing during the ten years period of the study. This might actually depend on the period on which the agents actualize their beliefs. Therefore, next subsection discusses the way firms' debt contract settings may depend on probability of disaster occurrence, and the way those details are incorporated in the empirical analysis.

### 3.2 Strategic default

I propose to understand how the debt contracts between a company and its creditors result from a strategic decision-making process that can be influenced by the disaster probability. In general, the firm has to negotiate with the debt holders how much and which maturity it can borrow (Leland & Toft, 1996; Hart & Moore, 1998). In doing so, a contract is set in which the debtor borrows a certain amount of money from the creditor and promises to pay back the loan and some interests (Aghion et al., 1992). In every period (in general, months) the firm faces a sequence of various choices to make while creditors might expect the capital to be paid.

Whenever a company faces financial difficulties, these can be resolved in different ways, among which the best-known are liquidation and reorganization, but also through private settlements. As pointed out in Bester (1994), when a collateral is engaged, there are more chances that the possibility for contract renegotiation arises and that reorganization would be contemplated by the creditors. According to Asquith et al. (1994), this type of renegotiation is frequent. If chapter 11 ("redressement judiciaire" in France) is the usual proceeding filed when firms decide to renegotiate their debt contracts, companies may also try to find other workouts with their creditors in order to avoid the stigma weighing on the firm filing for bankruptcy (Épaulard & Zapha, 2019). As explained in Chatterjee et al. (1996), the severity of the firm's liquidity crisis, the degree of its leverage, the magnitude of its economic distress as well as the extent of creditor's coordination may affect firm's restructuring decision. They find that economically distressed firms file for Chapter 11, while economically viable firms prefer workouts. According to a complementary work by John et al. (2013), firms that have high option value of assets and high cost of asset sales tend to file for Chapter 11 while those that have low cost of asset sales and low option value of equity tend to sell assets and restructure privately.

However, in some circumstances, the borrower may very well be able to use its liquidity to honour debt repayment but preferring to strategically renegotiate with its creditors either by falsely declaring that its debt interests exceed its investments' return (Bester, 1994) or by anticipating its difficulties through other workouts ("mandat ad-hoc", "accords de conciliation"). Some of the conditions under which incentive to default strategically emerges are explored in Chopard & Langlais (2007). They base their model on the information asymmetry existing between the borrower and debt holders: the company decides to renegotiate its debt contract not only when the benefit from this strategy is strictly superior to the gain associated with initial debt contract terms but also when diverging interests of borrowers and lenders give lenders the incentive to renegotiate the debt contract. Indeed, other solutions than liquidation may be contemplated when the latter decision draw high costs, or because the firm's assets are not enough to cover the firm liabilities and there is a race between creditors to get their money back first (Aghion et al., 1992). Zhang et al. (2015) test for the endogeneity of financial benefit from filing for bankruptcy (for households) in a model in which financial benefit and the bankruptcy decision are determined jointly, concluding that adverse events may affect financial benefit and, thus, exit decision. It is very likely to be the same in the case of natural disasters and that, independently of the "département" in which it occurs, the firm's behavior will be affected by the shock. Of course, the scheme described here is valid only for construction sector since it is assumed that firms' profits are not modified by natural events in other industries (agriculture is excluded from the analysis).

According to Kumar & Zhang (2019), the negotiation happens before observing the demand shock and thus captures the fact that neither the firm nor its creditors usually have complete information about the market demand of the next periods. This is why expectations are influenced by the probability of disaster occurrence which is a feature the agents have access to actualize their beliefs. States of nature can be high (after a demand shock occurs), or low (when there is no demand shock). The expected firm output is composed of its usual expected profit and another component which depends on the probability of disaster occurrence and its average magnitude. It leads the firm to maximizes its expected gain function with respect to the debt it takes in first period, knowing the probability of natural disaster occurrence and the gain it draws from going bankrupt (or not) given its implicit probability of bankruptcy.

While discussion on how the default boundary is affected by tax rates (Nejadmalayeri & Singh, 2012), company bargaining power (Fan & Sundaresan, 2000), bankruptcy code (Favara et al., 2012), the exit conditions invoked are often firm value, the debt collateral for secured debt and credit constraints. The credit constraints possibly faced by the agents (Wright et al., 2008; Mitman, 2016) and the collateral value of the credit that gives the company the incentive to pay back its debt (Vig, 2013) and may have a significant effect on bankruptcy (Benmelech & Bergman, 2011) may both be affected by the differences in disaster probabilities through notably the creditors expectations.

The econometric model explained in Section 5 is omitting contract features found in the literature (Davydenko & Franks, 2008; Favara et al., 2012) such as the average number of creditors, of loans by company, the percentage of loans amounts that are secured by a collateral or the leverage because these data are not available at the "département" level. Therefore, it possibly suffers from an omitted variable bias (Greene, 2003) if these contracts characteristics follow different trajectories among “départements” during the period of interest. Moreover, even if these data were available and fully relevant for our model, it is very likely that the contracts features would be endogenous and would suffer from reverse causality from bankruptcy. For instance, in areas where bankruptcy is increasing, creditors may ask for a higher collateral value, and companies may look for a higher number of creditors.

Because of the endogeneity of debt contract features, I will control for the probability of disaster occurrence in the empirical analysis through “département” fixed effects to capture, conditional on the latter probability, the impact of a demand shock when it happens. The contracts feature differences that are explained by the difference in disaster probability across “départements” will be taken into account through the “département” fixed effects, and the characteristics evolving similarly in all the areas will be captured through quarter-year fixed effects.

# 4 Data

In order to analyze natural disasters impacts on corporate dynamics at the “département” level, I build a dataset from different sources which contains decrees of natural disaster occurrence with meteorological data complements from the world meteorological stations. Data on insolvency proceedings is also used and complemented by a dataset on firm demographics produced by the national statistics institute. These are detailed further.

## 4.1 Natural disasters

### 4.1.1 GASPAR dataset

All the municipalities[6] being included in a natural disaster decree are recorded in the GASPAR dataset along with beginning and ending dates. However, I do not dispose of data on the number of affected people, nor on the damage magnitude. The natural disaster category is vague (very often, storms are recorded as floods). Both floods and droughts have an impact on the environment and on the economy. Spatial distribution is heterogeneous: floods mostly occurs around main rivers such as the Garonne, Rhône and Seine and the seaside because of massive precipitation or storms and lead to important damages on housing, agriculture lands. Droughts are responsible for landslides, deadly heat waves, damage on houses and crops. In both cases, locations that are disaster-free are mostly the mountainous regions such as the Alps, Pyrenees and the Massif

[6] “Commune” as it is defined by the national statistics institute

Central. In those geographical units, as explained in the strategic insolvency section, propensity for bankruptcy should be different. Other kinds of disasters also exist but take place less often even if damages can sometimes be substantial.

In the prospect of designing a Generalized Difference-in-difference, the percentage of municipalities hit by "département" is calculated to classify "département" as facing a natural disaster. To do so, I compute the percentage of municipalities concerned by a decree the same day and I create dummies accounting when that percentage is superior to 50%, 75% and 90% within the area the same day. Respectively 21, 17 and 16 disasters are accounted based on decree measurements. Figure 3 depicts the years and "département" of occurrence of natural disasters when measured by decrees at the 50% threshold (and rain as explained in next section). Overall, 19 different "départements" were hit, Paris being the only area where a disaster occurred more than once.

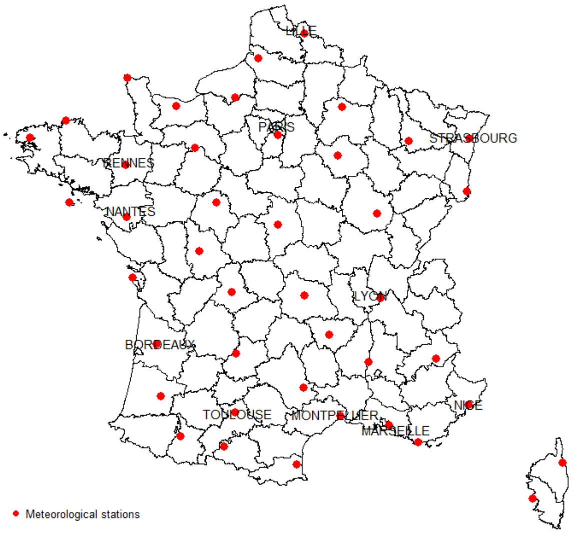
### 4.1.2 SYNOP

However, although the percentage of municipality "affected" according to decree issuance seems to be a good way to account for the threat intensity, it may be influenced by political and local economic factors. To abstract from this, I measure natural disasters through meteorological conditions. In particular, information on precipitations is used when available, because rainfall can also be a useful measure for floods intensity and building damage (Faridzad et al., 2018; E. H. Lee & Kim, 2018; Iadanza et al., 2016). To do so, I use the SYNOP open data from Meteo France which contains meteorological records on a 6-hours basis in 42 metropolitan stations. The first step is to aggregate the data in order to get a daily value for the three variables of interest within the dataset: wind speed average, maximum wind speed and precipitation. There are 96 "départements" in the dataset while only 42 stations are recorded[7] (Figure 2). Therefore, data is available only for 42 "départements" and it is necessary to derive an estimation of the other areas' values.

Since only 42 daily values are available whereas 96 are needed (one for each "département"), I make use of a binary contiguity matrix to approximate the data in the missing areas that is a simpler version of Iadanza et al. (2016)'s Inverse Distance Weighted interpolation of the rain gauge values. Depending on the number of neighboring "départements" containing data, I compute an average of the neighbors recorded values ("départements" with one neighbor will get the value of their neighbor). However, this work has to be done in two steps because some of the "départements" do not have any neighbor having a record at first (for instance in the Alpes "départements"). Every

[7] Overseas stations are not presented here because the DROMs are excluded from the analysis due to lack of economic data reasons

Figure 2: World Meteorological stations' geographical location



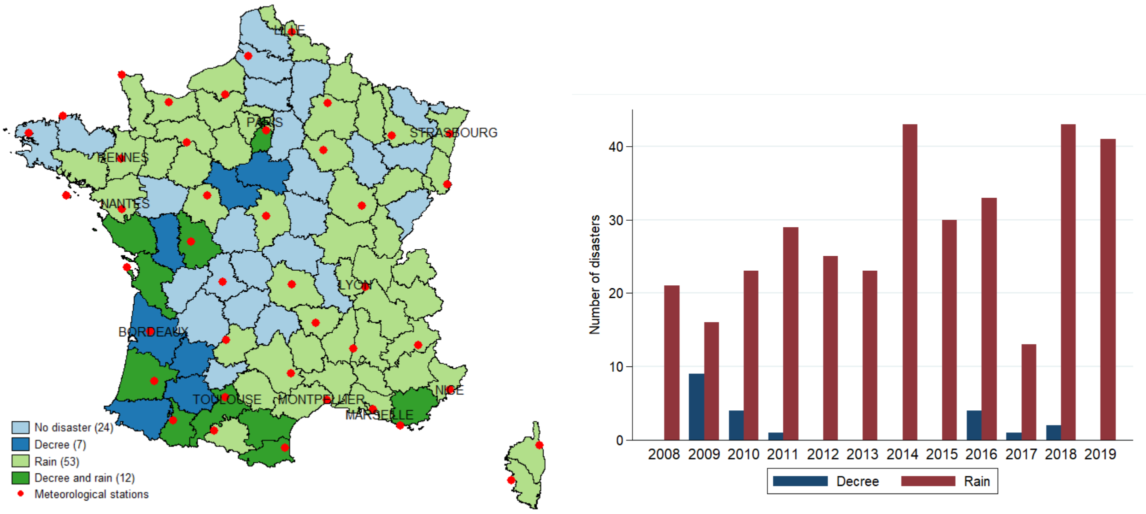

Source : World Meteorological Organization

time a "département" gets a value, it is not altered again in order to prevent data corruption. Eventually, a precipitation record is obtained for each of the 96 areas every day of the sample. To assess natural disasters proxy based on precipitation, the specificity inherent to the "départements" and their ability to resist extreme events are taken into account by building a ratio between the period record and average recorded values. For records beyond 25 times the precipitation average recorded values, a disaster dummy is set and equal to one considering the quarter as being a disaster quarter for concerned "départements". It appears that, according to that rain measurement, every year there are areas struck by a disaster (Figure 3). Doing so, an overall amount of 299 "rain" events is recorded and will be used to instrument disaster occurrence. Figure 3 accounts that years with high number of rainy events are not always associated with a high number of decrees (for instance year 2009). Nonetheless, there are 65 "départements" where rainy events occurred, of which 12 were also struck by a natural disaster according to decree measurements. This suggests some positive correlation between each series.

## 4.2 Bankruptcy proceedings

In France, a firm meeting financial difficulties has three options: it can either be liquidated (Liquidation), enter judicial reorganization ("Redressement Judiciaire") or another preventive procedure called "Sauvegarde" which could be translated as "Safeguard". Liquidation is the ultimate sentence for all companies that are not able to face their debt payment, after which the firm is either sold,

Figure 3: “Départements” and years of disaster accounted with rain and decrees




Source : GASPAR, SYNOP, WMO

or closed.[8]

The BODACC is the institution in charge of recording all the trial sentences concerning corporate insolvency proceedings in France. All those sentences are published in a journal within the following days and through gathering and treatment, data is extracted and compiled into a dataset that allows us to get the history of all the sentences for each firm that entered into bankruptcy, including various features such as the firm ID number (SIREN), the day and number of sentences, the type of procedure, the name of the tribunal and the place where the firm is located. Missing information on the ZIP Codes and sector of activity is completed with the SIRENE dataset.[9]

However, I neither have access to an open panel dataset on the universe of the companies and their serial characteristics nor to a random sample of it. Despite not having a firm panel, it is possible to build a zone panel by computing the number of insolvency proceedings for every sector in each “département”. To that data, a full set of characteristics of the areas complete the dataset: the number of firms by sector, the population, employment and other variables by area[10]. As a result, a panel of the percentage of insolvency proceedings by sector and by area is obtained along with other controls on the “département” characteristics and the activity sectors. The number of proceeding files opened is a seasonal process because commercial courts are mostly closed during

[8] In liquidation, the firm’s assets are either sold to a single buyer with the aim of keeping the firm as a going concern (potential buyers compete by sending bids to the court, which then chooses amongst them), or put on the market and purchased by various stakeholders.

[9] SIRENE2020 is a dataset produced by the INSEE containing the historical stock of all companies having been registered since the 1990s

[10] Firms demography, population estimations from the statistics national institute (INSEE), employment and job market data from the URSSAF, and local taxes data from the finance ministry (DGFIP)

summer (August mainly) and during that period the number of files opening is plummeting. As a result, serial correlation is expected in the panel and it will be necessary to take that into account.

## 5 Empirical strategy

As pointed out in many previous research (Noy, 2009; Raddatz, 2007; Skidmore & Toya, 2002; Ramcharan, 2007), there are few reasons to believe that disaster measures face reverse causality from economic growth (and here, insolvency proceedings). However, the most dynamic regions are also the one with highest population density and the latter characteristic increases the value of the intensity measure when based on the share of people affected, especially if exposition risk is low. Kirchberger (2017) underlines that housing quality is lower in poorer areas (thus causing higher levels of destruction for a given disaster magnitude) and that if these areas randomly have lower wage growth, one could conclude erroneously that the natural disasters led to lower wage growth. Buttenheim (2006) also considers the possibility that household flood exposure is endogenous. Controlling for omitted variables such as housing quality or poverty at the "département" level may be a way to remove that issue. The tax base on built property is included as a proxy for these omitted variables since it must reflect at the same time housing quality and area's wealth. As a first step, I use the timing of a large sudden natural disasters as exogenous event as in Cavallo et al. (2013) assuming the exogeneity of the publication of natural disaster decrees. In a second step, the exogeneity of the decree measurement is tested by using rain to instrument decree issuance.

Since panel data is used, it is likely that some characteristics of the framework are invariant across entities but vary over time such as macroeconomic shocks or financial conditions. For instance, it is crucial to account for peak in public demand before municipal elections that could have an influence on bankruptcy filings or seasonality in bankruptcy filings (commercial courts are almost closed during August, and their activity may be upper-bounded in case of filing inquiries overflow). Ewing et al. (2007) explain that local economies may be for instance influenced by state business cycles. As in Mueller & Quisumbing (2011), I control for those cycles and unobserved firm demand characteristics that vary over time but that are induced mainly by macroeconomic characteristics through use of quarter-year fixed effects. Moreover, it is also very likely that some of the areas features like the geographical position, entrepreneurial culture, sector trends as well as the disaster probability discussed in Section 3 can be invariant over time but vary across entity. As a result, "département" fixed effects are also included for each estimation.

I set the fixed effect model with various controls for area-specific and sectoral characteristics varying over time within each area, on a quarter-year basis. First, are added up population and gross tax base on built property that is a proxy of the area's ownership wealth that is supposed to influence the magnitude of the damages undergone by built areas. The variation of the number of firms in the sector $i$ in "département" $d$ at period $t$ ($n\_firm_{idt}$) is included as well as the share of France construction sector firms held in each "département" in order to account for spatial sectoral changes at the national level ($\frac{n\_firm_{idt}}{n\_firm_{it}}$). As a matter of fact, "départements" gaining momentum in the economy could be downward biased concerning propensity for insolvency proceedings. Thriving local conditions are not invariant over time and are not covered by fixed effects while they can affect firms' behaviors. The percentage of the firms of the "département" that are in the construction sector ($\frac{n\_firm_{idt}}{n\_firm_{dt}}$) is also added as another control for the intersectoral changes occurring quarter after quarter. Moreover, since firms behavior may be different across firm sizes, I set the firm distribution by size within the "département" as another control. Indeed, big firms make strategic decisions in a different way than smaller firms. As a result, the percentage of very small (TPE), small (PME) and intermediary (ETI) sized firms within the "département" construction sector ($\frac{n\_firm_{idt}[size]}{n\_firm_{idt}}$) is included in the model to capture this heterogeneity. Population and all the indicators on sector demographics are interpolated since I do not possess that information at the quarterly level. These control variables make up the $X_{idt}$ vector included in the model.

Nevertheless, it is likely that the frequency of bankruptcy is endogenous with the share of France construction sector firms held in each "Département" and with the percentage of the firms of the "Département" that are in the construction sector. As a result, the findings of the econometric model may probably suffer from an identification bias due to endogenous control variables. Most importantly, as explained in Lechner (2008), the assumption of independence between the outcome variable and participation to the treatment conditional on the control variables (CIA) may not hold whenever the latter variables are influenced by the treatment. We may be concerned that the number of firms, as well as the share of the sector in number of firms may be a function of bankruptcy that could be affected by the treatment. Indeed, it is very likely that the number of firms gets higher if natural disasters reduce insolvency. Since other sectors may not be influenced by natural disasters, it is also possible that the share of the sector in number of firms increases after a natural disaster, resulting from the reduced insolvency observed. In such a case, the estimated treatment effect will be lower than it is actually with the extreme case being zero whenever the control variable is equal to the outcome. Indeed, if there is a causal link from natural disaster to bankruptcy, it is likely to be the case also to the control variables related to the number of firms. In this case, according to Frölich (2008), we would be measuring only a partial effect of natural disaster on bankruptcy through that part of the effect that is not channelled via the endogenous control variables. In section 7, the robustness of the results obtained are discussed by omitting these variables from the model.

Following Imbens & Wooldridge (2007); Belasen & Polachek (2009), I regress the frequency of bankruptcy ($y_{idt}$) in sector $i$, in "département" $d$ in quarter-year $t$ on an indicator of natural disaster ($N_{dt}$), a full set of area-specific time-invariant effects ($\eta_d$) and a full set of quarter-year dummies ($\lambda_t$) (Equation 1). "Département" $\eta_i$ and year $\lambda_t$ fixed effects are aimed at taking into account differences in disaster occurrence probabilities as well as economic shocks that could bias the estimates. The vector of time-varying control variables described above ($X_{dt}$) is also included. Standard errors are clustered at the "département" level. By comparing the response of the construction sector to others with this generalized DiD methodology, I can show that the impact of the demand shock on the construction sector propensity to go bankrupt is not due to spurious correlations.

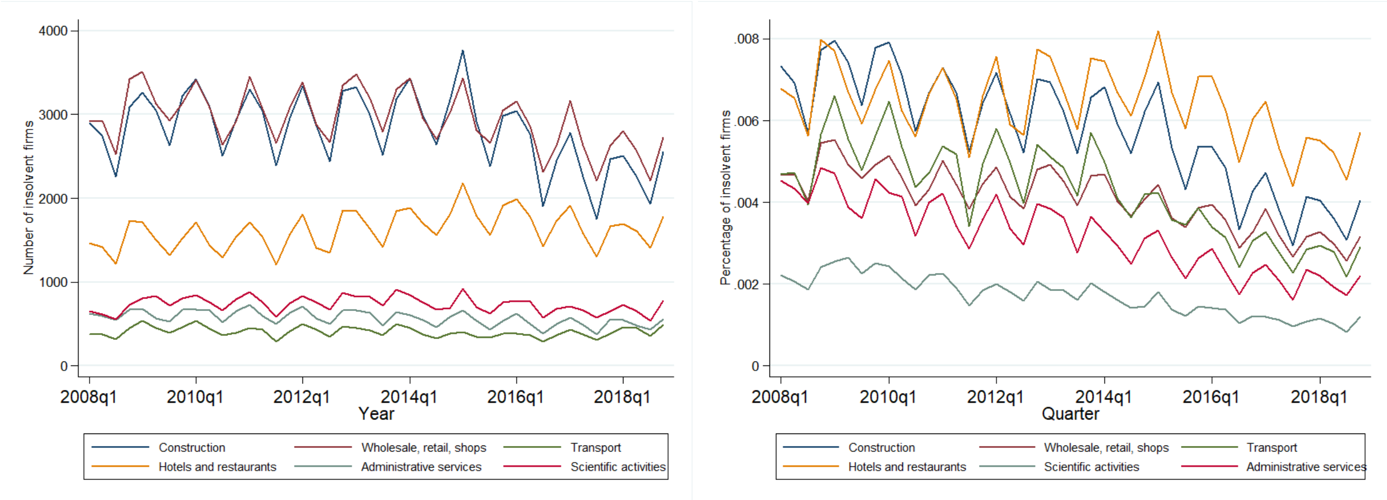
$$y_{idt} = \beta_i ND_{dt} + \gamma_i X_{dt} + \eta_d + \lambda_t + \epsilon_{idt} \tag{1}$$

$ND_{dt}$ is defined as being equal to one when more a natural disaster decree is issued in more than 50% of the municipalities within a "département", or when the precipitation is 25 times the "département" average (rain ratio superior to 25). The indicators based on rain and decrees respectively identify 65 and 19 "départements" for 299 and 21 treatments during the 2008-2018 period. Those measurements are inherently different: 12 "départements" are considered as being treated by both indicators, but this suggests a positive correlation between both measures.

Obviously, since there are more than only two periods, there are also more than just one treatment group because of repeated occurrence of natural disasters. I proceed to a Generalized Difference-in-Difference (Imbens & Wooldridge, 2007) to account for the different groups and time periods, following a proceeding similar to the one of Belasen & Polachek (2009). The dependent variable to be studied is defined as the percentage of bankruptcy filings in the sector by "département".

Once the specification is set, it is necessary to find another sector to compare construction to it. Due to their similarity to the Construction sector according to size and propensity for bankruptcy indicators, the sector Wholesale, retail and shops, Transport, Hotels and restaurants as well as Administrative services companies are selected to be compared with. Wholesale, retail and shops is the industry closer to Construction sector since the number of firms is high and have the same trend, the number of insolvent firms is almost the same, and propensity for insolvency is highly correlated (Figure 4). Indeed, even if insolvency percentage seems more similar to transport one, the correlation coefficient between insolvency percentage in construction and transport is 0.9657 whereas it is 0.9839 between construction and wholesale, retail and shops (Appendix A).

Figure 4: Number of insolvent firms and percentage of insolvency per sector




Source : BODACC

## 6 Results

The effect of the publication of natural disaster decrees is compared across the different sectors to understand how the demand shock generated by natural events is perceived by local firms (Table 1). To understand if decree issuance indeed have a differentiated influence on other sectors, the GDD model is applied on other sectors insolvency output. It reveals that no other sector but transport is affected by these demand shocks. Indeed, all the coefficients are not significantly different from zero but for construction and transportation sectors. This measure can be interpreted that whenever a decree recognizing the state of natural disaster has been issued in more than half of the municipalities of the "département", it reduces the insolvency propensity of 0.119 percentage points on average from a base of 0.484. It does not seem surprising that the effect is positive in the construction sector since France is subject to small natural disasters, mainly floods. These events do not damage physical capital since their intensity is quite low unlike large magnitude disasters such as earthquakes or hurricanes. As a result, firms of other sectors do not feel the impact of those demand shocks, but in transportation sector. The latter result is quite unexpected since the reduction in bankruptcy propensity is even higher in that sector than in construction.

Since insolvency can occur through three different administrative channels, it is interesting to

Table 1: Impact of decree issuance on insolvency in different sectors: 2008-2018

| VARIABLES | (1)<br>Construction | (2)<br>Wholesale, shops | (3)<br>Transport | (4)<br>Hotels, restaurants | (5)<br>Administrative Work |
|---|---|---|---|---|---|
| Decree disaster[1] | -0.119*** | -0.00649 | -0.145*** | -0.00951 | -0.0269 |
| | (0.0385) | (0.0179) | (0.0458) | (0.0581) | (0.0217) |
| Observations | 4,128 | 4,128 | 4,128 | 4,128 | 4,128 |
| $R^2$ | 0.376 | 0.309 | 0.102 | 0.172 | 0.165 |
| Number of Departement | 96 | 96 | 96 | 96 | 96 |
| Quarter-year FE | YES | YES | YES | YES | YES |
| Departement FE | YES | YES | YES | YES | YES |
| Firm type | All | All | All | All | All |
| F-stat | 33.45 | 54.17 | 25.03 | 30.67 | 34.41 |
| Ind. var. mean | 0.484 | 0.405 | 0.398 | 0.672 | 0.273 |

[1] More than 50% of the municipalities are hit according decree measurement.
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

understand at which margin the demand shock is influencing firm insolvency. Indeed, although safeguard, reorganization and liquidation are different kind of insolvency proceedings, they have really few characteristics in common. While liquidation is the last step before the end of activity, reorganization and safeguard allow the enterprise to still be functioning while paying back its debts to the creditors. Being a preventive proceeding, safeguard is the only filing in which the company has not defaulted yet. Liquidation is by far the most used proceeding and the average size of the companies filing for safeguard and reorganization is fairly higher to the ones filing for liquidation proceedings. As a result, safeguard and reorganization may be more subject to strategic firm behaviors than liquidation. Moreover, since safeguarded and reorganized firms are generally bigger than liquidated ones, the companies entering that type of proceeding should not be that much affected by disasters of low incidence such as floods. I thus propose to study how the demand shock affects these insolvency proceedings by changing the independent variable of the model in order to account for these three types of bankruptcy separately. The results obtained in (1), (2) and (3) of Table 2 suggest that it would have no effect on reorganization and safeguard, while it would decrease the liquidation percentage in the area significantly by 0.108 percentage points at a 1% level of confidence.

In order to understand if it affects the construction market in another way, I also propose an analysis on various dependent variables such as the number of job pre-employment declarations by the firms of the sector (3), the number of posts (jobs) in the construction sector (4), the overall payroll (5) and the average wage per capita in the area (6). None of these features seem to be affected by the demand shock. An interpretation of this phenomenon is that firms in difficulty were

Table 2: Impact of demand shock on different outcomes in the construction sector: 2008-2018

| VARIABLES | (1) Liquidation | (2) Reorganization | (3) Safeguard | (4) Pre-employment declaration | (5) Number of jobs | (6) Average income | (7) Percentage new jobs |
|---|---|---|---|---|---|---|---|
| Decree disaster | -0.108*** | -0.0116 | 0.000714 | -74.54 | 224.7 | -4.069 | -0.00488 |
| | (0.0383) | (0.0181) | (0.00307) | (105.8) | (145.5) | (26.88) | (0.00619) |
| Observations | 4,128 | 4,128 | 4,128 | 4,128 | 4,128 | 4,128 | 4,128 |
| $R^2$ | 0.303 | 0.181 | 0.025 | 0.456 | 0.518 | 0.898 | 0.755 |
| Number of Departement | 96 | 96 | 96 | 96 | 96 | 96 | 96 |
| Quarter-year FE | YES | YES | YES | YES | YES | YES | YES |
| Departement FE | YES | YES | YES | YES | YES | YES | YES |
| F-stat | 26.52 | 16.45 | 5.250 | 10.01 | 28.51 | 540.1 | 228.7 |
| Ind. var. mean | 0.316 | 0.161 | 0.00745 | 1752 | 14385 | 5503 | 0.115 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

suffering from insufficient demand. The decree issuance can be seen in this case as a demand shock the firm may benefit from. In turn, underused capital and labor of these firms would be mobilized to the disaster market, allowing struggling companies to relieve from financial distress. This could explain why bankruptcy is reduced from the demand shock while neither employment nor wages rise.

Table 3: Effect on liquidation with neighborhood effects, lag and by disaster magnitude: 2008-2018

| VARIABLES | (1) More than 50% municipalities hit | (2) More than 75% municipalities hit | (3) More than 90% municipalities hit |
|---|---|---|---|
| Decree in t | -0.109*** | -0.132*** | -0.128*** |
| | (0.0393) | (0.0438) | (0.0471) |
| Decree in t-1 | -0.0395 | -0.0349 | -0.0316 |
| | (0.0349) | (0.0431) | (0.0463) |
| Neighborhood decree | -0.00399 | -0.00507 | -0.00513 |
| | (0.00990) | (0.00988) | (0.00987) |
| Observations | 4,128 | 4,128 | 4,128 |
| $R^2$ | 0.303 | 0.303 | 0.303 |
| Number of Departement | 96 | 96 | 96 |
| Quarter-year FE | YES | YES | YES |
| Departement FE | YES | YES | YES |
| F-stat | 26.49 | 26.24 | 26.31 |
| Ind. var. mean | 0.316 | 0.316 | 0.316 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Two other concerns for public policies are whether the demand shock has an effect on the neighborhood, and also if it is transitory or long-lasting. To understand these effects, neighboring “départements” are defined as the areas where less than 50% of the municipalities were concerned by a decree while another “département” with a common border is considered to be hit by a natural disaster at the same 50% municipality threshold. In addition, to understand if there is a lasting effect, I look at how bankruptcy is affected one period after the shock. When including these features into the model (Table 3), the results show that demand shock is not lasting, and that there is no spillover onto the neighborhood economy. Indeed, when more than half of the municipalities suffer from a disaster according to decrees issued (1), it still decreases by 0.109 percentage points propensity for insolvency in the same period but it neither has an effect on the following period insolvency nor on neighbors bankruptcy. Moreover, increasing the threshold at which a "département" is considered to be hit by a natural disaster do not change that result: when more than 75% (respectively 90%) of the municipalities of a "département" are concerned by a decree, it reduces by 0.132 (respectively 0.128) percentage points the percentage of companies liquidated (its average being 0.316). I can draw from this that either the means of reconstruction are sufficient to take care of the destruction within the area in the same period the disaster has occurred, or that "départements" are too large to permit that kind of spillover. As a matter of fact, it is not that surprising that disasters occurring in France do not have this kind of effect at the "département" level since these areas can have up to 2,6 million inhabitants and 900 municipalities.

# 7 Robustness checks

In this section, the validity of the results obtained is discussed through the econometric assumptions of the model, the mispecifications that could threaten identification of the effect and the exogeneity of decree measurement.

## 7.1 Autocorrelation

Since the percentage of firms filing for bankruptcy is a cyclical process, a concern could be that serial correlation among residuals would arise. In the chosen specification, time fixed effects are included in order to control for the auto-regressive process, and standard errors are clustered at the "département" level since correlation across the observations in the groups in a panel is likely to be a substantive feature of the model. Resulting from this treatment, correlation among observations is allowed within groups (example in Appendix D) while it is assumed to treat the aggregate autocorrelation of residuals issue. As a result, autocorrelation is not considered to be a threat to the identification of the effect of natural disaster on propensity for insolvency.

## 7.2 Parallel trends

The difference-in-difference methodology is based on a crucial assumption: control and treatment groups independent variables follow the same parallel trends before the occurrence of the exogeneous event. In this case, the assumption is exactly the same but it is more difficult to prove since treatment and control groups vary over time because natural disasters may occur various times leading some areas to be treated more than once. However, a fundamental issue is to understand to what extent these results can be validated and used to do inferences. Parallel trends assumption is tested through three channels. First, it is supposed that disaster have occurred at a different moment than what really is. For this, disasters are assumed to have occurred in the preceding and following periods of real occurrences. I thus use leads and lags of the decree variables to run the regressions with the same specification as usual. The results presented in Table 4 do not enable us to attribute any effect of previous changes in insolvency to disasters, for any of the four periods preceding the disasters occurrence (1) to (4) when running the placebos separately. To say it differently, if it was assumed the decrees were stating the disaster had occurred the periods before, it would not be concluded that disasters have an effect on insolvency in the construction sector. Since the effect is not lasting (5), I also try to predict the effect on two (6), three (7) and four (8) periods after the disaster occurrence. Results suggest that the placebo has an effect significant at a 5% level only for the third regression. However, when testing for the placebo effects jointly (in a unique regression), placebos become significant at a 10% level for (1) and (4). According to this first test, some doubts about assuming parallel trends remain.

Table 4: Placebos effect on insolvency in the construction sector: 2008-2018

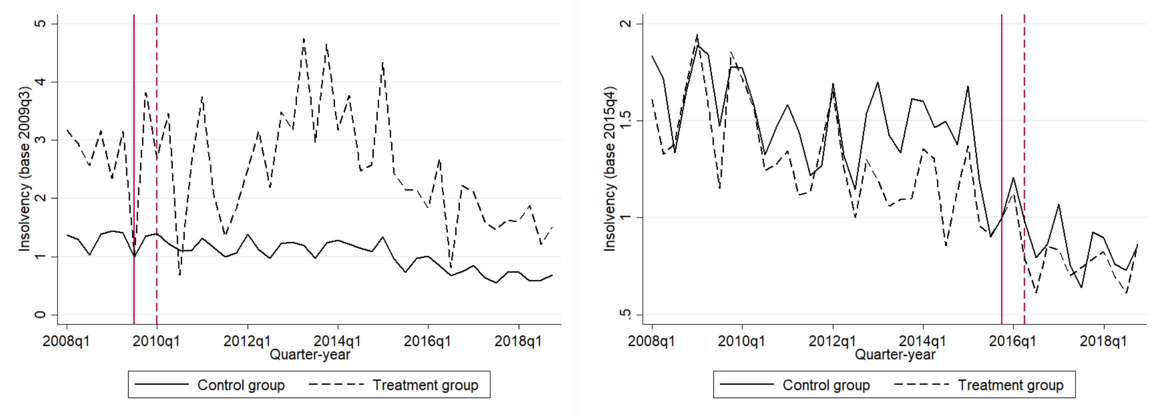
| VARIABLES | (1) 1 period before | (2) 2 period before | (3) 3 period before | (4) 4 period before | (5) 1 period after | (6) 2 period after | (7) 3 period after | (8) 4 period after |
|---|---|---|---|---|---|---|---|---|
| Placebo | -0.0504 | -0.0461 | -0.0167 | -0.106 | -0.0363 | -0.0451 | -0.0574** | -0.0468 |
| | (0.0343) | (0.0398) | (0.0351) | (0.0673) | (0.0336) | (0.0336) | (0.0244) | (0.0301) |
| All in one regression | -0.0521* | -0.0428 | -0.0206 | -0.1087* | -0.0338 | -0.0492 | -0.0608** | -0.0519 |
| | (0.0312) | (0.0305) | (0.0338) | (0.0645) | (0.0295) | (0.0331) | (0.0237) | (0.0310) |
| Observations | 4,128 | 4,128 | 4,128 | 4,128 | 4,128 | 4,128 | 4,128 | 4,128 |
| $R^2$ | 0.301 | 0.301 | 0.300 | 0.302 | 0.301 | 0.301 | 0.301 | 0.301 |
| Number of Departement | 96 | 96 | 96 | 96 | 96 | 96 | 96 | 96 |
| Quarter-year FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Departement FE | YES | YES | YES | YES | YES | YES | YES | YES |
| F-stat | 25.21 | 25.57 | 24.74 | 24.30 | 26.84 | 25.07 | 25.19 | 25.73 |
| Ind. var. mean | 0.316 | 0.316 | 0.316 | 0.316 | 0.316 | 0.316 | 0.316 | 0.316 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In another step and although the repeated treatment of the different areas makes the visualization of the parallel trends more difficult, I try to graph it the way it is done in various event studies by scaling the independent variables and comparing its behaviors among treatment and control groups on average. Figure 5 shows that parallel trends assumption based on the previous periods is not always valid. For instance, when looking at the 2010 disaster it is not verified because treatment group varies much more over the previous periods than the control group (on average).

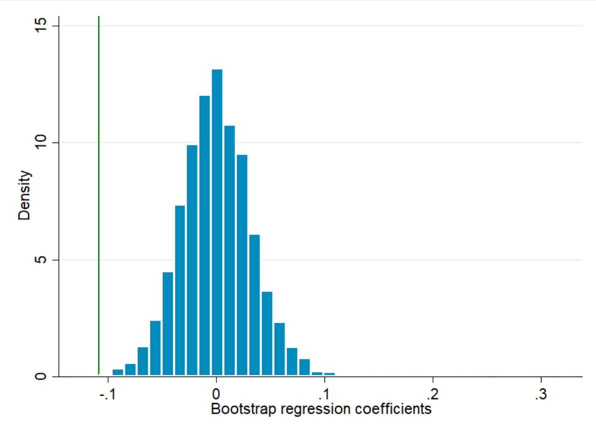
On the other hand, the parallel trend assumption seems to be more valid when comparing control and treatment in the case of 2016 disaster. However, it is not possible to validate the parallel trend assumption in all the cases (Appendix E), fact that may be also due to non-strict exogeneity of the decree measurement.

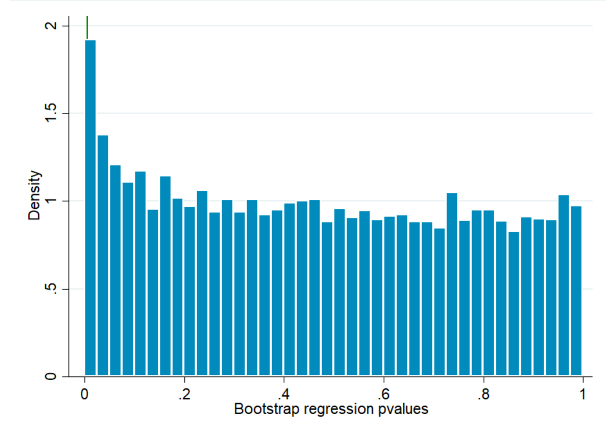
Figure 5: Event study graph for two natural disasters




A bootstrap-based approach is eventually proposed by removing the test restriction to the hit areas. Therefore, it is now assumed that any of the "département" can get natural disaster decrees at any time since the aim is to understand if the conclusion that placebo has an effect on insolvency would have been the same if non-treated areas would have been considered to be treated. To do so, the treatment is randomized and constrained to non-treated units. The treatment dummy is replaced by a randomized dummy with the same average than the decree dummy at the 50% municipality threshold and the regression is reproduced 10 000 times based on the same model. It appears that 8.24% of the regressions have a coefficient significantly different from zero at a 5% level, of which 4.96% is negative (Figure 6). It actually means that less than 5% of the placebo regressions on the negative side consider the placebo disaster to have an effect on insolvency. In such conditions, even if the overall percentage 8.24% is higher than the 5% level of confidence, it is not sufficient to invalidate the asymptotic proprieties of the sample. Moreover, coefficients are distributed around zero in contrast with the coefficient for the actual natural disaster decree which is on the left of the distribution. Indeed, only 6 of the bootstrap coefficients out of 10 000 are lower than the actual coefficient (-0.109). This is strong evidence that the effect of decree issuance on insolvency is not random or due to coincidence. When repeating the same proceeding for the 90% municipality threshold (Appendix C), the results reveal to be less reliable since 10,46% of the p-values are under the 5% threshold (even if only 20 of the bootstrap coefficients are inferior to -0.128).

Figure 6: Distribution of coefficients and p-values from bootstrap regressions




Note : vertical lines for coefficients when 50% of the municipalities are hit

### 7.3 Endogenous controls

After having discussed theoretically the implications of endogenous control variables in our specification in Section 5, I propose to study the empirical robustness of the model. In Appendix B, raw correlation between decrees and bankruptcy is compared along with the model including respectively only the non-endogenous control variables (population and tax base on built property), and the model including all the control variables. While raw correlation may suffer from omitted variable bias treatment being correlated with unobservable factors, the enhanced model may be subject to endogenous variable bias. Both result in an estimation bias for the coefficient of interest, depending on how the treatment is related to the unobservable factors in the first case and to the endogenous control in the second case. However, the model seems to remain quite stable even after inclusion of endogenous controls. According to the results shown in Appendix B, the inclusion of the control variables does not appear to change the significance of the coefficients, all remaining very significant at a 1% level of confidence. Nevertheless, if the incorporation of the population and the tax base on built property control variable almost does not change the coefficient and the R-squared of the model (2), the inclusion of the endogenous controls (3) does a little bit. Indeed, the coefficient shifts from -0.124 to -0.119, and the R-squared from 0.364 to 0.376. Although these changes suggest that there was indeed an omitted variables bias, it did not affect much the magnitude and the precision of the results. The coefficient still remains biased because of endogeneity (and because of other possible omitted variables as previously explained in Section 3), but the variance of the outcome explained by the model is slightly increased so we will keep the last model as our preferred one. As pointed out in Frölich (2008), nonparametric models are less subject to inconsistency of the estimators when there are endogenous variables. Loayza et al. (2012) use a system-GMM model by first-differencing all the variables and using lags of the endogenous controls to treat the endogeneity. The same model may be applied to test the robustness of our results, but such a work is left for further research.

### 7.4 Exogeneity of the demand shock

Human-related measures may be subject to endogeneity because damage is to be more important in areas where activity is localized and decree issuance relies on loss declaration from the citizens. In particular, to understand why exogeneity of decrees may not be assumed, it is necessary to understand in which cases the natural disaster victims are compensated. The $13^{th}$ of July 1982[11] law defines the situations in which a natural event is considered to be a natural disaster and the requirements for compensation of the damage undergone. Legally, to get compensated for any natural disaster damage, a decree has to be published at the *Journal Officiel de la République* stating the occurrence of a natural disaster and defining the area where goods are to be compensated. It must be empathized that if the mayor does not ask for the recognition of the natural disaster state, the latter will not appear at the *Journal Officiel de la République* and the victims will not be compensated. This may lead politicians of areas where the construction sector is struggling to be more prone to ask for natural disaster recognition even in case of small damages than areas where the construction sector is thriving. This is why this endogeneity issue is solved by instrumenting decree issuance by using rain ratios. In Table 5, it is shown that intense precipitations has an influence on decree issuance, at a high level of significance. In particular the ratios thresholds that seem to be relevant would be the one in (1), (2), (3) and (4) since they are significant. These regressions may be seen as a first step of a 2SLS regression for which, although being not very correlated, the coefficient is strongly significant for rain ratio thresholds between 10 and 25.

To then understand if the same results are obtained when natural disasters are instrumented with rain, I reproduce the GDD estimation based on the precipitation indicator. However, I find that rainfall has a weaker effect on liquidation in the construction sector than decrees. In Table 6, only two of the instruments chosen seem to conclude that natural disasters based on rain have an effect significantly different from zero. Indeed, only the regressions with $ND_{idt}$ equal to one when the rain ratio is respectively superior to 10 or 25 seem to conclude that natural disasters may reduce propensity for liquidation. Moreover, not only the coefficients are lower but the

[11]This law has been modified four times, but last modification has been made on March 2007, $13^{th}$, before 2008 first year of the study, so that there is a full continuity in compensation from 2008 to 2016

Table 5: Impact of rain on decree issuance by proceeding type: 2008-2018

| VARIABLES | (1) $ratio > 10$ | (2) $ratio > 15$ | (3) $ratio > 20$ | (4) $ratio > 25$ | (5) $ratio > 30$ | (6) $ratio > 50$ |
|---|---|---|---|---|---|---|
| Rain disaster | 0.00523*** | 0.00540*** | 0.00839*** | 0.0116** | 0.00602 | 0.0258 |
| | (0.00145) | (0.00192) | (0.00288) | (0.00472) | (0.00434) | (0.0185) |
| Observations | 7,296 | 7,296 | 7,296 | 7,296 | 7,296 | 7,296 |
| $R^2$ | 0.048 | 0.048 | 0.049 | 0.049 | 0.047 | 0.049 |
| Number of Departement | 96 | 96 | 96 | 96 | 96 | 96 |
| Quarter-year FE | YES | YES | YES | YES | YES | YES |
| Departement FE | YES | YES | YES | YES | YES | YES |
| Ind. var. mean | 0.00370 | 0.00370 | 0.00370 | 0.00370 | 0.00370 | 0.00370 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

precision of the estimator is also weakened. Indeed, coefficients of regressions (1) and (4) conclude that intense precipitation events respectively decrease by 0.00841 and 0.0145 percentage points propensity for liquidation, at a 10% and 5% respective level of confidence. This effect is almost ten times inferior to the one found with decree issuance. So, if intense precipitations increase the decree issuance probability with high level of certainty but actually affect much less the propensity for bankruptcy in the construction sector than decrees, it is because a part of the decree issuance not motivated by precipitations is also having an influence on insolvency. The corollary of this result is that decree issuance is probably endogenous to the condition of the construction sector although natural disasters actually seem to reduce bankruptcy. Therefore, it is very likely that correlation between decree and insolvency overestimates the real effect of natural disaster on bankruptcy in the construction sector. Nevertheless, other factors may be involved, for instance the fact that soils saturated with water becomes more prone to other events such as mudslides, ground movements and that rivers with yet high levels of water need less precipitations to end up into natural disasters. These features may explain why precipitations are not the only factor leading to a revival in the construction sector.

Table 6: Impact of rain on bankruptcy with different rain ratio thresholds: 2008-2018

| VARIABLES | (1) Ratio > 10 | (2) Ratio > 15 | (3) Ratio > 20 | (4) Ratio > 25 | (5) Ratio > 30 | (6) Ratio > 40 | (7) Ratio > 50 |
|---|---|---|---|---|---|---|---|
| Rain disaster | -0.00841* | -0.000258 | -0.000376 | -0.0145** | -0.00491 | -0.00285 | 0.0170 |
| | (0.00489) | (0.00519) | (0.00657) | (0.00726) | (0.00789) | (0.0117) | (0.0146) |
| Observations | 4,128 | 4,128 | 4,128 | 4,128 | 4,128 | 4,128 | 4,128 |
| $R^2$ | 0.316 | 0.316 | 0.316 | 0.316 | 0.316 | 0.316 | 0.316 |
| Number of Departement | 96 | 96 | 96 | 96 | 96 | 96 | 96 |
| Quarter-year FE | YES | YES | YES | YES | YES | YES | YES |
| Departement FE | YES | YES | YES | YES | YES | YES | YES |
| F-stat | 30.40 | 29.96 | 29.98 | 30.39 | 31.74 | 31.54 | 31.56 |
| Ind. var. mean | 0.316 | 0.316 | 0.316 | 0.316 | 0.316 | 0.316 | 0.316 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In addition, since rain is more exogenous than decrees, it is likely that the result may also be due to a selection bias linked with human behavior. First suggestion is that decree issuance may suffer from a reverse causality from propensity for bankruptcy. In particular, it is possible that incentive for decree queries may be higher in “départements” where the construction sector is on the wane, or suffers from low demand. Indeed, any politician worried about the local economic environment may see in any natural event (even the smallest), the opportunity to foster the local construction market. Even if the measure taken (more than 50% of the municipality asking for and receiving a decree) should control for unilateral behavior, it is not obvious that the construction sector dynamics is that local. Indeed, it is quite likely that, if construction sector is struggling in some municipality, it is also in the “département” in general and that this kind of behavior is actually broader. Moreover, it is possible to ask for disaster recognition until 18 months after the end of the event. At observing their peers asking for a decree in the neighbor municipalities, it is possible that mayors in turn do the same.

Based on a political literature (Cerda & Vergara, 2008; Do et al., 2015), another possibility may come from decree issuance selection based on political alignment with the government political edge. Indeed, it might be possible that if the mayor is at the same political edge than the government, it may increase the probability of decree issuance (because ministry of national accounts, economics and finance are the institutions in charge of accepting the decree queries). First preliminary results suggest inconclusively that this would not be the case when focusing on the 1821 municipalities over 3500 inhabitants that were under a political flag both in 2007 and in 2014. Indeed, when including political alignment in the first step it has no effect on decree issuance (Appendix F), and neither when I proceed to a regression discontinuity design by using vote margins at the municipal election for the ruling party as an assignment variable (same reasonning as in D. S. Lee (2008) - Appendix G). However, this research is still beginning and these results only are suggestive and led at orienting the debate around possible behavioural endogeneity in this study.

## 8 Conclusion

From the results obtained, I can conclude that there seems to be evidence that floods cause reduction of the propensity for insolvency in the construction sector, in particular through the liquidation channel. However, as explained in the previous section, the results obtained through the decree measurement overestimates the real effect of natural disasters. Therefore, it is likely that natural disasters estimates actually lie between the results found with rain measurements (since not all rainy events end up in a natural disaster) and the ones obtained from decree issuance.

As a result, decree issuance is associated with a reduction in propensity for bankruptcy by 0.109 percentage points in the same period without affecting employment and wages, suggesting that companies may suffer from lack of demand and underused labour and capital in the short-term. In that sense, making use of demand-oriented policies when the sector suffers from struggles may be useful. This kind of policy may reduce insolvency directly linked with demand issues and allow firms to face the struggles. However, knowing that this kind of public market strategy may not only be expensive and non-sustainable in the long-run but also that the effects might not last, it should be used carefully and only against temporary shocks.

Nevertheless, the model developed in this study has its limits: it may suffer from a possible omitted variable bias as well as endogenous control variables, and has struggles in proving its principal identification hypothesis. Moreover, the treatment variable is likely to suffer from reverse causality since decree issuance is probably endogenous. As a matter of fact, the work provided on a more exogenous measure such as precipitations conclude to a weaker effect on insolvency, and actually the reduction in bankruptcy might mainly be due to other factors, and in particular the condition of the construction sector. As a result, some components of disaster decree issuance remain unexplained and may be the actual reason why bankruptcy decreases so much in struck “départements” after the establishment of a decree. I leave the exploration of this pattern to further research.

In the end, this provides new evidence on the links existing between natural disasters and the local economy by exploring new channels of propagation in the construction sector. In France, this sector being much larger than the agricultural sector and providing jobs for a large number of citizens, these results may be useful at least to enhance the general discussion existing around natural events by moving the interest that had been developed in agriculture onto another economic sector.

# 9 Bibliography

## References

Aceto, L., Caloiero, T., Pasqua, A., & Petrucci, O. (2016). Analysis of damaging hydrogeological events in a mediterranean region (calabria). *Journal of Hydrology*, *541*, 510–522.

Aghion, P., Hart, O., & Moore, J. (1992). *The economics of bankruptcy reform* (Tech. Rep.). National Bureau of Economic Research.

Albala-Bertrand, J.-M. (1993). Natural disaster situations and growth: A macroeconomic model for sudden disaster impacts. *World Development*, *21*(9), 1417–1434.

Asquith, P., Gertner, R., & Scharfstein, D. (1994). Anatomy of financial distress: An examination of junk-bond issuers. *The Quarterly Journal of Economics*, *109*(3), 625–658.

Baker, S. R., Bloom, N., Canes-Wrone, B., Davis, S. J., & Rodden, J. (2014). Why has us policy uncertainty risen since 1960? *American Economic Review*, *104*(5), 56–60.

Barrot, J.-N., & Sauvagnat, J. (2020). Input specificity and the propagation of idiosyncratic shocks in production networks. *The Quarterly Journal of Economics*, *131*(3), 1543–1592.

Belasen, A. R., & Polachek, S. W. (2009). How disasters affect local labor markets the effects of hurricanes in florida. *Journal of Human Resources*, *44*(1), 251–276.

Benmelech, E., & Bergman, N. K. (2011). Bankruptcy and the collateral channel. *The Journal of Finance*, *66*(2), 337–378.

Bester, H. (1994). The role of collateral in a model of debt renegotiation. *Journal of money, credit and banking*, *26*(1), 72–86.

Blakeslee, D. S., & Fishman, R. (2018). Weather shocks, agriculture, and crime evidence from india. *Journal of Human Resources*, *53*(3), 750–782.

Boustan, L. P., Kahn, M. E., Rhode, P. W., & Yanguas, M. L. (2020). The effect of natural disasters on economic activity in us counties: A century of data. *Journal of Urban Economics*, 103257.

Buttenheim, A. (2006). Flood exposure and child health in bangladesh. *UCLA CCPR Population Working Papers*.

Campbell, J. Y., & Cocco, J. F. (2015). A model of mortgage default. *The Journal of Finance*, *70*(4), 1495–1554.

Cavallo, E., Galiani, S., Noy, I., & Pantano, J. (2013). Catastrophic natural disasters and economic growth. *Review of Economics and Statistics*, *95*(5), 1549–1561.

CCR, C. C. d. R. (2019). Les catastrophes naturelles en france. *Natural Disasters in France, CCR, Paris (bilingual version available at http://www. ccr. fr).*

Cerda, R., & Vergara, R. (2008). Government subsidies and presidential election outcomes: evidence for a developing country. *World Development*, *36*(11), 2470–2488.

Chalfin, A. (2014). What is the contribution of mexican immigration to us crime rates? evidence from rainfall shocks in mexico. *American Law and Economics Review*, *16*(1), 220–268.

Chatterjee, S., Dhillon, U. S., & Ramirez, G. G. (1996). Resolution of financial distress: Debt restructurings via chapter 11, prepackaged bankruptcies, and workouts. *Financial Management*, 5–18.

Chopard, B., & Langlais, E. (2007). Strategic bankruptcy with accountable and judicial risks.

Cole, M. A., Elliott, R. J., Okubo, T., & Strobl, E. (2013). Natural disasters and plant survival: The impact of the kobe earthquake. *Discussion Papers*, *13063*.

Crespo Cuaresma, J., Hlouskova, J., & Obersteiner, M. (2008). Natural disasters as creative destruction? evidence from developing countries. *Economic Inquiry*, *46*(2), 214–226.

Davydenko, S. A., & Franks, J. R. (2008). Do bankruptcy codes matter? a study of defaults in france, germany, and the uk. *The Journal of Finance*, *63*(2), 565–608.

De Mel, S., McKenzie, D., & Woodruff, C. (2012). Enterprise recovery following natural disasters. *The Economic Journal*, *122*(559), 64–91.

Dessaint, O., & Matray, A. (2017). Do managers overreact to salient risks? evidence from hurricane strikes. *Journal of Financial Economics*, *126*(1), 97–121.

Do, Q.-A., Lee, Y. T., & Nguyen, B. D. (2015). Political connections and firm value: Evidence from the regression discontinuity design of close gubernatorial elections.

Épaulard, A., & Zapha, C. (2019). Bankruptcy costs and the design of preventive restructuring procedures.

Ewing, B. T., Kruse, J. B., & Sutter, D. (2007). Hurricanes and economic research: An introduction to the hurricane katrina symposium. *Southern Economic Journal*, *74*(2), 315–325.

Fan, H., & Sundaresan, S. M. (2000). Debt valuation, renegotiation, and optimal dividend policy. *The Review of Financial Studies*, *13*(4), 1057–1099.

Faridzad, M., Yang, T., Hsu, K., Sorooshian, S., & Xiao, C. (2018). Rainfall frequency analysis for ungauged regions using remotely sensed precipitation information. *Journal of hydrology*, *563*, 123–142.

Favara, G., Schroth, E., & Valta, P. (2012). Strategic default and equity risk across countries. *The Journal of Finance*, *67*(6), 2051–2095.

Frölich, M. (2008). Parametric and nonparametric regression in the presence of endogenous control variables. *International Statistical Review*, *76*(2), 214–227.

Gignoux, J., & Menéndez, M. (2016). Benefit in the wake of disaster: Long-run effects of earthquakes on welfare in rural indonesia. *Journal of Development Economics*, *118*, 26–44.

Greene, W. H. (2003). *Econometric analysis*. Pearson Education India.

Hallegatte, S., & Dumas, P. (2009). Can natural disasters have positive consequences? investigating the role of embodied technical change. *Ecological Economics*, *68*(3), 777–786.

Hart, O., & Moore, J. (1998). Default and renegotiation: A dynamic model of debt. *The Quarterly Journal of Economics*, *113*(1), 1–41.

Iadanza, C., Trigila, A., & Napolitano, F. (2016). Identification and characterization of rainfall events responsible for triggering of debris flows and shallow landslides. *Journal of Hydrology*, *541*, 230–245.

Imbens, G., & Wooldridge, J. (2007). Difference-in-differences estimation. *National Bureau of Economics Research Working Paper*.

Imberman, S. A., Kugler, A. D., & Sacerdote, B. I. (2012). Katrina's children: Evidence on the structure of peer effects from hurricane evacuees. *American Economic Review*, *102*(5), 2048–82.

John, K., Mateti, R. S., & Vasudevan, G. (2013). Resolution of financial distress: A theory of the choice between chapter 11 and workouts. *Journal of Financial Stability*, *9*(2), 196–209.

Kirchberger, M. (2017). Natural disasters and labor markets. *Journal of Development Economics*, *125*, 40–58.

Kruttli, M., Roth Tran, B., & Watugala, S. W. (2020). Pricing poseidon: extreme weather uncertainty and firm return dynamics.

Kumar, P., & Zhang, H. (2019). Productivity or unexpected demand shocks: What determines firms'investment and exit decisions? *International Economic Review*, *60*(1), 303–327.

Lechner, M. (2008). A note on endogenous control variables in causal studies. *Statistics & Probability Letters*, *78*(2), 190–195.

Lee, D. S. (2008). Randomized experiments from non-random selection in us house elections. *Journal of Econometrics*, *142*(2), 675–697.

Lee, E. H., & Kim, J. H. (2018). Development of a flood-damage-based flood forecasting technique. *Journal of hydrology*, *563*, 181–194.

Leland, H. E. (1994). Corporate debt value, bond covenants, and optimal capital structure. *The journal of finance*, *49*(4), 1213–1252.

Leland, H. E., & Toft, K. B. (1996). Optimal capital structure, endogenous bankruptcy, and the term structure of credit spreads. *The Journal of Finance*, *51*(3), 987–1019.

Loayza, N. V., Olaberria, E., Rigolini, J., & Christiaensen, L. (2012). Natural disasters and growth: Going beyond the averages. *World Development*, *40*(7), 1317–1336.

Long, F. (1978). The impact of natural disasters on third world agriculture: An exploratory survey of the need for some new dimensions in development planning. *American Journal of Economics and Sociology*, *37*(2), 149–163.

Lorenzoni, G. (2009). A theory of demand shocks. *American Economic Review*, *99*(5), 2050–84.

Mahajan, K. (2017). Rainfall shocks and the gender wage gap: Evidence from indian agriculture. *World Development*, *91*, 156–172.

Mitman, K. (2016). Macroeconomic effects of bankruptcy and foreclosure policies. *American Economic Review*, *106*(8), 2219–55.

Mueller, V., & Quisumbing, A. (2011). How resilient are labour markets to natural disasters? the case of the 1998 bangladesh flood. *Journal of Development Studies*, *47*(12), 1954–1971.

Munshi, K. (2003). Networks in the modern economy: Mexican migrants in the us labor market. *The Quarterly Journal of Economics*, *118*(2), 549–599.

Nejadmalayeri, A., & Singh, M. (2012). Corporate taxes, strategic default, and the cost of debt. *Journal of Banking & Finance*, *36*(11), 2900–2916.

Noy, I. (2009). The macroeconomic consequences of disasters. *Journal of Development economics*, *88*(2), 221–231.

Noy, I., & Nualsri, A. (2011). Fiscal storms: public spending and revenues in the aftermath of natural disasters. *Environment and Development Economics*, *16*(1), 113–128.

Raddatz, C. (2007). *Are external shocks responsible for the instability of output in low income countries?* The World Bank.

Ramcharan, R. (2007). Does the exchange rate regime matter for real shocks? evidence from windstorms and earthquakes. *Journal of International Economics*, *73*(1), 31–47.

Skidmore, M., & Toya, H. (2002). Do natural disasters promote long-run growth? *Economic inquiry*, *40*(4), 664–687.

Strobl, E. (2011). The economic growth impact of hurricanes: Evidence from us coastal counties. *Review of Economics and Statistics*, *93*(2), 575–589.

Strobl, E. (2012). The economic growth impact of natural disasters in developing countries: Evidence from hurricane strikes in the central american and caribbean regions. *Journal of Development economics*, *97*(1), 130–141.

Uchida, H., Miyakawa, D., Hosono, K., Ono, A., Uchino, T., & Uesugi, I. (2013). Natural disaster and natural selection. *Available at SSRN 2320878*.

Van Verseveld, H., Van Dongeren, A., Plant, N. G., Jäger, W., & Den Heijer, C. (2015). Modelling multi-hazard hurricane damages on an urbanized coast with a bayesian network approach. *Coastal Engineering*, *103*, 1–14.

Vig, V. (2013). Access to collateral and corporate debt structure: Evidence from a natural experiment. *The Journal of Finance*, *68*(3), 881–928.

Vinet, F., Boissier, L., & Defossez, S. (2011). La mortalité comme expression de la vulnérabilité humaine face aux catastrophes naturelles: deux inondations récentes en france (xynthia, var, 2010). *[VertigO] La revue électronique en sciences de l'environnement*, *11*(2).

Von Thadden, E.-L., Berglöf, E., & Roland, G. (2010). The design of corporate debt structure and bankruptcy. *The Review of Financial Studies*, *23*(7), 2648–2679.

White, M. J. (1989). The corporate bankruptcy decision. *Journal of Economic Perspectives*, *3*(2), 129–151.

Wright, B. D., et al. (2008). A foundation for the solution of consumption-saving behavior with a borrowing constraint and unbounded marginal utility. *Journal of Economic Dynamics and Control*, *32*(3), 695–708.

Zhang, S., Sabarwal, T., & Gan, L. (2015). Strategic or nonstrategic: The role of financial benefit in bankruptcy. *Economic Inquiry*, *53*(2), 1004–1018.

# 10 Appendix

## A Insolvency correlation between sectors

| | Construction |
|---|---|
| Wholesale, shops | 0.984*** |
| Transport | 0.966*** |
| Hotels and restaurants | 0.857*** |

$t$ statistics in parentheses

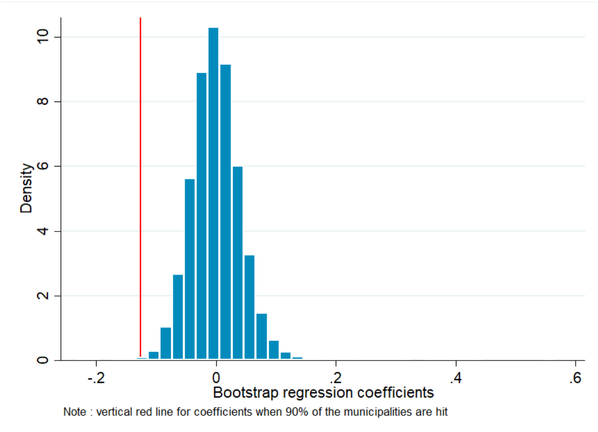
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

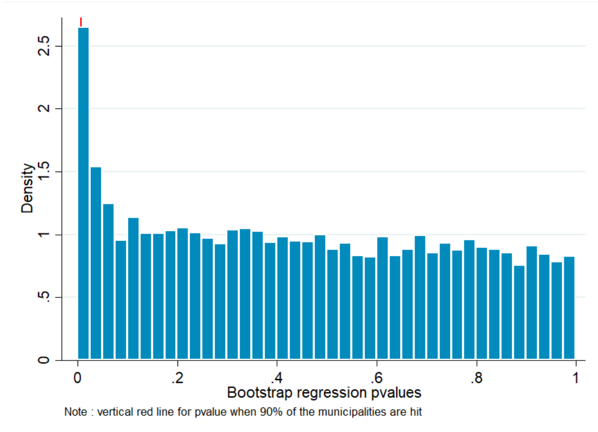
## B Endogenous control variables

| VARIABLES | (1) No controls | (2) Some controls | (3) All controls |
|---|---|---|---|
| Decree disaster | -0.124*** | -0.125*** | -0.119*** |
| | (0.0383) | (0.0385) | (0.0385) |
| Observations | 4,224 | 4,128 | 4,128 |
| $R^2$ | 0.364 | 0.366 | 0.376 |
| Number of Departement | 96 | 96 | 96 |
| Firms control | NO | NO | YES |
| Other control | NO | YES | YES |
| Quarter-year FE | YES | YES | YES |
| Departement FE | YES | YES | YES |
| F-stat | 31.62 | 31.05 | 33.45 |
| Ind. var. mean | 0.484 | 0.484 | 0.484 |

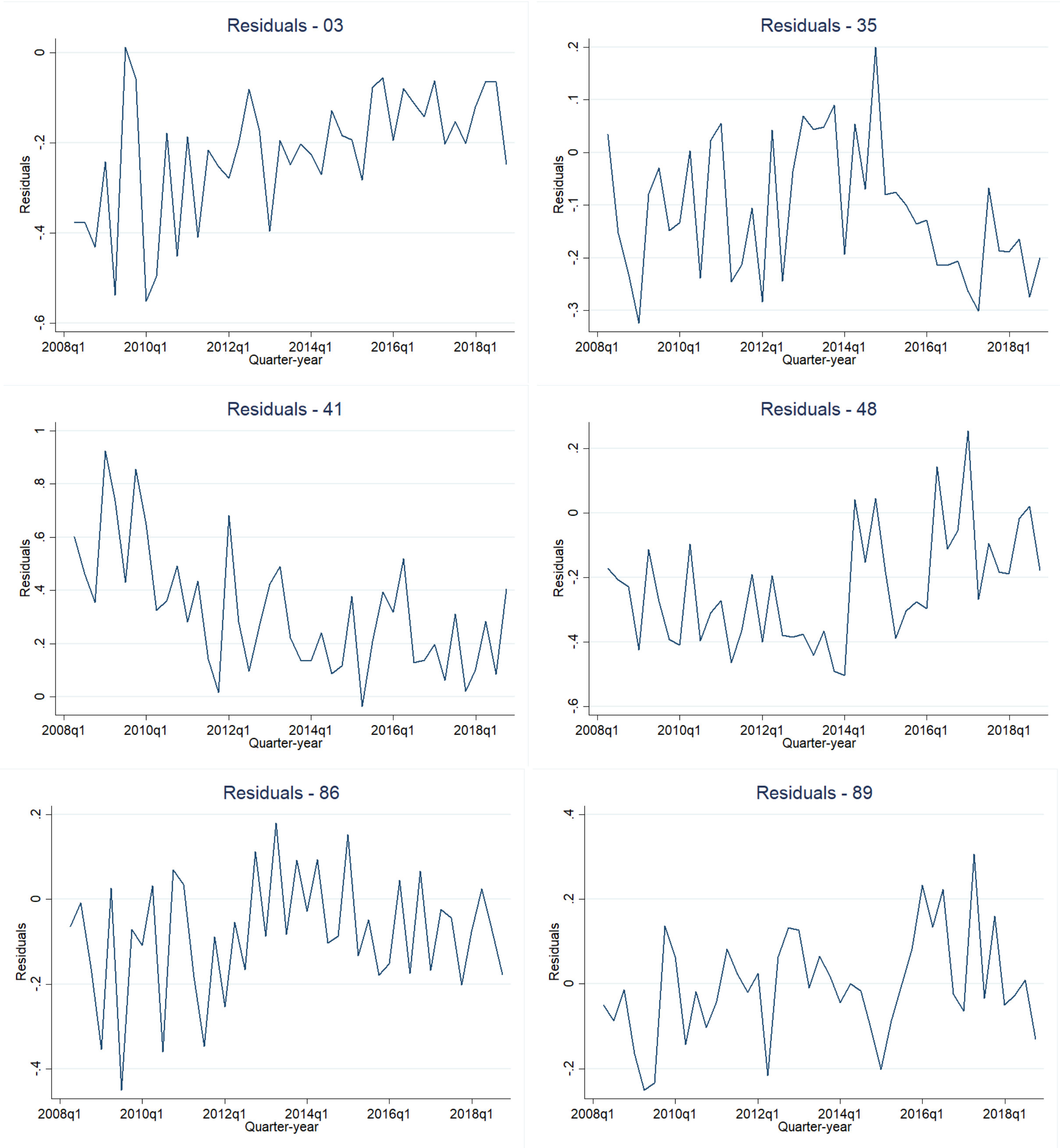
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

# C Bootstrap regression results for the 90% municipalities with decree disasters case

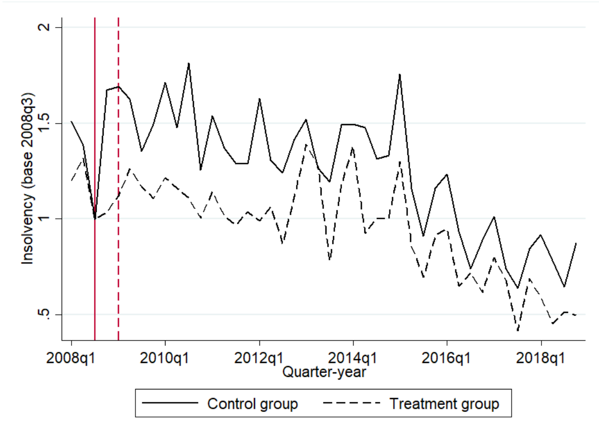


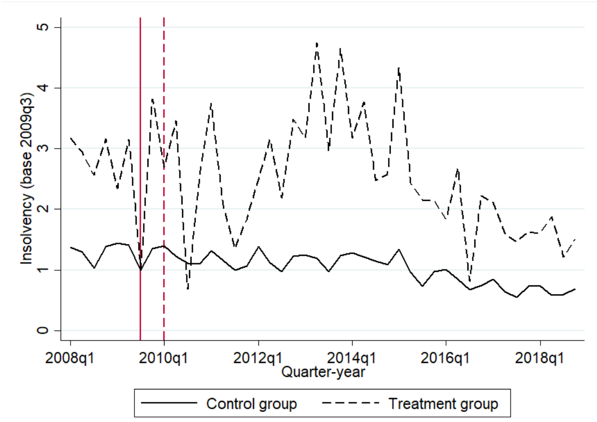



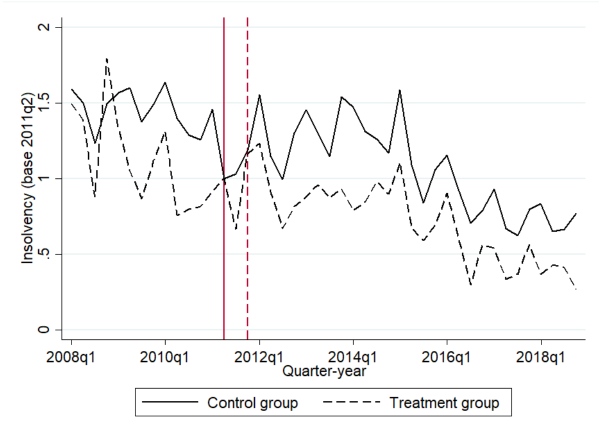
# D Residuals from regression in various "départements"

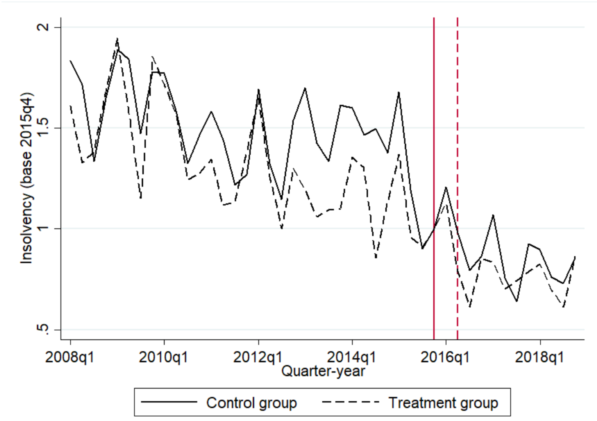


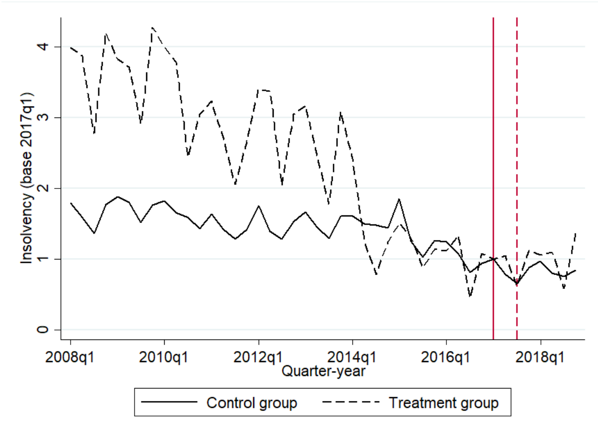
# E Parallel trend based on event study for each natural disaster

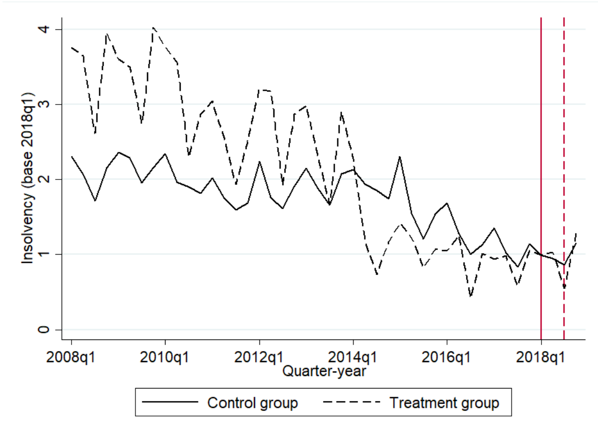


# F Influence of politics on decree issuance - Regressions - Preliminary work

Impact of rain and politics on decree issuance: 2008-2018

| VARIABLES | (1) Departement Rain ratio | (2) Departement Rain ratio > 25 |
|---|---|---|
| Rain disaster | 0.149*** | 0.0115* |
| | (0.0143) | (0.00619) |
| Insolvency in t-1 | -0.259 | -0.00426 |
| | (0.746) | (0.00754) |
| Insolvency in t-2 | -0.244 | -0.00163 |
| | (0.952) | (0.00990) |
| Insolvency | 0.0429 | 0.00221 |
| | (0.646) | (0.00631) |
| Percentage of mayors with the political majority | -0.0310 | -0.00362 |
| | (0.953) | (0.00977) |
| Observations | 4,320 | 4,320 |
| $R^2$ | 0.087 | 0.056 |
| Number of Departement | 96 | 96 |
| Quarter-year FE | YES | YES |
| Departement FE | YES | YES |
| Ind. var. mean | 1.147 | 0.00370 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

# G Influence of politics on decree issuance - Regression discontinuity design - Preliminary work