Do bankers want their umbrellas back when it rains? Evidence from typhoons in China

Pauline Avril* Grégory Levieuge† Camelia Turcu‡

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Abstract

This study investigates how typhoons affect bank lending in China. Our difference-in-difference estimates, based on a sample of more than 161,000 bank branches held by 327 Chinese banks from 2004 to 2019, show that on average typhoons trigger a decrease in lending that accounts for 2.8 percent of total bank assets. This decline is driven by commercial banks, presumably due to worsening information asymmetries. On the contrary, rural banks act as shock absorbers. This may be the consequence of long-term lending relationships and banks' better knowledge of local economic and physical risks. The absence of rural banks is even found to be detrimental to local post-typhoon growth. Last, government ownership and external political pressure mitigate the relative decline in lending by typhoon-hit commercial banks.

JEL Classification: G21, Q54, O40

Keywords: Typhoons, lending, banking system, China, shock absorbers, shock transmitters.

* Univ. Orléans, LEO, F-45067, Orléans, France. E-mail: pauline.avril@univ-orleans.fr.

† Banque de France, DGSEI-DEMFI-RECFIN, 31, rue Croix des Petits Champs, 75049 Paris Cedex 01, France, and Univ. Orléans, LEO, F-45067, Orléans, France. E-mail: gregory.levieuge@banque-france.fr.

‡ Univ. Orléans, LEO, F-45067, Orléans, France. West University of Timisoara, FEEA, Timisoara, Romania. E-mail: camelia.turcu@univ-orleans.fr.

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1 Introduction

The increased frequency and severity of natural disasters (NDs) in the wake of global warming are largely acknowledged (Hoeppe, 2016; Botzen et al., 2019), and their impact on the real side of the economy is rather well-documented (Noy, 2009; Crespo Cuaresma et al., 2008; Schumacher and Strobl, 2011; Cavallo et al., 2013; McDermott et al., 2013). A significant strand of the literature agrees that this impact is particularly important in emerging and developing countries. However, the financial dimension of physical risks has been less studied, whereas financial institutions, and especially banks, are highly exposed to this risk (Noth and Schüwer, 2023; Gramlich et al., 2023). This is critical, as banks have a crucial role to play in financing the development of emerging economies in general and in providing post-disaster recovery lending in particular.

Generally speaking, the reaction of banks may be ambivalent. On the one hand, by destroying capital and wealth, NDs cause a worsening of information asymmetries.[1] According to the financial accelerator and the bank capital channel, less-diversified banks and/or banks having clients with initially large informational asymmetries are likely to tighten credit conditions and ration credit.[2] In this case, banks would act as shock transmitters. On the other hand, banks having a strong local anchor through lending relationships would be willing to provide recovery lending. Indeed, a good knowledge of local firms, markets, and risks – including climate risks[3] – gives advantages in screening and monitoring projects. In such a context, banks would act as shock absorbers.

Against this background, this paper aims to empirically study the impact of NDs on the banking sector in China, a leading emerging economy that is highly exposed to NDs. Focusing on China is interesting in several respects. Overall, the Chinese banking sector has characteristics that are representative of emerging economies (Ruch, 2020), such as India and Brazil. In particular, state-owned banks in these countries play a prominent role in providing financial services (Ping, 2006), and the government has historically been a key player in shaping banking policies (through, e.g., the Industrial Development Bank of India, or the Banco do Brasil and Caixa Economica Federal). Moreover, the banking system is used to channel funds into sectors that are considered strategically important for national growth and economic development. Last, efforts are made to expand access to credit and financial services, especially to underserved populations in rural and remote areas.

Beyond that, our analysis addresses the reaction of the banking sector of an emerging country that plays a key role in the global economy. China has the largest share of the world GDP (over 18% in 2022) and has been, since 2011, the world's undisputed top exporter. Moreover, China's banking sector has expanded rapidly. For example, domestic credit to the private sector as a

[1] See Avril et al. (2022) for details on these transmission channels.

[2] See Kiyotaki and Moore (1997); Bernanke et al. (1999); Cerqueiro et al. (2016); Di Tella (2017) for examples of the financial accelerator mechanism and borrowers' balance sheet effects, as well as Gertler and Karadi (2011); Gertler et al. (2012); Brunnermeier and Sannikov (2014); He and Krishnamurthy (2019) for theoretical and empirical evidence of banks' balance sheet effects.

[3] See Xu and Xu (2023) for evidence of the importance of local natural hazard information.

percentage of Gross Regional Product (GRP) increased by about 80% from 2008 to 2020 (World Bank WDI, 2021). This is one of the consequences of the liberalization of the banking sector.[4] However, this liberalization is fairly recent, so banks may not have yet developed avoidance strategies against NDs. Moreover, the insurance market remains underdeveloped. Insurance claims have historically accounted for less than 1% of direct economic losses in major large-scale disasters in China (Ye and Mu, 2020). Therefore, the banking sector is expected to play a crucial role in facilitating post-natural disaster recovery, rendering it an intriguing field for analysis.

Interestingly, the Chinese banking sector gathers different types of banks, which exhibit distinct features in terms of ownership (public versus private), objectives (ranging from strategic investments in the core sector to the financing of small private local firms), and geographic diversification (spanning from nationwide to rural counties). These specific characteristics, especially with respect to the local anchoring, are interesting to consider and can help us understand why banks could act as transmitters or absorbers of shocks. More precisely, we will focus on the difference between commercial banks' and rural banks' reactions to natural disasters. These two types of institutions have different business models and features. In particular, rural banks are smaller and less diversified than commercial banks, but their close relationships with their clients give them easier access to soft information.[5]

More specifically, our strategy for identifying banking *supply-side* effects is based on the following rationale. First, we assume that banks' effective exposure to NDs is representative of their clients' exposure to these events. The reason is that bank branches have a circumscribed geographical scope. This is obvious, de facto, for rural banks. It is also true, de jure, for commercial bank branches, which are required to serve mainly local clients. For instance, Article 5 of the Notice of the General Office of the China Banking and Insurance Regulatory Commission on further standardizing the Internet loan business of commercial banks, issued by the State Council in 2021, states[6]: "*We will strictly control cross-regional business. Where local banks conduct Internet loan business, they shall serve local customers and shall not carry out Internet loan business across the jurisdiction of its registration place*." Consequently, beyond the damage suffered by a bank itself, the exposure of its branches reflects that of its clients. Next, the literature overwhelmingly shows that there is an increase in *demand* for credit following natural disasters (Del Ninno et al., 2003; Berg and Schrader, 2012; Czura and Klonner, 2023; Benincasa et al., 2024). Consequently, a slowdown in credit activity can be attributed to a decline in loan supply.

As for natural disasters, we focus on typhoons. China is confronted with high levels of disaster risk, as indicated by its ranking (67 out of 191 countries) in the 2019 INFORM Risk Index from the Climate Change Knowledge Portal (CCKP) of the World Bank. This ranking

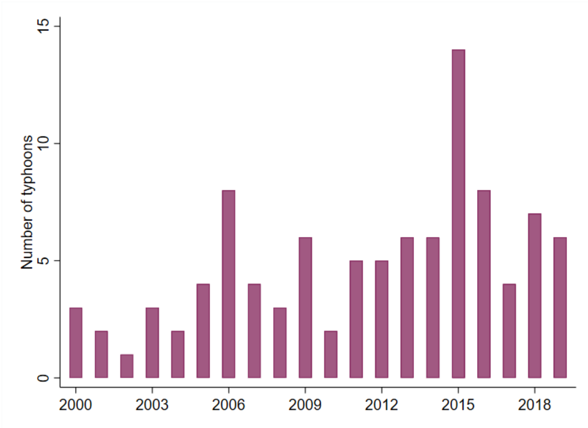
[4] China joined the World Trade Organization (WTO) in 2001, whose General Agreement on Trade in Services (GATS) includes banking services. Some of the limits on lending and deposits were removed in 2004.

[5] It is worth mentioning that even though there are only five state-owned banks, they hold a significant share of the loan market within the banking sector. We also note that only few foreign banks operate in the country.

[6] See `https://www.gov.cn/zhengce/zhengceku/2021-02/20/content_5587989.htm`. This is in line with the Article 9 of the "Interim Measures for the Administration of Internet Loans by Commercial Banks", issued by the State Council in 2020. As a rule, the supervision of commercial banks' loans has been upgraded to strictly control cross-regional operations.

primarily stems from China's extensive exposure to tropical cyclones (called typhoons) and the associated hazards (the country is ranked 6th worldwide in terms of typhoon exposure).[7] Moreover, these natural disasters represent an important and growing threat in China (Park et al., 2014; Yao et al., 2021). According to Figure 1, between 2009 and 2018, there was a significantly higher occurrence of intense typhoons reaching the maximum intensity, as per the Chinese National Standard for Grade of Tropical Cyclones, compared to the period from 2000 to 2009. Deadly typhoons such as Haiyan in 2013, Meranti in 2016, and Doksuri in 2023 are only several examples. Moreover, China is even more vulnerable to typhoons as they mainly hit the country's highly urbanized east coast (Fischer et al., 2015). Therefore, despite national public management strategies, the negative impact of typhoons on Chinese GDP has increased over time (Elliott et al., 2015).

Figure 1: Number of intense typhoons in China



Note: Number of typhoons of maximum intensity (level 6) according to the Chinese National Standard for Grade of Tropical Cyclones. Source: China Meteorological Administration (CMA). Authors' calculations.

Thus, in this paper, we study the impact of major typhoons on loans, but also on non-performing loans (NPLs), liquidity ratios, and leverage ratios of different types of banks. We rely on a difference-in-difference methodology on a sample of about 161,100 branches held by 327 banking groups and dispersed over 31 Chinese provinces. We consider as treated banks that have actually been exposed to a typhoon. To this end, we develop an original measure of banks' exposure to the 23 most intense typhoons from 2004 to 2019. This measure is based on localized disaggregated data regarding the geographical position of banks' branches. Note that by relying on the intensity of typhoons, our measure allows us to investigate the exposure and reaction of the Chinese banking system to exogenous shocks.

We find that, on average, typhoons trigger a decrease in the variation of loans that accounts for 2.8% of total bank assets and an increase in NPLs of 0.30 percentage points. However, it is primarily commercial banks that reduce their lending activities, presumably due to the worsening of information asymmetries. In addition, as commercial banks also suffer from a decrease in

[7] Furthermore, China also experiences significant exposure to floods and droughts The country's overall disaster risk is further compounded by moderate levels of social vulnerability.

their liquidity ratio, balance-sheet effects could explain why they act as shock transmitters. On the contrary, rural banks do not significantly decrease their lending. Faced with an increase in NPLs, they seem to act as shock absorbers. This may be a consequence of a lending relationship, as well as of a better knowledge of local economic activity and physical risks.

The contribution of this research is at the crossroads of several strands of the literature. First, we contribute to the emerging literature that investigates the impact of NDs on the banking system. It is widely acknowledged that funding needs increase to replenish damaged capital and cover financial losses in the wake of a disaster (Del Ninno et al., 2003; Berg and Schrader, 2012; Czura and Klonner, 2023; Benincasa et al., 2024). This growing demand can be met by recovery lending from banks, albeit depending on the structure of the banking system (Cortés, 2014; Schuwer et al., 2019). Chavaz (2016) for instance suggests that recovery lending is facilitated by small local banks that take advantage of the opportunities arising from increased demand and/or have long-term relationships with their clients. Further, these loans are transferred through the secondary market to more diversified financial institutions that can better support the associated risks. Koetter et al. (2020) also find that local lenders play a key role in providing recovery lending, particularly to small local firms. Cortés and Strahan (2017) show that multi-market banks protect their core markets by reallocating capital when local demand for credit increases after an ND. This reallocation comes at the cost of regions that are unaffected and where banks do not have branches. Moreover, as credit supply may have positive externalities on local house prices, local banks may be more prone to continue lending to an area in which they have a high share of outstanding loans (Favara and Giannetti, 2017). Thus, by providing recovery lending, banks act as substitutes for insurance contracts covering disaster risks, which might typically lack comprehensive coverage for disaster risks. In this respect, it should be noted that the insurance market for natural disasters is poorly developed in emerging countries, such as China (Wang et al., 2012). However, some studies do not support the recovery lending hypothesis (Noy, 2009; Hosono et al., 2016).[8] Therefore, our study sheds new light on the question of whether NDs dampen or stimulate credit activity. We confirm that this depends on the banking market structure: the presence of local banks is crucial to ensure recovery lending.

Second, by focusing on banking market structure, and by distinguishing the response of different types of banks in terms of scope and diversification, we contribute to the literature on financial intermediation. It is widely acknowledged that banks can mitigate information asymmetries through lending relationships which allow them to exploit soft and qualitative information. In doing so, they expect to compensate for any short-term temporary losses in the future. Therefore, they can alleviate the financing constraints that small firms otherwise face, due to a lack of hard and quantitative information. Hence, for firms, building close ties with a bank not only offers advantages in terms of financing availability (Petersen and Rajan, 1994; Elsas and Krahnen, 1998; Brown et al., 2021; Bolton et al., 2016), but also in terms of credit conditions (Berger and Udell, 1995), especially following unexpected adverse

[8] From a more structural point of view, Garmaise and Moskowitz (2009) and Faiella and Natoli (2018) find a negative correlation between lending and exposure to physical risk, especially in case of insurance market imperfections.

shocks.[9] Small local banks, in particular, are better at using this qualitative information, since soft information circulates better within a small organization (Stein, 2002; Berger et al., 2005; Agarwal and Hauswald, 2010; Canales and Nanda, 2012; Berger et al., 2017). Consequently, they are more likely to provide liquidity and interest-rate insurance to their clients. For example, Alvarez-Roman et al. (2023), who examine the financial consequences of wildfires in Spain, find that local banks reduce their loans to opaque affected firms to a lesser extent than outsider banks. Nevertheless, as they are less diversified and benefit less from government guarantees than large banks, the liquidity support from small banks could be limited during a financial crisis (Berger et al., 2015).[10] In this paper, we confirm that banks having a local anchorage, i.e. a good knowledge of local economic and natural risks with possibly long-term customer relationships, are likely to dampen the economic impact of NDs. In contrast, financial intermediaries that do not have such informational advantages in screening and monitoring projects are more likely to exacerbate the adverse effects of such exogenous shocks.

Third, the majority of studies on the financial consequences of NDs predominantly involve developed countries (See, e.g., Noth and Schüwer, 2023), which generally have a more mature insurance market (Melecky and Raddatz, 2014).[11] In emerging economies, such as China, the insurance market is less developed and the banking sector often has a distinct structure characterized by more government involvement, which in turn increases the political pressures experienced by banks. Moreover, empirical evidence suggests that emerging and developing countries are the most affected by natural disasters (Kellenberg and Mobarak, 2011; McDermott et al., 2013; Klomp, 2014). Nevertheless, this remains only briefly addressed in the literature. Focusing on the Chinese case fills in this gap and contributes to a better understanding of the functioning of emerging economies that extensively rely on the banking system to finance their growth. To the best of our knowledge, this is the first study on the impact of typhoons on Chinese banks.[12]

Last, our findings contribute to the emerging new economic and financial geography field (Zhao and Jones-Evans, 2017; Dixon, 2012; Basker and Miranda, 2018). We consider a disaggregated regional approach in analyzing the reaction of banks to localized natural disasters and we take a closer look at recovery patterns in Chinese provinces following these extreme events. Our analysis takes into account the structure of the local banking system as well as the political interference and pressure that could influence the behavior of banks within the regions (Chu and Zhang, 2022). From this perspective, we find that the absence of rural banks is detrimental to local post-typhoon growth. Furthermore, our results do not rule out a significant impact of political pressure on lending activity following a typhoon.

The rest of the paper is organized as follows. Section 2 presents our balance sheet data and

[9]See also the survey of Boot (2000) and the meta-analysis proposed by Kysucky and Norden (2016).

[10]Moreover, competition is not neutral (Duqi et al., 2021; Crawford et al., 2018). We will control for bank market power in our empirical analysis.

[11]One exception is Brei et al. (2019), who find that withdrawals of bank deposits are used to compensate for the decline in the supply of bank lending following hurricanes in the Eastern Caribbean islands.

[12]The contribution of Zhang et al. (2024) deals with the physical and transition risks in China in a more general way, and considers their impact on NPLs only.

describes our measure of the exposure of Chinese banks to typhoons as well as all our control variables. Section 3 is dedicated to the presentation of the difference-in-difference framework that we use to gauge the reactions of Chinese banks to typhoons. Section 4 presents the baseline results, additional results with alternative control groups, and robustness checks. Section 5 explores post-typhoon local growth according to local banking sector structures. Finally, we investigate the role of political pressure on the reaction of banks to typhoons in Section 6. Section 7 concludes.

2 Data

This section is dedicated to the source of banks balance sheet data and to the way we measure banks' exposure to typhoons. Beyond the direct damage to a given bank branch caused by a typhoon, its exposure is crucial in our analysis in that it is representative of the exposure of its clients. Indeed, each branch of rural or commercial banks operates in a legally defined geographical area. Thus, if a branch is affected by a natural disaster, so are its clients. This risks exacerbating information asymmetries and worsening borrower creditworthiness. As demand for loans generally increases following a natural disaster, any reduction in credit in this context would be an evidence of a supply restriction. In any case, we will control for some demand factors. The last subsection is precisely dedicated to the definition of the control variables.

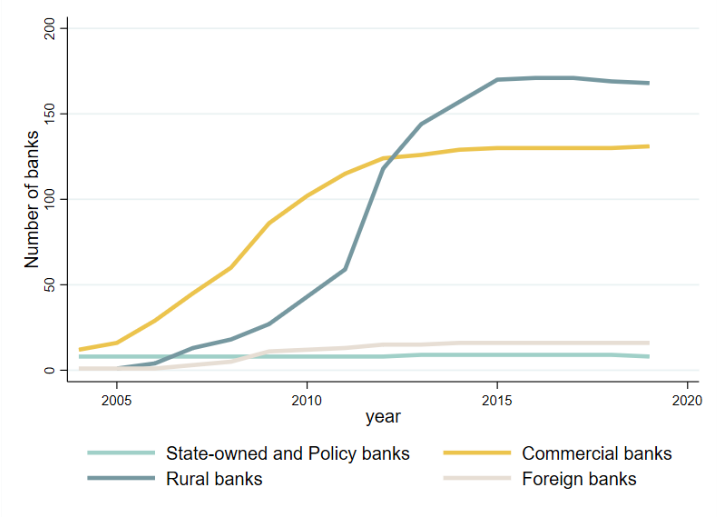
2.1 Source of banks' balance sheet data and dependent variables

Our analysis relies on banks' balance sheet information, collected from the China Stock Market Accounting Administration (CSMAR), from 2004 to 2019. The starting date is justified by the Chinese financial system's liberalization, which has been strengthened since the beginning of the 2000s. After the creation of the China Banking Regulatory Commission (CBRC), dedicated to the supervision and regulation of the financial system, in 2004, China removed its limitations on lending rates and those related to the deposit rate.

As a consequence, Figure 2 shows that the number of commercial and rural banks has increased significantly, from almost zero in the very early 2000s to about 130 and 170, respectively, in 2019. Furthermore, they have developed many branches in different regions. Rural banks encompass rural commercial banks, rural cooperative banks, and rural credit unions. They provide loans and financial services to the agricultural sector, small and medium-sized businesses, and households in counties and rural areas. Thus, their business is highly concentrated in terms of geography and customers (see evidence below). Commercial banks include joint-stock commercial banks and (lower-size and less sprawling) city commercial banks. These institutions have a rather flexible ownership structure and provide services mostly to medium and small enterprises in the private sector (Tan, 2017). Although they can diversify their activities over a wider territory, this remains circumscribed by law. As these two types of banks have distinct business models, it will be interesting to compare their behavior in the wake of typhoons.

Figure 2 also shows that the number of state-owned and foreign banks has not increased since the late 2000s. However, state banks still cover 60% of loans nationwide, compared to 35% for commercial banks and 5% for rural banks.

Figure 2: The number of Chinese banks, by type of bank



Source: CSMAR, Authors' calculations.

By considering banks as they are created[13], our analysis is conducted on an unbalanced panel of 327 banks for which data is available. This panel is composed of 9 state-owned and policy banks, 16 foreign banks, 131 joint-stock, and city commercial banks, and 171 rural banks.[14]

While investigating the reactions of these different banks to NDs, we are mainly interested in four variables stemming from banks' balance sheets. First and foremost, we examine the variation of the total amount of loans (expressed in trillion yuan). This is a key variable for detecting whether banks practice recovery lending or whether they cut credit following the deterioration of creditworthiness generated by typhoons. Second, we consider the non-performing loan (NPL) ratio, defined as the percentage of substandard loans, doubtful loans, and loss loans over the total of loans. Typically, an increase in NPLs can be the corollary of a shock-absorbing effect by banks. Third, we will also study the impact of typhoons on banks' liquidity ratios, defined as liquid assets over short-term liabilities, and on their leverage ratios, computed as the ratio of total equity to total assets. For the two former dependent variables, the reason under their investigation is that the adverse effects of natural disasters on banks' liquidity (e.g., due to important withdrawals of deposits) and capital (e.g., due to a fall in retained earnings) could explain banks' reluctance or inability to offer recovery lending, as suggested by the bank capital channel. Last, we limit our analysis to data up to 2019 to exclude any singular effects related to the COVID-19 crisis.

[13]The sole requirement for inclusion in the sample is that banks should have a minimum existence of four years, with at least one observation available for all dependent variables.

[14]Note that Postal Savings Bank of China, which was a state-owned institution, became a joint-stock bank during the investigation period and is included in our study.

2.2 Measuring banking groups' exposure to typhoons

In this section, we present our methodology used to quantify the exposure of each banking group to geo-localized typhoons. First, we extract information on typhoons from the Tropical Cyclone Best Track provided by the China Meteorological Administration (CMA).[15] From this dataset, we retrieve the precise location and intensity of each typhoon, every six hours. While typhoons can impact large areas of the territory (Holland et al., 2010; Yang, 2005), the radius considered as damaging is generally about 100 km around the eye, which is the calmest part of the typhoon. However, in order not to lose any information on the potential impact of typhoons, we follow Berlemann and Wenzel (2018) by considering that these events can have an impact within a radius of 160 km all along their trajectory.

Second, we precisely locate branches of the 371 banks in our sample based on the information provided by the China Stock Market & Accounting Research (CSMAR) in the China Bank Research Database. This dataset provides precise information on the full names of banks' branches, their addresses, their geographic coordinates, the banks they are affiliated with, and their opening and closing dates. In doing so, our sample includes up to 161,504 bank branches in 2019.

Third, we use the QGIS software and a China shapefile to combine the location of banks with the trajectories of typhoons.[16] In doing so, we can measure to what extent each bank has been affected by typhoons, given the location of its branches. Figure 3 illustrates our approach. The green dots represent the location of branches, while the red hatched areas correspond to the trajectories of the 2019 typhoons, in a radius of 160 km. Each bank branch located in the red area can be viewed as potentially affected. Nevertheless, in practical terms, banking groups are actually affected only if the typhoon reaches a certain level of intensity and affects a sufficient number of their local branches. To address this, we impose two restrictions. To eliminate low-intensity events from the analysis, we narrow our focus only on major typhoons with an intensity level[17] of at least 3. In addition, we consider a bank as affected at the consolidated level if more than 50% of its branches have been hit. Note that these hypotheses will be examined in the section dedicated to robustness checks.

Finally, we measure the overall exposure of the affected banking group i to a typhoon d at time t by reporting the number of its affected branches over its total number of branches across the country, weighted by the intensity of the typhoon, such as:

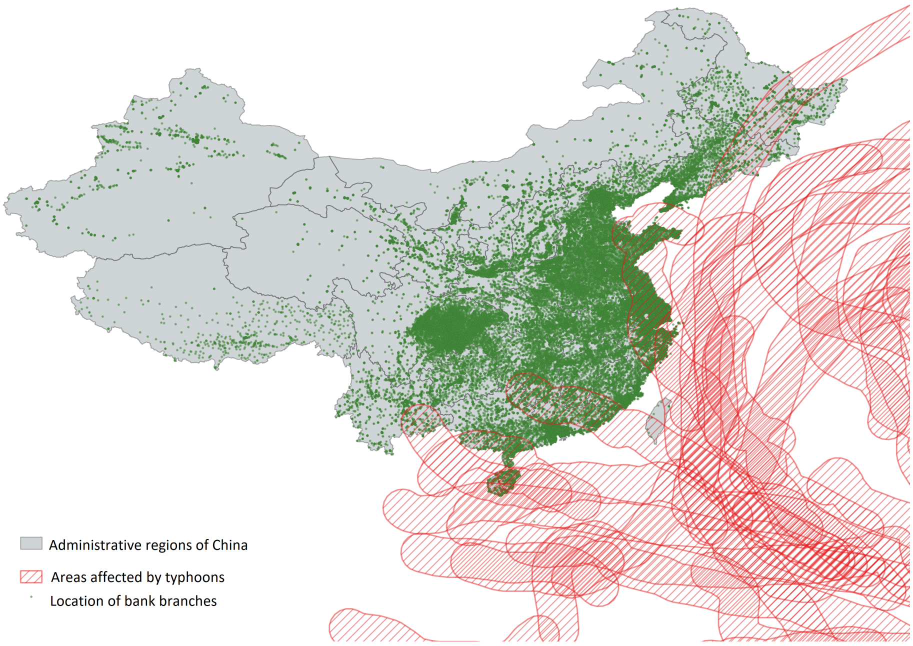
$$\text{Exposure}_{i,t} = \sum_{d=1}^{D} \frac{\text{local branches affected}_{i,t,d}}{\text{total banking activities}_{i,t}} \times \text{typhoon intensity}_{t,d} \tag{1}$$

[15] The data is obtained from `tcdata.typhoon.org.cn`. See Ying et al. (2014) and Lu et al. (2021) for more details.

[16] Shapefiles at all administrative levels can be downloaded at `https://data.humdata.org/dataset/cod-ab-chn?` and are provided by OCHA Regional Office for Asia and the Pacific (ROAP).

[17] The intensity category is defined according to the Chinese National Standard for Grade of Tropical Cyclones, since 15 June 2006: categories range from 0 to 6, according to wind speed, with 6 being the highest level. Level 3 corresponds to a minimum speed of 86.4 km/h.

Figure 3: Branches affected by 2019's typhoons



Source: CSMAR, Authors' calculations. The green dots correspond to the location of all bank branches. The red-hatched areas correspond to a buffer of 160km around the trajectories of typhoons.

This measure is in line with Schuwer et al. (2019), who consider the share of banking business located in the affected counties, weighted by the damage incurred within the county. Nevertheless, our approach has the advantage of using weights derived from an exogenous measure, i.e. the geophysical intensity of the typhoons, unlike damages that are strongly correlated to the economic, financial, and social contexts (Noy, 2009; Felbermayr and Groschl, 2014; McDermott et al., 2013).

Table 1 presents some descriptive statistics for our measure of exposure. It appears that rural banks, which are less diversified and have fewer branches (See Table A.4 in Appendix), are likely to be more affected than commercial banks. Note that on the extreme opposite, state-owned and policy banks are highly diversified geographically and have numerous branches. As a result, they are never classified as affected according to our definition of exposure (which requires that at least 50% of the branches should be affected) and our restrictions on the intensity of the considered typhoons. Note that given the two aforementioned restrictions, in theory, the minimum value of our indicator is 1.5, characterizing a banking group having just 50% of its branches being hit by a typhoon of intensity 3 at year t.

2.3 Control variables

While natural disasters can affect bank lending, NPLs, liquidity, and leverage ratios, these variables also depend on the intrinsic characteristics of the banking industry and demand-side effects. Therefore, it is crucial to consider both dimensions in our analysis.

Regarding the banking supply-side characteristics, we first consider the logarithm of the

Table 1: Descriptive statistics on banks' exposure

	Mean	Sd	Min	Max
All banks	6.49	3.89	1.55	24.00
(229 banks affected vs 98 never affected)				
Commercial banks	5.18	2.90	1.55	18.72
(73 banks affected vs 59 never affected)				
Rural banks	7.08	4.13	1.61	24.00
(156 banks affected vs 15 never affected)				

Note: This table gives information on the distribution (mean, standard deviation, minimum, and maximum) of the exposure to typhoon score we construct at a bank level. We also detail the number of banks that have been affected at least once and the ones that are never affected. We detail the information for all, commercial and rural banks.

number of banks' branches as a proxy for banks' size. This information may be important, as small banks may have comparative informational advantages in alleviating financial constraints, especially under adverse economic conditions (Stein, 2002; Berger et al., 2005; Agarwal and Hauswald, 2010; Canales and Nanda, 2012; Berger et al., 2017). Moreover, we consider the geographic concentration of banks. Loutskina and Strahan (2011), show, on the one hand, that geographic diversification can lead to a decline in screening by lenders. On the other hand, lenders that are concentrated in a few markets invest more in information collection and are better positioned to price risks and ration credit less. We measure geographic concentration by computing a Herfindahl-Hirchmann Index (HHI) based on the location of banks' branches. Denoting m the total number of regions, this index is the sum of the squared shares of branches at each region level, following

$$\text{Geographic concentration}_{i,t} = \sum_{j=1}^{m} \left(\frac{n_{i,j,t}}{N_{i,t}} \right)^2 \equiv \sum_{j=1}^{m} (r_{i,j,t})^2, \tag{2}$$

where $n_{i,j,t}$ is the number of branches of bank i in region j, and $N_{i,t}$ is the total number of branches owned by i. Hence $r_{i,j,t}$ represents the shares of bank i's branches located in region j. Note that this index is equal to one if all the branches of a bank are located in a single province.

Next, we consider competition in the banking market. Duqi et al. (2021), for example, find that banks continue to lend following a natural disaster, especially in less competitive markets. Our market power indicator builds on Chong et al. (2013). For the sake of clarity, its construction is described in two steps, by defining successively (i) the regional banking concentration and (ii) the contribution of each bank to this concentration. First, we compute an HHI to measure banking concentration at the regional level. This index relies on the number of branches owned by the bank i in region j over the total number of bank branches in this region (denoted $N_{j,t}$), such as

$$\text{Banking concentration}_{j,t} = \sum_{i=1}^{k} \left(\frac{n_{i,j,t}}{N_{j,t}} \right)^2 \equiv \sum_{i=1}^{k} (s_{i,j,t})^2, \tag{3}$$

where k designates the total number of banks. Notice that this regional banking concentration index is equal to one if all the branches in a given region belong to a single bank. Second, we measure the contribution of each bank i to the local concentration, such as

$$\text{Local market power}_{i,j,t} = \frac{(s_{i,j,t})^2}{\sum_{i=1}^{k}(s_{i,j,t})^2}. \tag{4}$$

Note that this local market power index is equal to one if only one bank has branches in region j. Finally, given these definitions, we can gauge the global market power of bank i operating in various regions j, such as

$$\text{Market power}_{i,t} = \sum_{j=1}^{m}\left(\frac{(s_{i,j,t})^2}{\sum_{i=1}^{k}(s_{i,j,t})^2}\right)r_{i,j,t}, \tag{5}$$

which refers to the sum of the local market power of bank i over the m regions, weighted by the share of branches this bank owns in each region where it operates ($r_{i,j,t}$).

Regarding demand-side controls, we focus on local unemployment rates and GRP growth. These variables are initially available at the province level. To evaluate the demand conditions that each bank faces, these two variables are weighted by each bank's activities in province j over its total activities in the country (i.e., by $r_{i,j,t}$).

Descriptive statistics concerning the dependent and explanatory variables defined so far are reported in Table A.1 in Appendix A.

3 Empirical strategy

We use a generalized difference-in-difference (DiD) approach to assess the impact of typhoons on Chinese banks. Within this framework, we consider as "treated" the banks that have actually been exposed to a typhoon according to the definition (1), with an exposure indicator higher than 1.5. Banks that are not affected belong to the control group. Hence, we create a dummy variable labeled $Treated_i$, which is equal to one if the bank i belongs to the treated group, and zero otherwise (meaning that i belongs to the control group). We also create a dummy variable denoted $Post_{i,t}$ that is equal to one during three years after a bank i has been treated and zero otherwise. Subsequently, a treated bank can move into the control group three years after being affected by a typhoon, provided it is not hit again by another typhoon during that interval.[18] The interaction between $Treated_i$ and $Post_{i,t}$ captures the difference between banks before and after being treated and the difference between being treated and not being treated.

The average treatment effect (ATE) is given by the parameter β in the following equation that is estimated:

$$Y_{i,t} = \alpha_i + \tau_t + \beta(Treated_i \times Post_{i,t}) + X_{i,t}\eta + \varepsilon_{i,t}, \tag{6}$$

[18] Since we are in a multiple-event case with exogenous timing, such as, for example, Masiero and Santarossa (2021), there is no constant pre- and post-period for the control group. Hence, the $Post_{i,t}$ dummy is specific to the banks i that are - temporary - in the treated group.

where Y successively represents the variation of total loans, the non-performing loans ratio, the liquidity ratio, and the leverage ratio. $X_{i,t}$ contains a set of control variables related to individual banking characteristics and local demand-side features, as described in Section 2.3. The model also embeds individual fixed effects α_i. They aim at capturing potential time-invariant unobserved differences between the treated and non-treated banks. Specifically, a considerable number of banks in China are concentrated in the southeast of the country, which is both the most economically dynamic region and the most typhoon-prone area due to geographical and climatic conditions. In addition, we consider year-fixed effects τ_t, which are intended to capture events that may affect the entire Chinese banking system. Finally, $\varepsilon_{i,t}$ stands for standard errors, which are clustered at the bank level. Consequently, after controlling for time and bank-fixed effects, typhoons can be viewed as random and exogenous events. As a result, our estimated treatment effect can be considered as consistent, i.e. the conditional independence assumption is met.

However, the identification of a causal impact through the DiD methodology relies on the parallel trend assumption, according to which the dependent variables of treated banks would have evolved in parallel to those of untreated banks in the absence of treatment. In this respect, we conduct a preliminary examination to ascertain whether the evolution of all the variables used in the regressions is similar in the two groups. Table A.3 in Appendix reports, based on Imbens and Wooldridge (2009), t-statistics for tests of normalized differences of variations. It shows that one year before a typhoon occurs, the null hypothesis of mean equality is never rejected, except for geographic concentration. Furthermore, we will test the parallel trend hypothesis using a joint test on leads significance (Cerulli and Ventura, 2019) for each estimated model. This test is well suited for time-varying treatment (i.e. with the case of many pre- and post-intervention periods). It is conducted while accounting for 3 periods before the event takes place and 3 periods after the event.

4 Results

In this section, we first present the baseline results of the DiD estimates. Then, we check their robustness by considering alternative control groups and definitions of the treatment.

4.1 Baseline results

The columns labeled "Full sample" in Table 2 report the baseline results of the DiD estimations for banks' loan variation, non-performing loans (NPLs), liquidity ratios, and leverage ratios following intense typhoons. All the banks of our sample are considered on a yearly basis from 2004 to 2019. The results indicate that being exposed to a typhoon, and so to a deteriorated creditworthiness context, triggers a significant decrease in the variation of loans. This suggests that banks may act as shock amplifiers. The year-on-year loan variation is reduced by an average of 0.021 trillion yen during the three years following a typhoon compared to banks not affected. Considering that the mean of total assets is equal to 0.738 trillion, a typhoon leads to a yearly average cut in lending of 2.8% of the value of total assets (i.e. 0.021 trillion yuan) over the three years after the disaster, for the treated banks, compared to the control group.

Next, in line with Zhang et al. (2024), we observe an increase in the non-performing loans ratio (at the 10% level) for treated banks, compared to the control group. This tends to confirm that a typhoon can affect the solvency of borrowers, by mitigating production capacity and economic activity. This increase represents about 15% of the average NPL ratio in our sample. Nevertheless, being affected by a typhoon does not seem to impact banks' liquidity and solvency ratios. Brei et al. (2019), Noth and Schüwer (2023) and Nie et al. (2023) find a similar decline in loans and a rise in NPLs for other countries (i.e., in the Caribbean islands, the USA, or the Philipines respectively).

Table 2: Baseline results - all banks

	Total loans		NPL ratio		Liquidity ratio		Leverage ratio	
	Full sample	Matched sample	Full sample	Matched sample	Full sample	Matched sample	Full sample	Matched sample
Treated × Post	-0.021***	-0.011**	0.291*	0.284	0.080	0.032	-0.003	0.001
	(0.006)	(0.005)	(0.157)	(0.182)	(0.066)	(0.055)	(0.003)	(0.004)
No. of branches (Log)	-0.003	0.005	0.565**	0.418*	-0.009	-0.007	-0.008	-0.007
	(0.011)	(0.004)	(0.279)	(0.238)	(0.051)	(0.054)	(0.006)	(0.008)
Geog. concentration	0.241***	-0.044*	-3.356***	-3.856***	-0.153	-0.261	0.051	0.041
	(0.077)	(0.023)	(1.018)	(1.060)	(0.351)	(0.190)	(0.033)	(0.043)
Unemployment rate	0.009	0.008	-0.018	-0.028	-0.079	-0.107	-0.006	-0.010
	(0.007)	(0.005)	(0.217)	(0.305)	(0.062)	(0.099)	(0.004)	(0.007)
GRP growth	-0.002	0.035	-1.760	1.738	0.609	0.504	-0.068**	-0.047
	(0.063)	(0.027)	(1.957)	(1.782)	(0.640)	(0.810)	(0.032)	(0.040)
Market power	-0.942**	0.105**	16.545**	18.433**	-1.190**	-0.622	-0.014	-0.071
	(0.464)	(0.048)	(7.794)	(7.501)	(0.564)	(0.473)	(0.031)	(0.060)
No. of banks	327	242	327	248	327	232	327	232
No. of obs.	2557	863	2808	962	2394	852	2396	853
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
R^2	0.230	0.276	0.274	0.503	0.018	0.025	0.061	0.077
Parallel trend	YES	YES	YES	YES	YES	YES	YES	YES

Note: Significance levels: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Columns labeled as "Full sample" correspond to the regressions on the sample of banks that we consider in our analysis. Columns labeled as "Matched sample" correspond to the regressions on a sample that is restricted to banks that are similar enough, based on a one-to-one nearest neighbour propensity score matching.

The results of the tests of parallel trend hypothesis are displayed at the bottom of Table 2. "YES" means that the null hypothesis of a similar pre-treatment trajectory between treated and control banks cannot be rejected at usual confidence levels. We note that this null hypothesis cannot be rejected in any case. Therefore, differences between treated and untreated, if any, are attributable to the effects of the typhoons and not to any other unobserved causes.

Next, we focus on the specific reactions of rural and commercial banks to typhoons. According to Table A.4 in the Appendix, rural banks are generally smaller (both in terms of assets and number of branches) and more geographically concentrated (with a very low within-variability) than commercial institutions. In particular, they are more exposed to typhoons and have larger shares of affected branches while having a stronger market power compared with commercial banks. Furthermore, the sample split allows to work with two more homogeneous treatment and control groups. Note that state-owned banks cannot be studied alone: not only they are too few, but their strong geographical diversification throughout China implies that they are never categorized as "treated" according to our criteria.

The results for commercial banks only are reported in the columns "Full sample" of Table 3. We can observe that the commercial banks that are exposed to typhoons suffer from a decrease in their liquidity ratios and, to a lesser extent, in their leverage ratios, compared to unaffected commercial banks. These negative bank balance sheet effects are therefore likely to compound the effect of deteriorating creditworthiness to explain their significant slowdown in lending, which reach which reaches 0.016 trillion yuan for a bank of average size, i.e. 3.4% of the average total asset. Such pro-cyclical behavior is likely to amplify the financial effects of the disaster.

Table 3: Baseline results - commercial banks

	Total loans		NPL ratio		Liquidity ratio		Leverage ratio	
	Full sample	Matched sample	Full sample	Matched sample	Full sample	Matched sample	Full sample	Matched sample
Treated × Post_t	-0.016***	-0.014*	-0.001	0.017	-0.044**	-0.002	-0.005*	-0.009*
	(0.005)	(0.007)	(0.155)	(0.171)	(0.019)	(0.014)	(0.003)	(0.005)
No. of branches (Log)	0.037***	0.027***	0.718***	1.280***	0.003	-0.044**	-0.014	-0.022*
	(0.013)	(0.010)	(0.248)	(0.409)	(0.023)	(0.020)	(0.010)	(0.012)
Geog. concentration	0.031	-0.029	-1.502*	-1.527	0.049	-0.143	0.043	0.053
	(0.037)	(0.040)	(0.853)	(1.180)	(0.150)	(0.115)	(0.039)	(0.059)
Unemployment rate	0.014**	0.006	-0.090	0.056	-0.004	-0.013	-0.006	-0.013**
	(0.006)	(0.007)	(0.211)	(0.339)	(0.018)	(0.021)	(0.004)	(0.006)
GRP growth	0.023	-0.012	0.231	3.870***	-0.118	-0.353	-0.061*	-0.116*
	(0.046)	(0.057)	(1.568)	(1.359)	(0.196)	(0.216)	(0.032)	(0.069)
Market power	-0.516	-0.316	-10.050*	-13.018**	-0.582	0.724	0.029	0.053
	(0.351)	(0.255)	(5.107)	(6.570)	(0.770)	(0.648)	(0.161)	(0.258)
No. of banks	124	127	132	126	132	124	132	124
No. of obs.	1243	498	1363	549	1226	501	1225	500
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
R^2	0.316	0.418	0.415	0.535	0.069	0.064	0.116	0.177
Parallel trend	YES	YES	YES	YES	YES	YES	YES	YES

Note: Significance levels: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Columns labelled as "Full sample" correspond to the regressions on the sample of banks that we consider in our analysis. Columns labelled as "Matched sample" correspond to the regressions on a sample that is restricted to banks that are similar enough, based on a one-to-one nearest neighbour propensity score matching.

Next, the columns labeled "Full sample" in Table 4 report the results for rural banks alone. Contrary to affected commercial banks, affected rural banks do not cut lending. This can be explained by a better knowledge of local markets, local borrowers, and local risks, as well as by the long-term relationships facilitated by a local presence (Petersen and Rajan, 1994; Elsas and Krahnen, 1998; Brown et al., 2021; Bolton et al., 2016). In doing so, local banks would act as shock absorbers. Moreover, because of their limited diversification, and probably because they do not cut lending, affected rural banks suffer from an increase in non-performing loans of 0.59 bp (which is twice as much as the estimates for the full sample), compared to the control group. Zhang et al. (2024) also find that rural banks are more exposed to climate risk.

We note certain regularities when analyzing the control variables' signs and coefficients. For example, when significant, the banks' size proxied by the logarithm of the number of branches positively affects the variation of loans and the NPL ratio. The geographic concentration seems to matter especially for the NPL ratio: a higher concentration is associated with fewer

Table 4: Baseline results - rural banks

	Total loans		NPL ratio		Liquidity ratio		Leverage ratio	
	Full sample	Matched sample	Full sample	Matched sample	Full sample	Matched sample	Full sample	Matched sample
Treated × $Post_t$	-0.000	0.002	0.593*	1.577**	0.207	0.013	-0.002	0.013
	(0.001)	(0.001)	(0.301)	(0.666)	(0.170)	(0.035)	(0.005)	(0.012)
No. of branches (Log)	-0.001	-0.001	0.503	0.511	0.018	0.021	-0.001	0.007
	(0.001)	(0.003)	(0.422)	(0.454)	(0.114)	(0.022)	(0.011)	(0.019)
Geog. concentration	-0.043	-0.003	-37.253***	-68.724***	-1.462	-1.334	-0.026	-0.973***
	(0.074)	(0.043)	(11.831)	(24.918)	(0.951)	(0.923)	(0.068)	(0.291)
Unemployment rate	0.002	0.002	-0.010	-0.193	-0.208	-0.029	-0.001	-0.007
	(0.002)	(0.001)	(0.491)	(0.775)	(0.198)	(0.035)	(0.004)	(0.012)
GRP growth	0.007	-0.025	-2.648	-7.196	3.877	-0.081	-0.031	-0.017
	(0.013)	(0.029)	(5.053)	(7.891)	(2.696)	(0.425)	(0.053)	(0.180)
Market power	-0.004	-0.056**	5.635	8.119	-2.049***	-1.240***	0.009	-0.166
	(0.017)	(0.022)	(3.494)	(14.829)	(0.453)	(0.363)	(0.024)	(0.177)
No. of banks	171	58	171	66	171	55	171	55
No. of obs.	1036	129	1198	157	877	132	879	132
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
R^2	0.070	0.683	0.138	0.467	0.026	0.567	0.150	0.187
Parallel trend	YES	-	YES	-	YES	-	YES	-

Note: Significance levels: * p < 0.10 ; ** p < 0.05 ; *** p < 0.01. Columns labelled as "Full sample" correspond to the regressions on the sample of banks that we consider in our analysis. Columns labelled as "Matched sample" correspond to the regressions on a sample that is restricted to banks that are similar enough, based on a one-to-one nearest neighbour propensity score matching.

non-performing loans, which aligns with the hypothesis that geographically concentrated banks have an enhanced local knowledge and this plays a crucial role in managing loan risks effectively. The regional context, specifically regarding unemployment and GRP growth, does not seem to be of primary significance concerning our balance sheet data-dependent variables. Finally, the local market power of a bank seems to increase NPL when considering all banks. This effect is reversed when focusing solely on commercial banks, where higher local market power is associated with a reduction of the NPL amount.

We conduct the same empirical strategy in the absence of controls. Table B.1 in Appendix B shows that the results remain the same.

4.2 Considering alternative control groups

Typhoons are highly localized phenomena. As shown in Figure 3, they usually occur along coasts, where most of China's economic and banking activity is concentrated. Therefore, the set of these treated banks located in southeastern China may differ significantly from untreated banks that are located elsewhere in the country. In this case, our model might capture a pattern in treated banks' behaviors that is not (only) due to typhoon exposure. Table A.5 in the Appendix shows balance statistics for each covariate, while considering all banks, as well as commercial and rural banks only. The tests confirm some differences between treated and control banks.

Hence, a possible pitfall in comparing treated and untreated banks is that they may be structurally different *a priori*. One way to deal with this potential issue is to compare banks that have common structural characteristics. This can be done by defining a control group on the basis of one-to-one nearest-neighbor propensity score matching (PSM). Having more similar groups of treated and untreated reduces unobserved heterogeneity and thus diminishes the risk of having a treatment potentially related to unobservable characteristics. In practical terms, the matching is based on all our control variables and time-fixed effects. Table A.5 in the Appendix shows that the differences in covariates turn out to be rarely significant in the "matched" sample, irrespective of the type of banks. Therefore, PSM ensures independence between the fact to be treated and the control variables.

The DiD results with control groups based on a PSM approach are reported in the columns labeled "Matched sample" in Tables 2 to 4. First, it is worth noting that this method leads to a reduction of the sample size, since the banks for which relevant matching is not possible are ignored. In particular, the number of rural banks under review drops from 171 to 55. In this case, it is no longer feasible to conduct parallel trend tests due to insufficient data.

In general, the results are rather similar to those obtained with the "full sample". First, they confirm a decline in the variation total loans when considering all banks and commercial banks only. The decrease in the liquidity ratio is not significant anymore for commercial banks. Nevertheless, as a decrease in the leverage ratio is confirmed, balance sheet effects cannot be ruled out as an explanatory factor of the credit decline.

Next, we address the issue of structural differences between treated and untreated banks by keeping only banks operating in typhoon-prone regions in the control group. The corresponding results are presented in Table B.2 in the Appendix. They remain the same as in the baseline estimations but without a significant increase in rural banks' NPLs.

Finally, we examine the results when removing from the control group the banks with 25% to 50% of their branches hit by a typhoon. These banks are considered as "non-treated" in our baseline specification, even though they were affected to some extent. Table B.3 in the Appendix shows that removing this grey area of control does not change the results.

4.3 Sensitivity to the definition of treatment

In addition to the various robustness checks conducted so far, the sensitivity analysis in this section focuses on examining more closely the definition of the treatment. Until now, a bank has been defined as "treated" for a period of three years after being actually affected by a typhoon. We now consider a bank as "treated" for a period of two or four years after being hit. The results are presented in Tables B.4 and B.5, respectively. They confirm the initial findings. Interestingly, the deterioration of borrowers' creditworthiness following disasters leads to an increase in non-performing loans for rural banks in the medium term (4-year window), but not in the short term (2-year window).

Furthermore, up until now, we have considered a bank to be affected if more than 50% of its branches were impacted. We modify this threshold to 40% and 60%, respectively. The corresponding results are presented in Tables B.6 and B.7, respectively. Once again, the results are unaffected by these changes.

4.4 Heterogeneous treatment effects

Up to this point, the treatment effects have been considered to be homogenous. Our last robustness checks relax this assumption. We do this to address potential limitations associated with time-fixed effects (TWFE) homogenous estimators (Goodman-Bacon, 2021). TWFE estimators assume constant treatment effects across groups and time, making them suitable for scenarios where lagged treatments influence current outcomes. However, when examining banks before and after a typhoon, allowing for varying and multiple-time hits, we note differences in event intensity and compound disaster composition across years: this can challenge the assumption of homogeneous treatment effects and potentially bias the coefficients. To tackle this, recent robust estimators to heterogeneous treatment effects which assign weights to treatment effects based on selected counterfactuals (as Baker et al. (2022), De Chaisemartin and d'Haultfoeuille (2022) and Roth (2022)) can be used. Among these recent estimators, only De Chaisemartin and d'Haultfoeuille (2022) accommodates treatments turning on and off at different periods, thus having a switching behavior. This makes it particularly suitable for our robustness test. Indeed, this adaptability is crucial for our analysis, if we consider that natural disasters' effects are not permanent once initiated.

The results obtained using De Chaisemartin and d'Haultfoeuille (2022) approach (see Appendix C) can be interpreted as follows. First, we confirm that the impact of NDs on loan variation is significant for all types of banks. While the findings suggest a decrease in loan variation in the case of commercial banks, a substantial increase is found for rural banks. This validates our baseline results suggesting that NDs have a tangible influence on the loan dynamics within Chinese banks, with more pronounced effects in the case of rural banks. Second, as already shown in the above sections, the effects of NDs on the NPLs of rural banks are significant and become visible several years after the event. This lag in impact underlines the importance of considering a medium-term perspective when assessing the consequences of the NDs on rural banks. As in our baseline analysis, the NPLs of commercial banks do not seem to be affected by the NDs. Last, no clear-cut impact of NDs on the liquidity and leverage ratios is found which is rather consistent with our overall results.

Overall, our robustness tests run in this section and the previous ones - that include changes in the composition and size of the sample, alternative treatment effect definitions, or heterogeneous treatment effects - confirm our key results.

5 Banking sector structure and post-typhoon growth

As an extension of our baseline results, we further assess whether the structure of the local banking sector can exert an influence on local economic recovery after a disaster. Noy (2009), Cortés (2014), Brown et al. (2021), and Alvarez-Roman et al. (2023), among others, find that local bank lending is crucial to dampen the negative economic effects of natural disasters. Duqi et al. (2021) show that recovery depends on competition in the banking market. In this vein, and given our previous findings, we assess whether GRP growth is relatively more affected by typhoons in prefectures with only commercial banks.[19]

To conduct this investigation, we need to identify affected areas at the prefecture level, which goes beyond the previous step of determining whether a bank's branch was within the radius of a typhoon. Still assuming that a typhoon affects a territory on a radius of 160km, we use the QGIS software to locate impacted areas at time t. We consider a prefecture as affected when more than 75% of its territory is actually hit. We create a dummy variable $Treated_p$ that is equal to one if the prefecture p is considered as affected, and zero otherwise. The list of the 299 prefectures of our sample, including the 175 prefectures that are treated at least once, is reported in Appendix D.[20] Further, we define $Post_{p,t}$ as a dummy variable that is equal to one during the three years after prefecture p has been treated, and zero otherwise. Last, we create $C_{p,t}$ the "only commercial" dummy variable that is equal to one in a prefecture where there are only commercial branches (and no rural branches at all). Hence, denoting $g_{p,t}$ the GRP growth of prefecture p, the regression is:

$$g_{p,t} = \alpha_p+\tau_t+\gamma_r+\beta_1 C_{p,t}+\beta_2(Treated_p \times Post_{p,t})+\beta_3(Treated_p \times Post_{p,t} \times C_{p,t})+\theta X_{p,t-1}+\varepsilon_{i,t}, \quad (7)$$

where α_p stands for prefecture-level fixed effects, τ_t for time-fixed effects, and γ_r for provincial fixed effects. We are especially interested in the triple interaction with the "only commercial" dummy ($C_{p,t}$): β_3 describes the additional effect of a local banking structure based solely on commercial banks on post-typhoon growth. $X_{p,t}$ designates control variables, i.e. some prefectures' characteristics that are likely to influence the post-disaster growth of GDP, such as the population, the growth of local government expenditures, and the local unemployment rate. These features are lagged one period to deal with possible reverse causality. We also control for the number of state-owned banks' branches in each prefecture p, to take into account their potential role in the post-typhoon growth.

The estimates of Eq. (7) are compiled in Table 5, for local economic growth from one to three years after a typhoon. Regardless of the horizon, we first note that all the covariates are significant, with the expected sign. Most importantly, we find a significant negative additional effect of having only a commercial-based structure (Treated × Post × Only Commercial) on GDP growth. On average, provinces without rural banks suffer from an additional decrease in GRP growth of 1.6 percentage points one year after a typhoon, compared to provinces with rural banks. Such a negative effect remains is also significant 2 and 3 years after the typhoon.[21] Hence, having a banking structure with no rural bank branches is detrimental to post-disaster growth.

[19]Prefectures with only state-owned branches (i.e. without commercial or rural branches at all) are excluded from this extension.

[20]Due to the availability of data on Gross Regional Product growth and the unemployment rate, our sample covers 299 out of the 339 Chinese prefectures.

[21]Note that a positive impact of being treated is found when considering a growth rate three years after the typhoon (but not before). This could be explained by productivity gains related to reconstruction and the replacement of destroyed capital by more productive capital, financed in particular by rural banks.

Table 5: The impact of having only commercial banks on local post-typhoon economic growth

	1 year	2 years	3 years
Treated × $Post_t$	0.704	0.754	1.724***
	(0.581)	(0.637)	(0.598)
Only Commercial	-0.798	-0.883	-0.483
	(0.715)	(0.812)	(0.838)
Treated × $Post_t$ × Only Commercial	-1.627**	-1.296*	-1.927***
	(0.665)	(0.740)	(0.743)
Number of state branches	0.013***	0.013***	0.013***
	(0.002)	(0.002)	(0.003)
Population	0.002**	0.002**	0.002**
	(0.001)	(0.001)	(0.001)
Growth of local government expenditures	5.378***	5.397***	5.402***
	(1.605)	(1.610)	(1.612)
Unemployment rate	-1.515*	-1.537*	-1.496*
	(0.809)	(0.808)	(0.805)
No. of obs.	3265	3265	3265
Bank FE	YES	YES	YES
Province FE	YES	YES	YES
Year FE	YES	YES	YES
R^2	0.526	0.526	0.526

Note: Significance levels: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Columns labelled as "1 year", "2 years" and "3 years" correspond to the different Post period p considered.

6 Considering political objectives and pressure

Another extension of our baseline results consists of assessing the possible influence of political pressure. Generally speaking, the literature acknowledges that political pressures can influence the allocation of credit and banks' performances (Iannotta et al., 2007; Shen and Lin, 2012; Carvalho, 2014; Gropp et al., 2020; Chu and Zhang, 2022). In the Chinese case, political pressure can be internal and/or external. Internal pressure is related to the public ownership of a bank. Wang et al. (2019) claim that, given their specific ownership structure, public banks pursue clearly different objectives than the other financial institutions. External pressure is possible due to certain institutional features. The political regime of China can be viewed as a form of federalism with a high level of economic decentralization but strong political centralization (Persson and Zhuravskaya, 2016). On the one hand, the management of the local economy is fully delegated to the respective local government, which has full responsibility in initiating, implementing, and conducting reforms (Xu, 2011). On the other hand, nominations, promotions, and removals of sub-national officials are fully centralized. Importantly, the promotion system encourages regional officials to follow the policies set by the central government (Wang, 2013; Wang et al., 2019) and is based on local economic performance (Maskin et al., 2000; Chen et al., 2005; Li and Zhou, 2005). This is likely to generate political pressure on banks to lend, especially in the wake of natural disasters (Kang et al., 2021).

We construct two indicators to measure the effects of political pressure. First, internal pressure is proxied by the percentage share of public ownership. We create a dummy that is equal to one if the state ownership of a bank i is higher than 19.5% of its total capital, and zero otherwise. The threshold of 19.5% corresponds to the 75% percentile of the distribution of state ownership in our sample. Second, given the institutional characteristics mentioned above, and following Qian et al. (2011), Wang et al. (2019) and Kang et al. (2021), external pressure faced by banks is supposed to depend on the relative economic performance of prefectures in which they operate.[22] Economic performance in each prefecture p, denoted $S_{p,t}$, is computed as the average of the performances $S_{x,p,t}$ related to economic variables x at time t. $x_{p,t}$ are the GRP growth rate, the fiscal surplus (i.e., local revenues minus local expenditures divided by local GRP), and the unemployment rate.

Like Wang et al. (2019), we assign a value $S_{x,p,t}$ between 0 and 3 to the three economic variables x, according to their values compared to the economic performance of the province P to which the prefecture p belongs.[23] For GRP growth rate and fiscal surplus, this score is

[22] Note that the prefecture level (p) is the second level of administrative division. It is more granular than the regional or provincial level (j) which is considered to compute the control variables. There are 339 prefecture-level areas in China. However, we exclude Taiwan, which contains six prefectures. Therefore, we have 333 prefectures in our sample.

[23] Since competition for political promotions occurs inside provinces, we only compare prefectures belonging to the same province.

computed as

$$S_{x,p,t} = \begin{cases} 0 & \text{if } x_{p,t} \in \left[(V_{P,max} + \bar{V}_P)/2; V_{P,max}\right] \\ 1 & \text{if } x_{p,t} \in \left[\bar{V}_P; (V_{P,max} + \bar{V}_P)/2\right[\\ 2 & \text{if } x_{p,t} \in \left[(\bar{V}_P + V_{P,min})/2; \bar{V}_P\right[\\ 3 & \text{if } x_{p,t} \in \left[V_{P,min}; \bar{V}_P + V_{P,min})/2\right[\end{cases}$$

with $\bar{V}_P$, $V_{P,max}$ and $V_{P,min}$ being respectively the mean, maximum, and minimum values of x in the province P. The higher $S_{x,p,t}$, the lower the economic performances, and so the higher the presumed external political pressure. On the contrary, for the unemployment rate, $S_{x,p,t}$ is computed as

$$S_{x,p,t} = \begin{cases} 0 & \text{if } x_{p,t} \in \left[V_{P,min}; \bar{V}_P + V_{P,min})/2\right[\\ 1 & \text{if } x_{p,t} \in \left[(\bar{V}_P + V_{P,min})/2; \bar{V}\right[\\ 2 & \text{if } x_{p,t} \in \left[\bar{V}_P; (V_{P,max} + \bar{V}_P)/2\right[\\ 3 & \text{if } x_{p,t} \in \left[(V_{P,max} + \bar{V}_P)/2; V_{P,max}\right] \end{cases}$$

Then, the overall score of external political pressure $S_{p,t}$ for prefecture p at time t is defined as the average of the three indicators $S_{x,p,t}$.

Finally, we evaluate the total external political pressure that a bank i might face as a weighted average of the pressure that may affect each of its branches (located in different prefectures) as a proportion of its total activities, such as

$$\mathrm{S}_{i,t} = \sum_{p=1}^{n} S_{p,t} \times r_{i,p,t} \tag{8}$$

where $r_{i,p,t}$ represents the shares of a bank i's branches located in prefecture p, at time t. This indicator of external political pressure can be resumed as follows. The higher the score, the lower the economic performance, and the stronger then external political pressure for the officials to improve the performance of their prefecture.

The impact of potential internal and external political pressure on bank loans is gauged through a triple DiD approach. The baseline model (6) is augmented by an interaction term (*treated* × *Post* × *political pressure*), measuring the relative impact of being hit by a typhoon conditional on the intensity of the political pressure.

The left side of Table 6 reports the results obtained while considering internal pressure. Despite a smaller sample size than for the baseline estimations[24], it is confirmed that being exposed to a typhoon makes commercial banks cut lending, while it is still not the case for rural banks. However, we find that government ownership mitigates the relative decline in lending by typhoon-hit commercial banks. With low state ownership (inferior to 19.5%), commercial banks' loan variation would decrease by 17 billion yuan for an average-size commercial bank. However, this negative impact is largely counteracted by state ownership; state ownership superior to 19.5% would imply a decrease in the variation loans of 3 billion yuan instead for an average-sized commercial bank.

[24]Certain ownership information was missing, especially for rural banks. Similarly, when computing external pressure, some economic performance data at the prefecture level were also incomplete. Lastly, banks were removed from the sample when information was missing for more than 50% of their branches.

Table 6: Influence of internal and external political pressure on the variation of total loans

	Internal pressure (state ownership)			External political pressure		
	All banks	Commercial	Rural	All banks	Commercial	Rural
Treated × $Post_t$	-0.019***	-0.017***	0.000	-0.020**	-0.036***	0.002
	(0.007)	(0.006)	(0.001)	(0.009)	(0.012)	(0.002)
Treated × $Post_t$ × State ownership	0.017**	0.014*	0.002			
	(0.007)	(0.007)	(0.004)			
Treated × $Post_t$ × Political pressure				0.002	0.016**	-0.002
				(0.004)	(0.007)	(0.002)
State ownership	-0.016**	-0.010	0.001			
	(0.007)	(0.007)	(0.002)			
Political pressure				-0.002	0.000	-0.001
				(0.004)	(0.004)	(0.001)
No. of branches (Log)	0.006	0.031**	-0.001	-0.002	0.038**	-0.001
	(0.012)	(0.014)	(0.001)	(0.011)	(0.015)	(0.001)
Geog. concentration	-0.123**	-0.122***	-0.096	0.149*	-0.005	0.005
	(0.051)	(0.046)	(0.096)	(0.079)	(0.046)	(0.019)
Unemployment rate	-0.000	0.011*	0.001	0.001	0.014**	0.003*
	(0.005)	(0.006)	(0.002)	(0.007)	(0.006)	(0.002)
GRP growth	-0.033	-0.027	0.001	0.016	0.044	-0.005
	(0.045)	(0.060)	(0.018)	(0.058)	(0.047)	(0.012)
Market power	-0.333*	-0.457	0.005	-1.916***	-0.691	-0.568
	(0.191)	(0.366)	(0.025)	(0.470)	(0.453)	(0.513)
No. of banks	288	125	155	307	127	162
No. of obs.	1729	903	757	2326	1155	950
Bank FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
R^2	0.042	0.168	0.063	0.278	0.325	0.080

Note: Significance levels: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Columns labeled "Internal pressure" and "External pressure" correspond to the two different indicators considered as mitigating features on bank loans' behavior. Sub-columns "All banks", "Commercial" and "Rural" corresponds to samples based on bank type.

The right side part of Table 6 reports the triple DiD results with external pressure. Once again, it is confirmed that commercial banks affected by a typhoon reduce their lending, compared to unaffected commercial institutions. Nonetheless, as external political pressure intensifies, exposed banks diminish their credit less in comparison with untreated banks. While an average-sized commercial bank cut lending by about 13% of its total assets in the presumed absence of external political pressure (i.e. for a score equal to 0), on the contrary, same-size banks increase their lending by 2.5% if they operate in a context of extreme external political pressure (i.e. with a score equal to 3).[25]

Therefore, a strong influence of political pressure on lending activity in the aftermath of a

[25] For a score equal to 3, $\Delta\text{Loans} = [3 \times 0.016 - 0.036] = 0.012$. Given the mean value of total assets of commercial banks is 0.471 trillion, $\Delta\text{Loans/Total assets} = 2.5\%$.

typhoon cannot be excluded.

7 Concluding remarks

A negative shock exacerbating information asymmetries can be expected to cause a bank credit cut. However, recovery lending may be possible for economic agents who have close ties with strongly locally-anchored banks. Against this background, this study is the first to examine the effect of typhoons on Chinese bank behavior, distinguishing between commercial and rural banks. These two types of institutions differ in terms of size, geographical concentration, and exposure to typhoons. We develop an original and granular measure of the natural disaster (ND) exposure of 327 banks, which relies on two main elements: the precise location of more than 161,000 of their branches, and a comprehensive analysis of the trajectories and intensities of the 23 most severe typhoons that hit China from 2004 to 2019. Basing the exposure measure on typhoon intensity ensures that we assess the response of banks to a strictly exogenous shock.

Our difference-in-difference estimates reveal that, on average, typhoons generate a decrease in lending that accounts for 2.8 percent of total bank assets. Further analysis shows that this decline is primarily due to commercial banks' behavior. This can be seen as the corollary of the exacerbation of information asymmetries, and possibly as a result of the negative effects on banks' balance sheets when they suffer from declining liquidity ratios. On the contrary, rural banks do not reduce their lending. Their stronger local anchorage through lending relationships makes them more prone to provide recovery lending. Moreover, since their activities are less diversified geographically, they have few alternatives but to continue lending to their close clients, even if the latter are adversely affected by typhoons. In doing so, they act as shock absorbers, at the expense of an increase in their NPLs by 0.59 percentage points on average.

We also find that the presence of local banks remains vital in facilitating post-typhoon recovery lending and supporting subsequent regional economic growth. For a given level of exposure, provinces without rural banks experience an additional decrease in GRP growth of 1.6 percentage points, compared to provinces with rural banks, one year after the typhoon.

Finally, we find that state ownership and external political pressure can mitigate the relative decline in lending by commercial banks operating in affected areas.

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A Summary and descriptive statistics

Table A.1: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
All banks					
Loan variation (trillion yuan)	0.05	0.18	-0.51	4.00	2397
Non-performing loan ratio	1.89	2.05	0	47.88	2808
Leverage ratio	0.08	0.05	0	0.81	2396
Liquidity ratio	0.65	0.71	0	21.32	2394
Total assets (trillion yuan)	0.74	2.73	5×10^{-4}	30.11	2396
Number of branches (Log)	4.26	1.47	0	10.61	3270
Geographic concentration	0.85	0.31	0.04	1	3270
Market power	0.01	0.07	0	0.89	3270
Unemployment rate	3.28	0.5	1.20	5.10	3270
Gross regional product growth	0.11	0.05	-0.04	0.3	3270
Commercial banks					
Loan variation (trillion yuan)	0.03	0.08	-0.51	0.70	1243
Non-performing loan ratio	1.56	1.41	0	20.03	1363
Leverage ratio	0.07	0.02	0.02	0.36	1225
Liquidity ratio	0.58	0.12	0	2.51	1226
Total assets (trillion yuan)	0.47	1.09	0	10.22	1226
Number of branches (Log)	4.55	1.08	0	10.60	1495
Geographic concentration	0.84	0.29	0.04	1	1495
Market power	0.006	0.02	10^{-6}	0.53	1495
Unemployment rate	3.40	0.48	1.30	5.10	1495
Gross regional product growth	0.11	0.05	-0.04	0.30	1495
Rural banks					
Loan variation (trillion yuan)	0.005	0.01	-0.07	0.21	1036
Non-performing loan ratio	2.24	2.18	0.06	47.88	1198
Leverage ratio	0.09	0.03	0	0.46	879
Liquidity ratio	0.64	0.90	0.25	21.31	877
Total assets (trillion yuan)	0.07	0.14	0.0005	1.03	879
Number of branches (Log)	3.84	1.10	0	7.60	1433
Geographic concentration	0.10	0.04	0.54	1	1433
Market power	0.01	0.08	6×10^{-8}	0.89	1433
Unemployment rate	3.18	0.51	1.20	4.40	1433
Gross regional product growth	0.11	0.04	0.005	0.26	1433

Table A.2: Cross-correlation table

Variables	Number of branches (Log.)	Geographic concent.	Unemploy. rate	GRP growth	Local market power
Number of branches (Log.)	1.000				
Geographic concentration	-0.458	1.000			
Unemployment rate	-0.011	0.046	1.000		
GRP growth	-0.017	-0.033	0.221	1.000	
Local market power	0.475	-0.144	-0.006	0.083	1.000

Table A.3: Mean differences between treated and untreated one year before a typhoon

Variable	Treated Mean (SE)	Non-treated Mean (SE)	t-test Difference (1)-(2)	Normalized difference (1)-(2)
Total loan	106.783	124.976	-18.193	-0.061
	(11.286)	(17.524)		
Non performing loans	36.031	17.514	18.518	0.057
	(12.532)	(6.731)		
Leverage ratio	4.134	1.604	2.530	0.073
	(1.339)	(1.700)		
Liquidity ratio	1.865	0.012	1.853	0.056
	(1.293)	(1.137)		
No. of branches (Log)	2.001	2.006	-0.005	-0.001
	(0.142)	(0.341)		
Geog. concentration	-1.747	-0.677	-1.070***	0.235
	(0.155)	(0.144)		
Unemployment rate	-1.531	-1.230	-0.301	-0.055
	(0.180)	(0.310)		
GRP growth	51.372	16.782	34.590	0.026
	(46.632)	(6.571)		
Market power	7.039	9.214	-2.176	-0.054
	(1.307)	(2.417)		

Note: ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.
Normalized difference larger than 0.25 indicates that the difference is significantly different from 0.

Table A.4: Main characteristics of commercial and rural banks

Variables	**Commercial**	**Rural**
Geographic concentration	0.835	0.996
	(0.28)	(0.04)
Percentage of affected branches	41.66	85.77
	(35.22)	(28.11)
Number of typhoons	2.35	4.27
	(3.07)	(2.37)
Total assets (Log)	25.62	23.92
	(1.47)	(1.48)
Number of branches	208.76	96.43
	(1082.30)	(210.91)
Market power	0.0064	0.0145
	(0.1939)	(0.0767)
Return on assets	0.90	1.09
	(0.40)	(0.58)
State ownership	22.50	1.28
	(23.26)	(5.99)

Note: This table reports the mean value of the mentioned variables for both commercial and rural banks, as well as their standard deviation in parentheses.

Table A.5: Covariates balance

Variables	Sample	Treated	Control	Diff
All banks				
Number of branches (Log)	Full	4.0293	4.7289	-0.6996***
	Matched	4.1584	4.0728	0.0856
Geographic concentration	Full	0.9487	0.6396	0.3091***
	Matched	0.9161	0.9210	-0.0049
Unemployment rate	Full	3.2185	3.4103	-0.1918***
	Matched	3.4231	3.3965	0.0266
GRP growth	Full	0.1093	0.1143	-0.0050***
	Matched	0.1101	0.1082	0.0019
Market power	Full	0.0055	0.0310	-0.0255***
	Matched	0.0092	0.0127	-0.0035
Commercial banks				
Number of branches (Log)	Full	4.4608	4.6593	-0.1985***
	Matched	4.5631	4.4353	0.1278
Geographic concentration	Full	0.8783	0.7798	0.0985***
	Matched	0.8427	0.8717	-0.0290
Unemployment rate	Full	3.2987	3.5379	-0.2392***
	Matched	3.4359	3.4733	-0.0374
GRP growth	Full	0.1097	0.1139	-0.0042
	Matched	0.1082	0.1067	0.0015
Market power	Full	0.0058	0.0070	-0.0010
	Matched	0.0065	0.0066	-0.0001
Rural banks				
Number of branches (Log)	Full	3.7635	4.5204	-0.7569***
	Matched	4.0091	3.8837	0.1254
Geographic concentration	Full	0.9979	0.9725	0.0254***
	Matched	0.9908	0.9954	-0.0046
Unemployment rate	Full	3.1659	3.3105	-0.1456***
	Matched	3.5306	3.4435	0.0871
GRP growth	Full	0.1081	0.1142	-0.0061
	Matched	0.1153	0.1104	0.0049
Market power	Full	0.0051	0.1040	-0.0989***
	Matched	0.01650	0.0198	-0.0033

Significance of the difference are: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

B Additional results and robustness checks

Table B.1: Baseline results without controls

	Loans			NPL ratio		
	All banks	Com. banks	Rural banks	All banks	Com. banks	Rural banks
Treated × Post_t	-0.019***	-0.015***	-0.000	0.220	-0.046	0.675**
	(0.005)	(0.005)	(0.001)	(0.157)	(0.160)	(0.320)
R^2	0.188	0.288	0.067	0.218	0.390	0.121
	Liquidity ratio			**Leverage ratio**		
	All banks	Com. banks	Rural banks	All banks	Com. banks	Rural banks
Treated × Post_t	0.079	-0.044**	0.175	-0.002	-0.005	-0.002
	(0.065)	(0.018)	(0.154)	(0.003)	(0.003)	(0.005)
R^2	0.016	0.068	0.019	0.022	0.057	0.148

Significance levels are: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Individual and time FE are included.

Table B.2: Results with a sample restricted to affected regions only

	Total loans			NPL ratio			Liquidity ratio			Leverage ratio		
	All banks	Com. banks	Rural banks	All banks	Com. banks	Rural banks	All banks	Com. banks	Rural banks	All banks	Com. banks	Rural banks
Treated × $Post_t$	-0.019**	-0.011***	0.001	0.242	-0.097	0.471	0.114	-0.048**	0.232	-0.001	-0.001	-0.001
	(0.007)	(0.004)	(0.001)	(0.164)	(0.162)	(0.306)	(0.084)	(0.022)	(0.189)	(0.002)	(0.003)	(0.003)
No. of branches (Log)	0.004	0.040**	0.001	0.551***	0.428**	2.851***	-0.023	0.007	0.032	-0.003	-0.005	0.005
	(0.020)	(0.017)	(0.003)	(0.192)	(0.209)	(1.068)	(0.068)	(0.030)	(0.212)	(0.004)	(0.009)	(0.018)
Geog. concentration	0.224***	0.035	-0.048	-2.549***	-1.421	-12.522*	-0.316	0.099	-1.544	0.057	0.062	-0.068
	(0.073)	(0.044)	(0.082)	(0.971)	(0.954)	(6.462)	(0.360)	(0.180)	(1.448)	(0.043)	(0.046)	(0.067)
Unemployment rate	0.002	0.008	0.000	0.404*	0.231	0.452	-0.060	-0.010	-0.265	-0.004	-0.007	-0.001
	(0.009)	(0.007)	(0.001)	(0.234)	(0.261)	(0.454)	(0.065)	(0.022)	(0.227)	(0.004)	(0.005)	(0.004)
GRP growth	-0.026	0.095	0.000	-2.185	0.773	-2.501	1.299	-0.014	6.291	-0.055	-0.045	-0.068*
	(0.094)	(0.059)	(0.014)	(2.939)	(2.255)	(6.549)	(1.224)	(0.410)	(4.458)	(0.036)	(0.046)	(0.035)
Market power	-1.599***	-1.105	0.048***	26.978***	1.153	18.659***	-0.780	-1.737	-1.669	-0.054*	-0.294	-0.073**
	(0.341)	(0.689)	(0.008)	(5.586)	(8.005)	(7.071)	(0.815)	(2.396)	(1.155)	(0.031)	(0.246)	(0.029)
No. of banks	238	87	143	238	87	143	238	87	143	238	87	143
No. of obs	1859	842	862	2059	911	996	1673	834	710	1674	833	711
Individual FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
R^2	0.265	0.390	0.182	0.270	0.366	0.094	0.024	0.119	0.030	0.115	0.116	0.200

Significance levels are: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

Table B.3: Results when excluding from the control group banks that have 25% to 50% of their branches affected

	Total loans			NPL ratio			Liquidity ratio			Capital ratio		
	All banks	Com. banks	Rural banks	All banks	Com. banks	Rural banks	All banks	Com. banks	Rural banks	All banks	Com. banks	Rural banks
Treated × $Post_t$	-0.020***	-0.011**	-0.001	0.332**	0.084	0.531*	0.085	-0.039**	0.214	-0.002	-0.004	-0.002
	(0.007)	(0.005)	(0.001)	(0.161)	(0.163)	(0.299)	(0.070)	(0.016)	(0.175)	(0.003)	(0.003)	(0.005)
No. of branches (Log)	-0.010	0.007	-0.001	0.392*	0.358*	0.489	-0.025	-0.003	0.023	-0.009	-0.010	-0.002
	(0.009)	(0.008)	(0.001)	(0.228)	(0.193)	(0.414)	(0.045)	(0.018)	(0.117)	(0.006)	(0.010)	(0.011)
Geog. concentration	0.291***	-0.088***	-0.010	-4.502***	-2.800***	-33.161***	-0.201	-0.030	-1.663	0.013	-0.010	-0.005
	(0.107)	(0.025)	(0.061)	(1.228)	(0.957)	(12.460)	(0.508)	(0.155)	(1.052)	(0.025)	(0.020)	(0.067)
Unemployment rate	0.008	0.009	0.002	-0.066	-0.159	0.041	-0.088	-0.014	-0.212	-0.009**	-0.009**	-0.001
	(0.007)	(0.006)	(0.002)	(0.224)	(0.217)	(0.497)	(0.065)	(0.017)	(0.203)	(0.004)	(0.004)	(0.004)
GRP growth	0.001	-0.013	0.010	-1.382	0.333	-2.249	0.656	-0.129	4.193	-0.051*	-0.046*	-0.041
	(0.065)	(0.039)	(0.013)	(1.947)	(1.458)	(5.383)	(0.651)	(0.178)	(2.853)	(0.027)	(0.028)	(0.055)
Market power	-0.990**	-0.016	-0.016**	14.315*	-4.431	2.953**	-1.188**	-0.593	-2.210***	-0.020	0.044	0.018
	(0.480)	(0.144)	(0.008)	(7.868)	(4.240)	(1.324)	(0.578)	(0.696)	(0.409)	(0.031)	(0.168)	(0.020)
No. of banks	312	122	168	312	122	168	312	122	168	312	122	168
No. of obs.	2358	1097	1015	2608	1212	1174	2208	1087	856	2209	1086	858
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
R^2	0.223	0.159	0.077	0.284	0.462	0.118	0.019	0.110	0.027	0.048	0.088	0.149

Significance levels are: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table B.4: Results when considering that the treatment lasts 2 years

	Total loans			NPL ratio			Liquidity ratio			Leverage ratio		
	All banks	Com. banks	Rural banks	All banks	Com. banks	Rural banks	All banks	Com. banks	Rural banks	All banks	Com. banks	Rural banks
Treated × $Post_t$	-0.013***	-0.011**	-0.000	0.172	-0.018	0.277	0.044	-0.044**	0.082	-0.003	-0.005	0.000
	(0.005)	(0.004)	(0.001)	(0.121)	(0.120)	(0.224)	(0.059)	(0.017)	(0.147)	(0.003)	(0.003)	(0.003)
No. of branches (Log)	-0.003	0.037***	-0.001	0.556**	0.718***	0.510	-0.011	0.004	0.067	-0.008	-0.014	-0.002
	(0.011)	(0.013)	(0.001)	(0.276)	(0.248)	(0.437)	(0.051)	(0.023)	(0.103)	(0.006)	(0.010)	(0.011)
Geog. concentration	0.239***	0.029	-0.043	-3.327***	-1.498*	-37.356***	-0.144	0.047	-1.452	0.050	0.043	-0.025
	(0.077)	(0.037)	(0.074)	(1.017)	(0.855)	(11.901)	(0.348)	(0.149)	(0.907)	(0.033)	(0.039)	(0.067)
Unemployment rate	0.009	0.014**	0.002	-0.013	-0.090	0.019	-0.078	-0.004	-0.196	-0.006*	-0.006	-0.001
	(0.007)	(0.006)	(0.002)	(0.218)	(0.211)	(0.494)	(0.062)	(0.018)	(0.193)	(0.004)	(0.004)	(0.004)
GRP growth	-0.007	0.019	0.008	-1.687	0.240	-2.934	0.633	-0.123	3.895	-0.068**	-0.061*	-0.030
	(0.063)	(0.046)	(0.013)	(1.949)	(1.571)	(5.079)	(0.649)	(0.196)	(2.789)	(0.032)	(0.032)	(0.053)
Market power	-0.945**	-0.512	-0.004	16.637**	-10.048*	5.943*	-1.174**	-0.555	-1.956***	-0.014	0.032	0.007
	(0.464)	(0.353)	(0.017)	(7.806)	(5.109)	(3.589)	(0.565)	(0.771)	(0.467)	(0.031)	(0.163)	(0.024)
No. of banks	327	132	171	327	132	171	327	132	171	327	132	171
No. of obs	2557	1243	1036	2808	1363	1198	2394	1226	877	2396	1225	879
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
R^2	0.230	0.313	0.070	0.273	0.415	0.135	0.018	0.070	0.024	0.062	0.117	0.149

Significance levels are: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

Table B.5: Results when considering that the treatment lasts 4 years

	Total loans			NPL ratio			Liquidity ratio			Leverage ratio		
	All banks	Com. banks	Rural banks	All banks	Com. banks	Rural banks	All banks	Com. banks	Rural banks	All banks	Com. banks	Rural banks
Treated × $Post_t$	-0.024***	-0.018***	-0.000	0.291	-0.045	0.641*	0.081	-0.053**	0.232	-0.003	-0.005	-0.002
	(0.007)	(0.005)	(0.001)	(0.179)	(0.190)	(0.333)	(0.068)	(0.023)	(0.190)	(0.003)	(0.003)	(0.005)
No. of branches (Log)	-0.003	0.037***	-0.001	0.563**	0.717***	0.504	-0.009	0.003	0.011	-0.008	-0.014	-0.001
	(0.011)	(0.013)	(0.001)	(0.277)	(0.248)	(0.419)	(0.051)	(0.023)	(0.113)	(0.006)	(0.010)	(0.011)
Geog. concentration	0.241***	0.031	-0.043	-3.352***	-1.490*	-37.396***	-0.153	0.051	-1.507	0.050	0.043	-0.025
	(0.077)	(0.037)	(0.074)	(1.017)	(0.854)	(11.827)	(0.352)	(0.150)	(0.995)	(0.033)	(0.039)	(0.068)
Unemployment rate	0.009	0.014**	0.002	-0.023	-0.090	-0.034	-0.080	-0.003	-0.214	-0.006	-0.006	-0.001
	(0.007)	(0.006)	(0.002)	(0.217)	(0.211)	(0.491)	(0.063)	(0.018)	(0.202)	(0.004)	(0.004)	(0.004)
GRP growth	-0.006	0.021	0.007	-1.698	0.253	-2.628	0.627	-0.123	3.909	-0.068**	-0.062*	-0.031
	(0.063)	(0.046)	(0.013)	(1.947)	(1.564)	(5.044)	(0.650)	(0.197)	(2.719)	(0.032)	(0.033)	(0.054)
Market power	-0.940**	-0.526	-0.003	16.535**	-10.101**	5.572	-1.195**	-0.599	-2.078***	-0.014	0.029	0.010
	(0.464)	(0.349)	(0.018)	(7.794)	(5.101)	(3.473)	(0.566)	(0.773)	(0.470)	(0.031)	(0.161)	(0.024)
No. of banks	327	132	171	327	132	171	327	132	171	327	132	171
No. of obs.	2557	1243	1036	2808	1363	1198	2394	1226	877	2396	1225.000	879
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
R^2	0.231	0.317	0.070	0.274	0.415	0.139	0.018	0.072	0.026	0.061	0.115	0.150

Significance levels are: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

Table B.6: Results when considering banks as treated when 40% of their branches are hit

	Total loans			NPL ratio			Liquidity ratio			Capital ratio		
	All banks	Com. banks	Rural banks	All banks	Com. banks	Rural banks	All banks	Com. banks	Rural banks	All banks	Com. banks	Rural banks
Treated × $Post_t$	-0.019***	-0.025***	0.000	0.206	-0.116	0.585*	0.052	-0.048**	0.206	-0.005	-0.007**	-0.002
	(0.005)	(0.008)	(0.001)	(0.170)	(0.180)	(0.304)	(0.059)	(0.021)	(0.171)	(0.003)	(0.003)	(0.005)
No. of branches (Log)	-0.004	0.036***	-0.001	0.561**	0.711***	0.502	-0.010	0.001	0.013	-0.008	-0.014	-0.001
	(0.011)	(0.013)	(0.001)	(0.278)	(0.247)	(0.421)	(0.052)	(0.022)	(0.113)	(0.006)	(0.010)	(0.011)
Geog. concentration	0.240***	0.032	-0.043	-3.352***	-1.472*	-37.306***	-0.150	0.051	-1.487	0.051	0.044	-0.026
	(0.077)	(0.036)	(0.074)	(1.022)	(0.856)	(11.829)	(0.352)	(0.150)	(0.952)	(0.033)	(0.038)	(0.068)
Unemployment rate	0.009	0.015**	0.002	-0.017	-0.091	-0.015	-0.079	-0.004	-0.210	-0.006	-0.006	-0.001
	(0.007)	(0.006)	(0.002)	(0.218)	(0.211)	(0.491)	(0.062)	(0.018)	(0.200)	(0.004)	(0.004)	(0.004)
GRP growth	-0.002	0.029	0.008	-1.730	0.311	-2.703	0.621	-0.117	3.855	-0.067**	-0.060*	-0.031
	(0.062)	(0.046)	(0.013)	(1.955)	(1.555)	(5.055)	(0.640)	(0.197)	(2.678)	(0.032)	(0.032)	(0.053)
Market power	-0.943**	-0.507	-0.004	16.608**	-10.080**	5.617	-1.179**	-0.581	-2.058***	-0.013	0.027	0.010
	(0.465)	(0.350)	(0.017)	(7.813)	(5.070)	(3.486)	(0.564)	(0.773)	(0.460)	(0.031)	(0.160)	(0.024)
No. of banks	327	132	171	327	132	171	327	132	171	327	132	171
No. of obs.	2557	1243	1036	2808	1363	1198	2394	1226	877	2396	1225	879
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
R^2	0.230	0.327	0.070	0.273	0.416	0.138	0.018	0.072	0.026	0.063	0.119	0.150

Significance levels are: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

Table B.7: Results when considering banks as treated when 60% of their branches are hit

	Total loans			NPL ratio			Liquidity ratio			Capital ratio		
	All banks	Com. banks	Rural banks	All banks	Com. banks	Rural banks	All banks	Com. banks	Rural banks	All banks	Com. banks	Rural banks
Treated × Post_t	-0.022***	-0.019**	-0.001	0.293*	-0.004	0.614**	0.087	-0.032*	0.210	-0.003	-0.005	-0.002
	(0.007)	(0.008)	(0.001)	(0.156)	(0.146)	(0.304)	(0.064)	(0.016)	(0.169)	(0.003)	(0.003)	(0.005)
No. of branches (Log)	-0.004	0.037***	-0.001	0.568**	0.718***	0.503	-0.008	0.002	0.016	-0.008	-0.014	-0.001
	(0.011)	(0.013)	(0.001)	(0.279)	(0.248)	(0.421)	(0.051)	(0.022)	(0.114)	(0.006)	(0.010)	(0.011)
Geog. concentration	0.242***	0.033	-0.044	-3.385***	-1.500*	-37.403***	-0.162	0.048	-1.461	0.051	0.043	-0.026
	(0.077)	(0.037)	(0.074)	(1.023)	(0.854)	(11.832)	(0.353)	(0.150)	(0.951)	(0.033)	(0.039)	(0.068)
Unemployment rate	0.009	0.015**	0.002	-0.024	-0.090	-0.003	-0.082	-0.002	-0.208	-0.006	-0.006	-0.001
	(0.007)	(0.006)	(0.002)	(0.217)	(0.210)	(0.491)	(0.063)	(0.018)	(0.198)	(0.004)	(0.004)	(0.004)
GRP growth	0.003	0.032	0.007	-1.808	0.234	-2.672	0.594	-0.118	3.876	-0.067**	-0.060*	-0.031
	(0.062)	(0.041)	(0.013)	(1.965)	(1.557)	(5.045)	(0.633)	(0.194)	(2.693)	(0.032)	(0.032)	(0.054)
Market power	-0.941**	-0.502	-0.003	16.529**	-10.048*	5.607	-1.199**	-0.535	-2.050***	-0.014	0.034	0.010
	(0.463)	(0.358)	(0.018)	(7.793)	(5.113)	(3.477)	(0.564)	(0.764)	(0.451)	(0.031)	(0.163)	(0.024)
No. of banks	327	132	171	327	132	171	327	132	171	327	132	171
No. of obs.	2557	1243	1036	2808	1363	1198	2394	1226	877	2396	1225	879
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
R^2	0.231	0.320	0.070	0.274	0.415	0.139	0.018	0.065	0.026	0.061	0.115	0.150

Significance levels are: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

C Heterogeneous treatment effect - De Chaisemartin and d'Haultfoeuille (2022)'s estimator

The figure plots the estimated coefficients and their 90% confidence using the estimator proposed by De Chaisemartin and d'Haultfoeuille (2022).

Figure C.1: Loans - Chaisemartin et d'Hautfoeuille (2022)'s estimator

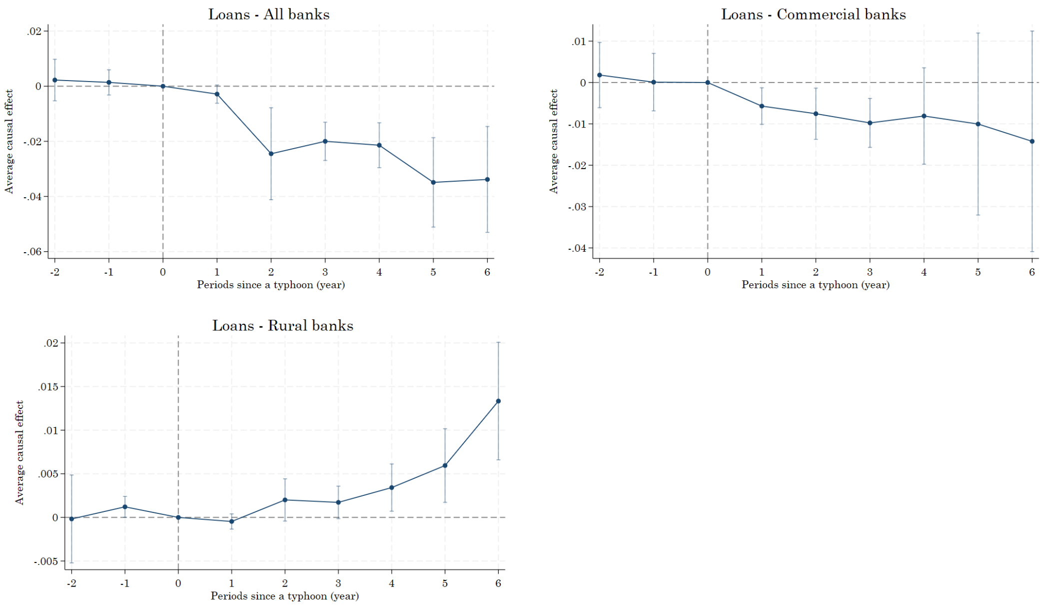


Figure C.2: NPL ratio - Chaisemartin et d'Hautfoeuille (2022)'s estimator

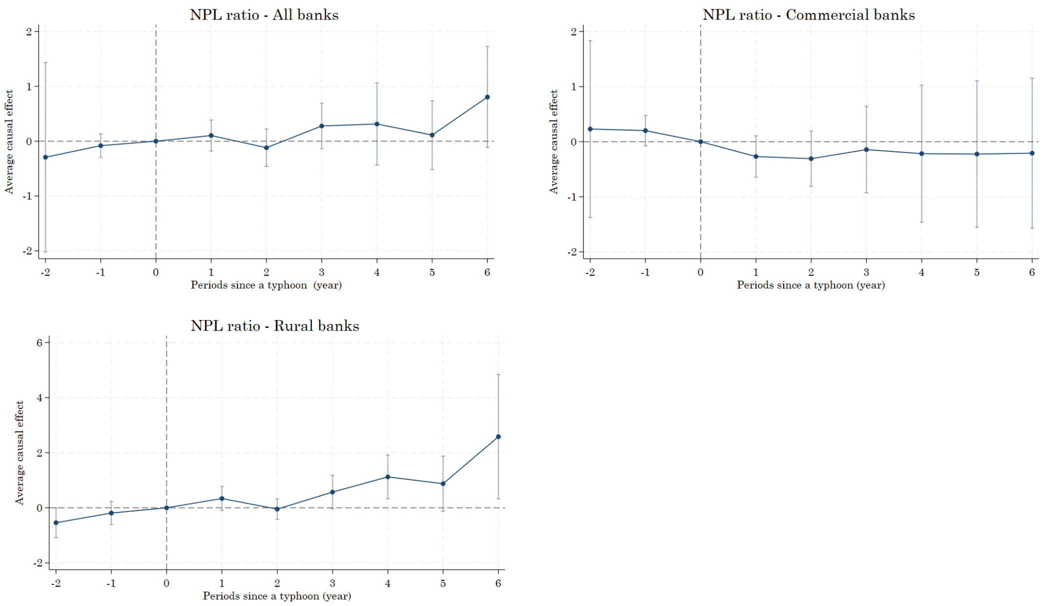


Figure C.3: Liquidity ratio - Chaisemartin et d'Hautfoeuille (2022)'s estimator

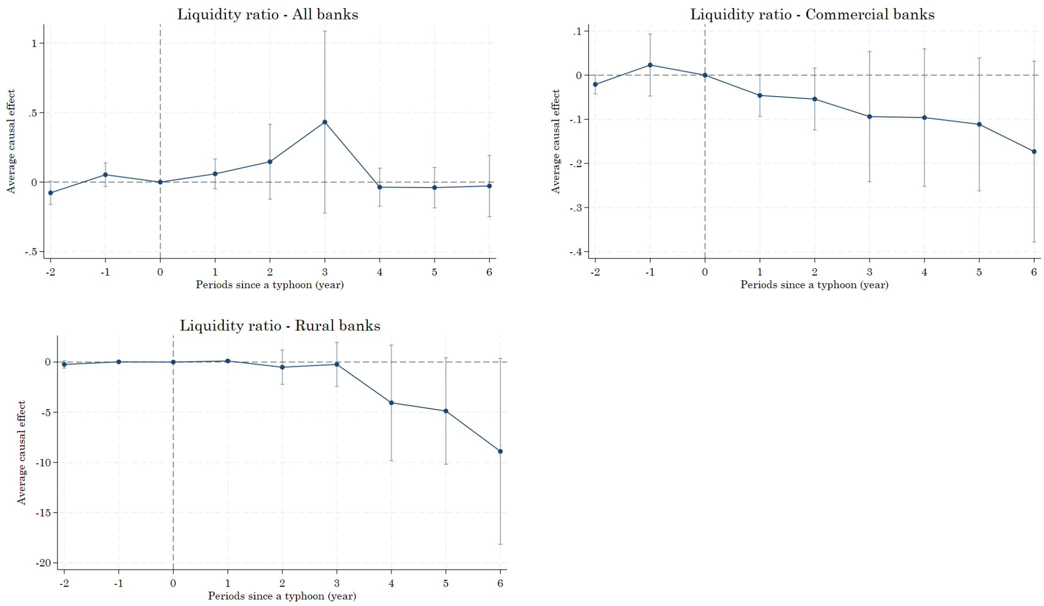
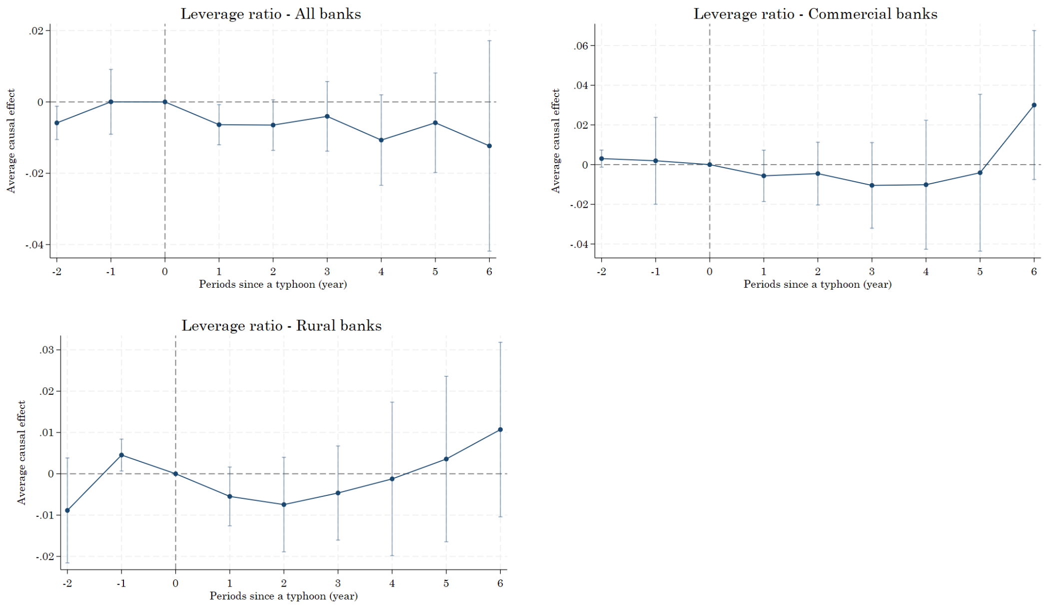


Figure C.4: Leverage ratio - Chaisemartin et d'Hautfoeuille (2022)'s estimator



D List of the Chinese prefectures by regions

In this appendix, we present the Chinese regions and their prefectures included in our analysis. Prefectures are designated as "prefectures, prefecture-level cities", "autonomous prefectures", and "leagues". Those that have indeed been affected by at least one typhoon are in bold characters.

- Anhui Province: **Anqing**, **Bengbu**, **Bozhou**, **Chizhu**, **Chuzhou**, **Fuyang**, **Hefei**, **Huaibei**, **Huainan**, **Huangshan**, **Lu'an**, **Maanshan**, Suzhou, **Tongling**, **Wuhu**, **Xuancheng**
- Fujian Province: **Fuzhou**, **Longyan**, **Nanping**, **Ningde**, **Putian**, **Quanzhou**, **Sanming**, **Xiamen**, **Zhangzhou**
- Gansu Province: Dingxi, Jiayuguan, Jinchang, Jiuquan, Lan'Zhou, Longnan, Pingliang, Qingyang, Silver, Tianshui, Wuwei, Zhangye
- Guangdong Province : **Chaozhou**, **Dongguan**, **Foshan**, **Guangzhou**, **Heyuan**, **Huizhou**, **Jiangmen**, **Jieyang**, **Maoming**, **Meizhou**, **Qingyuan**, **Shaoguan**, **Shenzhen**, **Yangjiang**, **Yunfu**, **Zhanjiang**, **Zhaoqing**, **Zhongshan**, **Zhuhai**, **Shantou**
- Guangxi Zhuang Autonomous Region: **Baise**, **Beihai**, **Chongzuo**, **Fangchenggang**, **Guigang**, **Guilin**, **Hechi**, **Hezhou**, **Laibin**, **Liuzhou**, **NanNing**, **Qinzhou**, **Wuzhou**, Yulin
- Guizhou Province: **Anshun**, Bijie, **Guiyang**, Liupanshui, **Tongren**, Zunyi
- Hainan: **Haikou**, **Sanya**
- Hebei Province: Baoding, **Cangzhou**, **Chengde**, Handan, Hengshui, **Langfang**, **Qinhuangdao**, Shijiazhuang, **Tangshan**, Xingtai, Zhangjiakou
- Heilongjiang Province: Daqing, Daxinganling, **Harbin**, **Hegang**, Heihe, **Jiamusi**, Jixi, **Mudanjiang**, Qiqihar, Qitaihe, **Shuangyashan**, **Suihua**, Yichun
- Henan Province: Anyang, Hebi, Jiaozuo, **Kaifeng**, **Luohe**, Luoyang, **Nanyang**, Pingdingshan, **Puyang**, Sanmenxia, **Shangqiu**, **Xinxiang**, **Xinyang**, **Xuchang**, **Zhengzhou**, **Zhoukou**, **Zhumadian**
- Hubei Province: **Ezhou**, **Huanggang**, **Huangshi**, **Jingmen**, **Jingzhou**, Shiyan, **Suizhou**, **Wuhan**, **Xiangyang**, **Xianning**, **Xiaogan**, Yichang
- Hunan Province: **Changde**, **Changsha**, **Chenzhou**, **Hengyang**, **Huaihua**, **Loudi**, **Shaoyang**, **Xiangtan**, **Yiyang**, **Yongzhou**, **Yueyang**, Zhangjiajie, **Zhuzhou**
- Inner Mongolia Autonomous Region: Alxa League, Baotou, Bayannur, Chifeng, Hohhot, Hulunbeir, Ordos, Tongliao, Wuhai, Wulanchabu, Xilin Gol League, Xing'an League

- Jiangsu Province: **Changzhou**, **Huaian**, **Lianyungang**, **Nanjing**, **Nantong**, **Suqian**, **Suzhou**, Taizhou, **Wuxi**, **Xuzhou**, **Yancheng**, **Yangzhou**, **Zhenjiang**
- Jiangxi Province: **Fuzhou**, **Ganzhou**, **Ji'an**, **Jingdezhen**, **Jiujiang**, **Nanchang**, **Pingxiang**, **Shangrao**, **Xinyu**, **Yichun**, **Yingtan**
- Jilin Province: **Baicheng**, **Baishan**, Changchun, **Jilin**, **Liaoyuan**, Siping, **Songyuan**, **Tonghua**, Yanbian Korean Autonomous Prefecture
- Lioaning Province: **Anshan**, **Benxi**, **Chaoyang**, **Dalian**, **Dandong**, **Fushun**, Fuxin, Huludao, Jinzhou, Liaoyang, Panjin, Shenyang, Tieling, **Yingkou**
- Ningxia Hui Autonomous Region: Guyuan, Shizuishan, Wuzhong, Yinchuan, Zhongwei
- Qinghai Province: Haidong, Xining
- Shaanxi Province: Ankang, Baoji, Hanzhong, Shangluo, Tongchuan, Weinan, Xi'an, Xianyang, Yan'an, **Yulin**
- Shandong Province: **Binzhou**, **Yantai**, **Dezhou**, **Dongying**, **Heze**, **Jinan**, **Jining**, **Liaocheng**, **Linyi**, **Qingdao**, **Rizhao**, **Tai'an**, **Weifang**, **Weihai**, **Zaozhuang**, **Zibo**
- Shanxi Province: Changzhi, Datong, Jincheng, Jinzhong, Linfen, Luliang, Shuozhou, Taiyuan, Xinzhou, Yangquan, Yuncheng
- Sichuan Province: Aba Tibetan and Qiang Autonomous Prefecture, Bazhong, Chengdu, Dazhou, Deyang, Ganzi Tibetan Autonomous Prefecture, Guang'an, Guangyuan, Leshan, Liangshan Yi Autonomous Prefecture, Luzhou, Meishan, Mianyang, Nanchong, Neijiang, Panzhihua, Suining, Ya'an, Yibin, Zigong, Ziyang
- Tibet Autonomous Region: Lhasa
- Xinjiang Uygur Autonomous Region: Changji Hui Autonomous Prefecture, Hami, Karamay, Turpan, Urumqi
- Yunnan Province: Baoshan, Chuxiong Yi Autonomous Prefecture, Dali Bai Autonomous Prefecture, Dehong Dai and Jingpo Autonomous Prefecture, **Honghe Hani and Yi Autonomous Prefecture**, Kunming, Lijiang, **Lincang**, **Pu'er**, Qujing, **Xishuangbanna Dai Autonomous Prefecture**, **Yuxi**, Zhaotong
- Zhejiang Province: **Hangzhou**, **Huzhou**, **Jiaxing**, **Jinhua**, **Lishui**, **Ningbo**, **Quzhou**, **Shaoxing**, **Taizhou**, **Wenzhou**, **Zhoushan**