Climatic Change (2023) 176:125
https://doi.org/10.1007/s10584-023-03599-w

Resilience to extreme weather events and local financial structure of prefecture-level cities in China

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Received: 27 January 2023 / Accepted: 8 August 2023 / Published online: 30 August 2023

Abstract
We study the local economic impacts of extreme weather events and the role of local finance in economic resilience. We use data on the physical intensities of extreme wind and precipitation events for 284 prefecture-level cities in China between 2004 and 2013. We estimate impulse response functions using a bias-corrected method of moments estimator to capture the dynamic responses of affected cities up to 5 years after such events. We find that extreme precipitation events depress the growth of local GDP per capita for multiple years, while the negative effects of storms vanish after the first year. We then use this model to measure the economic resilience of cities to extreme weather events. Regressions of economic resilience on indicators of the local financial structure suggest that cities with higher levels of debt are less resilient. Moreover, the presence of state-owned commercial banks appears to be instrumental to regional economic resilience. As extreme weather events are expected to become more frequent and severe due to climate change, our results inform the emerging debate about regional economic resilience to weather-related shocks.

Keywords China · Climate change · Economic resilience · Extreme weather events · Local economic impacts · Local finance

1 Introduction

In recent decades, China has experienced extraordinary economic development, transforming itself from an agrarian economy to a global economic powerhouse (Duffie 2020). At the same time, China is among the countries that experience the highest number of weather-related disasters in the world (World Bank and GFDRR 2020). The oftentimes disastrous consequences for people's economic well-being and livelihoods emphasize the need to understand and contain the impacts of such events, which are projected to become more frequent and severe as a result of climate change (Intergovernmental Panel on Climate Change 2022).

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In this paper, we study the economic impacts of extreme weather events at the local level for 284 prefecture-level cities in China between 2004 and 2013. Moreover, we explore the relationship between resilience of affected cities and local finance, using variation in pre-event levels of debt and local banking structure as proxies for the latter. We contribute to different strands of literature.

First, studies of the indirect economic effects of natural hazard shocks frequently focus on high levels of spatial aggregation, while deploying measures of event intensity that are constructed from direct impacts. Natural hazards, however, are inherently local by nature (Botzen et al. 2019), and using direct damage measures can bias the results due to endogeneity (Felbermayr and Gröschl 2014). Therefore, we add to the recent stream of literature that addresses these issues (e.g., Felbermayr et al. 2022) by presenting—to the best of our knowledge—the first study with a comprehensive focus on the impacts of multiple hazards on Chinese prefecture-level cities using credibly exogenous measures of physical intensities to quantify and control for the size and severity of the shocks.

Second, in light of progressing climate change, the academic and societal interest in resilience towards climate-related extremes is increasing rapidly. Resilience, however, has to be defined carefully to match the context in which it is discussed, and—consequently—it is hard to measure resilience precisely (Moser et al. 2019). We propose a simple approach to quantify and assess economic resilience in the context of natural hazards by comparing the actual economic outcomes of a city relative to its expected outcome given the physical intensity of the shock it experienced. This measure of resilience is useful to understand the economic consequences of natural hazards, without going into the depths of highly complex resilience indicators as they are used in, for example, disaster risk reduction frameworks.

Third, we study the relationship between local financial structure and city-level resilience. Exogenous shocks caused by natural hazards typically tend to increase the demand for credit in affected areas, as people need funds to finance the rebuilding of destroyed capital or to bridge liquidity gaps. At the same time, the destruction of collateral aggravates asymmetric information problems,[1] and uncertainty about economic opportunities increases, putting pressure on credit supply (Berg and Schrader 2012; Collier and Babich 2019). The vast literature on the finance-growth nexus suggests that the provision and allocation of credit matters for real economic outcomes (Levine 2005), at least up to a certain threshold (Arcand et al. 2015). In the case of an extreme shock, it may be counterproductive to have exhausted the local possibilities to take up new loans. This may limit the funds that can be acquired during the recovery phase. Furthermore, studies such as Cortés and Strahan (2017) and Koetter et al. (2020) suggest that banks differ in their ability and willingness to provide funds under adverse circumstances, e.g., depending on their size, network, and business model. Together with Celil et al. (2022), we are the first to explore these aspects for the case of China.

Empirically, we track the local responses of prefecture-level cities to severe storms and extreme precipitation events by employing impulse response models with up to five annual lags on the extreme weather variables. We find that while wind speeds exert negative effects on economic activity only in the year of their occurrence, extreme precipitation depresses the development of local economies several years after an event. With respect to the role of local financial structure, our results suggest that high levels of pre-event indebtedness reduce the overall resilience of local economies. This implies an additional trade-off to be

[1] Asymmetric information refers to the fact that the borrower has better information on the value of her project and her activities than the lender. Collateral reduces the problem because it gives a creditor security, independent of the behavior of the borrower, such that the creditor need not rely on information that the borrower knows best.

considered when using high levels of debt to finance economic expansion. Interestingly, and in contrast to the notion that the large, state-owned banks in China are associated with depressed economic growth (Chang et al. 2010); our findings further suggest that the "Big 4" state-owned commercial (SOC) banks contribute positively to the post-event recovery process. This effect may stem from the deep pockets that these large and diversified institutions have, in combination with an objective function that is more closely aligned with central government policy. It would therefore seem that while market competition promotes efficiency and growth in normal times, it may leave Chinese prefecture-level cities more vulnerable in the face of extreme weather shocks.

The remainder of this paper is organized as follows. Section 2 positions our paper in the related literature. Section 3 describes our data, and Section 4 introduces our empirical strategy and methodology. Our estimation results are presented and discussed in Section 5. Section 6 concludes and discusses potential follow-up research.

2 Impacts, resilience, and finance

2.1 Natural hazards in China

China is one of the countries in the world that is most frequently and severely affected by natural hazards, such as large-scale tropical cyclones and floods (World Bank and GFDRR, 2020). With climate change, the frequency and severity of such events are expected to increase even further (Intergovernmental Panel on Climate Change 2022). A growing literature analyzes the direct and indirect impacts of natural hazards on China and attempts to identify potential mitigating factors.[2] Over the past three decades, the direct impacts in terms of numbers of affected people, humanitarian, and economic losses have increased, while losses, expressed as a percentage of a rapidly growing GDP, have not shown a significant increase over time (Zhou et al. 2013). This suggests that a large part of the increases in the direct impacts can be attributed to the rapid economic development of China, in combination with a growing concentration of the population in hazard-prone areas. In terms of indirect impacts, these studies suggest that both geological and meteorological events cause significant but short-lived decreases in economic activity. Hu et al. (2019) find that extreme floods in particular and in contrast to other types of events have also caused more persistent adverse effects. A common theme in many studies is the emphasis on the coordinated and substantial post-disaster reconstruction and rebuilding efforts that are typically led by bodies of the central government in cooperation with local governments (e.g., Vu and Noy 2015).

The previous literature, however, comes with a few caveats, particularly if one is interested in the local resilience to such shocks. First, the selection of events based on direct impacts as reported by news agencies and insurance companies introduces selection bias, because fatalities and damages are endogenous to human exposure and socioeconomic conditions (e.g., Felbermayr and Gröschl 2014 and Lazzaroni and van Bergeijk 2014). Bakkensen et al. (2018) demonstrate that significant differences in measured disaster impacts can drive sub-

[2] Direct impacts include fatalities, physical damages, and reductions in human well-being, while indirect impacts are understood as the "higher-order" changes in economic activity that result from the direct impacts (Botzen et al. 2019). These include business interruptions, production losses that are directly due to asset losses, supply-chain disruptions, macroeconomic feedback effects, other long-term adverse consequences on economic growth, and possible production increases stemming from reconstruction investments (Hallegatte 2014). Table D.1 in the online supplementary material summarizes the main studies of this literature.

sequent differences in empirical results. In contrast, data on the actual physical intensities of events in any given location are more objective and capture the intensity of the exogenous shock more accurately (Felbermayr and Gröschl 2014; Felbermayr et al. 2022).[3]

Second, if the level of spatial detail is not chosen appropriately, the local impacts of disasters may be averaged out, resulting in a distorted picture of the actual effects (Strobl 2011; Botzen et al. 2019). Presumably driven by data availability, most previous studies on extreme events in China focus on provinces as their unit of observation. These, however, constitute in many cases very large economic and geographic units, with the biggest provinces being larger and more populated than, for example, countries like France or Germany. To make matters worse, the data included in damage databases are in many cases not detailed enough to allow for a precise mapping of disaster impacts to the local level (Zhou et al. 2014).

2.2 Economic resilience and local finance in China

Economic resilience can be understood as an economy's ability to cope, recover, and reconstruct after a shock in order to minimize consumption and welfare losses. This includes the instantaneous ability of a system to absorb or mitigate losses from a disaster for a given disaster intensity and the dynamic ability of a system to recover from the shock (Hallegatte 2014). A rather limited number of studies empirically investigate the determinants of economic resilience to natural hazard-related disasters (Lazzaroni et al. 2014; Noy and Yonson 2018). This literature emphasizes the benefits of economic, financial, and institutional development, diversification, openness, and education (Botzen et al. 2019), as well as insurance for mitigating the negative economic impacts of disasters at the country level (von Peter et al. 2012; Melecky and Raddatz 2015; Kousky 2019). Population density, infrastructure, and the degree of urbanization as well as income inequality can also play a role (Noy and Yonson 2018). Additionally, Hsiang and Jina (2014) point out the role of experience based on historical exposure in coping with natural events, in line with impacts being a function of disaster preparedness (Kahn 2005).

We focus on the role of the local financial system in resilience to extreme weather events. Previous studies established some general results about the relationship between banking and natural hazard-induced disasters. When firms and households are affected by natural hazards, credit demand is driven up by a need to rebuild damaged or destroyed capital, or to bridge financing and liquidity gaps. At the same time, natural hazards cause a deterioration in the creditworthiness of borrowers, if the values of assets are diminished and income streams are disrupted (Collier and Babich 2019). Banks' assets can also be affected directly, leading to increasing bank distress (Klomp 2014), and asymmetric information problems are aggravated when the monitoring of debtors is complicated by post-event uncertainty (Berg and Schrader 2012).

This implies that heterogeneity across local banking systems may play a role. First, the distinction between local and non-local banks is of interest here. In theory, local banks are more vulnerable to extreme events because a larger share of the customer base may be affected. At the same time, however, they may have a larger interest in supporting the local community after an event to protect their core customer base (Schüwer et al. 2019). Closely related to the geographical scope of banks is their business model. The presence of established relationships can decrease lending restrictions, with tacit knowledge being an

[3] Many studies use a direct impact threshold to define a disaster event in order to mitigate the endogeneity concerns associated with direct impact measures. This, however, comes at the cost of not using all the available information from the data and treating events of different intensities as the same.

important factor that allows for credit supply when collateral is damaged or when business operations are interrupted (Berg and Schrader 2012; Koetter et al. 2020). This argument goes back to the comparative advantage that local, relationship-oriented banks have in gathering information about small and less transparent borrowers (Agarwal and Hauswald 2010).

Another important aspect concerns bank diversification and networks. While some evidence suggests that banks can propagate shocks to unaffected regions (e.g., Rehbein and Ongena 2022), being part of a banking network can have beneficial effects for the credit supply in affected areas, e.g., through risk-sharing capabilities and credit reallocation (Doerr and Schaz 2021). In addition, bank and network size may play a role in determining banks' ability to provide recovery funding (e.g., Cortés and Strahan 2017).

Finally, bank ownership determines a bank's objective function and may thus determine a bank's behavior in the face of a shock to its customer base. Studies focusing on the behavior of banks of different ownership types during financial crises and economic recessions suggest that government-owned banks tend to lend more counter-cyclically than private banks, thereby reducing the threat of credit crunches and amplified economic downturns (e.g., Brei and Schclarek 2013 and Bertay et al. 2015).

The Chinese banking system is frequently characterized as special. First, it is heavily reliant on its banking institutions. Banks have accounted for over 75% of the aggregate financing to the real economy (AFRE) over the period 2003 to 2013 (Sun 2020), and the banking system has played an important role in China's rapid growth over the last decades, resulting in high levels of debt relative to GDP (Duffie 2020). Some studies posit that finance has spurred economic growth in China, while others find that the level of financial development has had no or only conditional effects on economic growth (Lin et al. 2015).[4] In the face of a severe natural hazard shock, excessive pre-event leverage may be a cause for concern if it constrains the availability of credit for the recovery.

Furthermore, while still dominated by the "Big 4" SOC banks which are active and reallocate funds nationwide (Chang et al. 2010), several waves of banking reforms have led to steady increases in the market shares and private ownership of financial intermediaries, most notably city commercial banks, rural cooperative banks, and joint-stock commercial banks (Berger et al. 2009).[5] There is active debate about the role of state ownership in the Chinese banking industry. Several scholars argue that the dominance of the "Big 4" SOC banks causes inefficiency because their lending is biased towards relatively inefficient state-owned enterprises (e.g., Chang et al. 2010). Due to their size, these banks are considered ill-positioned to fund small- and medium-sized enterprises which are seen as the engine of growth in modern China. Indeed, recent evidence suggests that growth is indeed more dynamic in regions that are less heavily banked by the "Big 4" (Lin et al. 2015).

Against this background, we investigate the role of the composition and development of local banking markets for local economic resilience to extreme weather events in China. Competing hypotheses can be established, and it is an empirical question which hypothesis finds support in the data. On the one hand, a higher share of regional, relationship-oriented banks may be favorable, due to their important role in financing small- and medium-sized enterprises that are typically the most vulnerable to shocks. On the other hand, the "Big 4" SOC banks have large, diversified networks and "deep pockets" at their disposal which allow them to absorb extreme weather shocks and support the local economy with counter-cyclical lending in times of need. Beyond this, due to their ownership structure, the state-owned

[4] Lin et al. (2015) also provide a more detailed discussion of this literature.

[5] Figure D.1 in the supplementary material illustrates the development of bank branch shares by ownership type at the city level over the sample period.

banks may be instrumental in distributing public recovery funding by the central government and in financing infrastructure rebuilding projects after major events. This would suggest a prominent role for the "Big 4" SOC banks in the response to natural hazard-induced shocks.

3 Data

3.1 Prefecture-level socioeconomic data

Prefecture-level cities represent the second administrative level in the People's Republic of China (PRC), below provinces and above counties.[6] Data on city-level economic activity stems from the China City Statistical Yearbooks and the CEIC Database.[7] At this level of regional disaggregation, data is available from 2003 to 2019. In our final sample, and after constructing the growth rates of our dependent variables, we use data on 284 prefecture-level cities for the years 2004 to 2013, the last available year of our meteorological data.[8] Table 1 presents descriptive statistics of some key variables. Table D.2 in the online supplementary material presents detailed descriptions of all variables used in the analyses.

The relevance of differences in local financial conditions is substantiated by the local loans-to-GDP ratio and the local market share of the "Big 4" SOC banks. The former variable is calculated as the local loan balance of financial institutions at the end of the year over GDP. The importance of different types of banking institutions in the local banking market is approximated by the share of branches that is associated with the "Big 4" SOC banks in any given prefecture-level city. The characterization of local banking market conditions with information on local bank branch shares is a well-established approach in the literature (e.g., Berger et al. 2014). Data on the number of bank branches of different banks at the city level is available from 1948 to 2019 and is collected from the China Banking and Insurance Regulatory Commission.[9] Based on our discussion in Sect. 2.2, we focus on the share of the "Big 4" SOC banks in the local banking market.

3.2 Meteorological data

To identify extreme weather events, we use the gridded GAME-LIGHTS database (Felbermayr and Gröschl 2014; Felbermayr et al. 2022). GAME-LIGHTS contains meteorological data on weather anomalies for 0.5 by 0.5° grid cells spanning the entire globe for the period 1992–2013. This high geographical resolution of the data allows us to investigate the impacts of extreme weather events at the most local layer for which administrative socio-economic data for China is available. In line with comparable literature (Kotz et al. 2022), the 0.5° grid cell raster of GAME-LIGHTS was mapped onto the administrative areas of 284 Chinese prefecture-level cities to match the meteorological data with its city-level locations (see a detailed description of the procedure in Section A of the online supplementary material). To

[6] These "cities" are not to be understood in the strict sense of the term as purely urban agglomerations, since they typically comprise continuous urban areas *and* the surrounding rural districts.

[7] We first use the China Statistical Yearbooks to query most of the data we need. For incomplete data, we use the CEIC database to supplement it. CEIC Data is a private provider of economic data with special expertise in developing markets, including China (CEIC 2022).

[8] For reasons of data availability, we focus our analysis on Mainland China.

[9] To examine the consistency of our processing of the bank branch data, we compared our data with the geo-coded bank branch data set kindly provided by Liu (2022). We found no significant deviations.

Table 1 Summary statistics: prefecture-level data (2004–2013)

	N	Mean	Median	SD	P1	P99
Socio-economic data						
GDP p.c	2840	24,510.19	16,130.73	29,657.88	3624.36	130,602.59
Δ log GDP p.c	2840	0.12	0.12	0.04	0.02	0.21
Loan/GDP	2840	0.94	0.77	0.67	0.29	3.19
Big 4 share	2840	0.40	0.36	0.16	0.14	0.85
Population (10,000 people)	2840	431.15	364.50	303.71	46.83	1224.35
Population density (people per sqkm)	2840	421.36	346.91	323.64	17.79	1328.68
Meteorological data						
Avg. sustained wind speed (kt)	2840	16.12	15.89	2.96	10.76	24.59
Max. sustained wind speed (kt)	2840	30.86	25.30	15.50	14.68	88.00
Max. sustained wind speed: treated	218	72.29	68.00	14.32	56.30	116.00
Avg. positive precipitation difference (in local SD)	2840	0.39	0.37	0.14	0.12	0.78
Max. positive precipitation difference (in local SD)	2840	2.65	2.50	0.99	0.95	5.47
Max. positive precipitation difference: treated	157	5.05	4.86	0.62	4.42	6.80
Resilience indicators						
Resistance	336	0.03	0.04	0.23	−0.74	0.64
4-year recoverability	188	0.02	0.05	0.15	−0.54	0.39

Monetary variables expressed in 2002 Yuan. The sample period is 2004–2013. Tables D.2 and D.3 in the online supplementary material present detailed explanations of all included variables and additional descriptive statistics this end, we preserve the maxima of the GAME-LIGHTS weather variable x of weather type p for each prefecture i by selecting the maximum value of x in year t of all intersect fractions j that form the geographic area a of prefecture i:

$$x_{i,t}^{p} = \max_{j \in J} \{x_{j,i,t}^{p}\} \text{ with } \sum_{j \in J} a_j = a \tag{1}$$

In the analysis, we focus on weather-related sudden-onset events, i.e., on extreme wind speed and extreme precipitation events.[10] In our baseline specification, extreme wind speeds are measured as the absolute maxima of sustained wind speeds that occurred in a given city i in year t, reflecting the notion that it is the absolute intensity of wind speed that determines the harmfulness of the event. The extreme precipitation measure is originally constructed at the cell-month level by subtracting the long-run (1979–2014) mean precipitation of a given month from the observed precipitation and standardizing this by dividing it by the long-run standard deviation of that month for that cell. To isolate observations with *excessive* amounts of rainfall at the city-year level, we drop observations below zero and take the annual maximum. The measure is then spatially aggregated as above. Our indicator of extreme precipitation is thus a relative measure that takes the "usual" amount of precipitation in a place into account and identifies events that are "unusual" relative to the local benchmark.[11]

Table 1 presents descriptive statistics of the most important weather variables. Figure D.2 in the online supplementary material presents the distributions of the annual physical intensities of wind speeds and precipitation in the full sample of prefectures, while Figs. D.5 to D.8 show the spatial distribution of extreme weather events during the sample period. We refer to section A in the online supplementary material as well as Felbermayr and Gröschl (2014) and Felbermayr et al. (2022) for more detailed descriptions of the construction and compilation of the GAME-LIGHTS database and the weather variables.

3.3 Measuring resilience

To assess whether the resilience of Chinese prefecture-level cities can be explained by differences in their local financial constitution, we adapt the operationalization of Martin et al. (2016), who propose indicators to measure *resistance* (the initial depth of the impact of the shock) and *recoverability* (the degree of recovery in the post-event period) as dimensions of resilience. In comparison to existing approaches to resilience measurement,[12] these indicators allow for an explicit quantification of immediate and adaptive economic resilience and require relatively little data to calculate.

Martin et al. (2016) consider a nationwide recessionary shock, and measure resilience as the relative ability of a region to withstand and recover from the shock compared to the *expected* counterfactual national benchmark. This entails the strong assumption that a shock affects all regions equally and at the same point in time. This is clearly not the case for

10 We abstain from geological events such as earthquakes and volcanic eruptions as our focus is on climate-related hazards. We also disregard slow-onset climate-related events such as droughts because these are often difficult to measure precisely in terms of spatial delimitation, duration, and intensity (Vu and Noy 2015).

11 While precipitation extremes do not necessarily translate into flood events, increases in both extreme precipitation and total precipitation have contributed to increases in severe flooding events in many regions of the world. Thus, measures of extreme rainfall indeed provide valuable insights for assessments of the occurrences and impacts of floods (e.g., Kotz et al. 2022). In addition, heavy precipitation events in China also increase the risk of landslides and degrade water quality (e.g., Shi et al. 2016).

12 See, e.g., Noy and Yonson (2018) and Moser et al. (2019) for discussions of different approaches.

extreme weather events, which are by nature localized phenomena that differ in their physical intensity (wind speed and amount of rainfall) and timing. To address this, we propose to use the predicted values of an impulse response model[13] as the counterfactual outcome for cities affected by extreme weather events. By construction, these predicted values include the average expected deviation in city c in year t from that city's growth path *given* the specific weather shock of intensity p, their specific pre-shock growth rate and city-specific intercept (fixed effect). This means that we measure resilience as the realized economic growth outcome relative to the *expected* outcome given the actual weather shock. Our adapted measures of regional resistance $Resis_{i,t}$ and recoverability (k years after an event) $Recov^k_{i,t}$ can thus be expressed as follows:

$$Resis_{i,t} = \frac{\Delta y_{c,t} - \Delta \hat{y}_{c,t}}{\Delta \hat{y}_{c,t}} \tag{2}$$

and

$$Recov^k_{i,t} = \frac{\sum_{k=1}^{K} \Delta y_{c,t+k} - \sum_{k=1}^{K} \Delta \hat{y}_{c,t+k}}{\sum_{k=1}^{K} \Delta \hat{y}_{c,t+k}} \tag{3}$$

In Eq. 2, $\Delta y_{c,t}$ is the actual growth rate of regional GDP of city c in year t. $\Delta \hat{y}_{c,t}$ is the predicted counterfactual growth rate for the same city-year. In Eq. 3, $\sum_{k=1}^{K} \Delta y_{c,t+k}$ is the sum of the actual growth rates of regional GDP of city c over t+k years after an event, while $\sum_{k=1}^{K} \Delta \hat{y}_{c,t+k}$ is the sum of the predicted growth rates for the same time frame. In our baseline, we measure recoverability 4 years after the event (i.e., $K = 4$), in line with the duration of negative effects from extreme weather events in our data. Following Martin et al. (2016), we scale differences between actual and counterfactual by the counterfactual growth rates. Both measures are centered around zero by construction. Positive values show a relatively strong resistance/recovery for the given event intensity, while negative values indicate relatively weak resistance/recovery. It is useful to emphasize that these indicators measure the *relative* resistance and recoverability of prefecture-level cities given the intensity of the respective shock. Unlike the results presented in Sect. 5.1, they are not informative about the absolute (or average) responses to extreme weather events, but make use of heterogeneity in post-event outcomes given the observed event intensity.

In order to actually measure *resilience*, our units of observation need to experience a sufficiently strong shock (henceforth referred to as "event") in order to reveal their "true" resilience. Since our measures of physical intensities are continuous, any definition of an event will inevitably include an arbitrary cutoff above which we consider a city as "treated." To endogenize the choice of these cut-off values and to verify the explanatory power of our GAME-LIGHTS data for extreme events, we make use of the Emergency Events Database EM-DAT (CRED / UCLouvain 2022). Based on the share of damages that we can "locate" by including city-year observations above a certain percentile of the physical weather intensity distribution, we select the 92$^{\text{nd}}$ percentile in wind intensity (at which we can "locate" 91% of all city-level storm damages recorded in EM-DAT) and the 95$^{\text{th}}$ percentile in precipitation intensity (at which we can "locate" 72% of all city-level flood damages recorded in EM-DAT) as cut-offs and define observations above these thresholds as treated by an event in our baseline sample. Consequently, we calculate our measures of resilience for these treated city-year observations. Section B in the online supplementary material provides a detailed explanation of the procedure employed to select these thresholds. In Section C.3 in the online supplementary material, we provide additional robustness checks using different cut-off values. Descriptive statistics of the measures are reported in Table 1.

[13] As described in Sect. 4.1, Eq. 4.

4 Methodology

4.1 Baseline specification

The starting point for our investigation into the indirect economic impacts of extreme weather events on Chinese prefecture-level cities is a simple dynamic growth model that comprises one lag of the dependent variable alongside five lags of our weather intensity measures which capture the impulse responses of our dependent variable over time, in line with previous literature (von Peter et al. 2012; Melecky and Raddatz 2015). Our main specification thus takes the following form:

$$\Delta y_{c,t} = \beta \Delta y_{c,t-1} + \sum_{l=0}^{5} \gamma_l D_{c,t-l} + \alpha_c + \theta_t + \epsilon_{c,t} \tag{4}$$

where $\Delta y_{c,t}$ is the change in the logarithm of the economic outcome variable of interest $y_{c,t}$ in city c in year t. In our base model, this represents the growth rate of real GDP per capita. Alternative specifications in the online supplementary material also use employment growth. $D_{c,t-l}$ is a C x P matrix of weather intensities p for all C cities and P different types of weather events, i.e., storms and extreme precipitation. In the baseline specification, this is the maximum sustained wind speed and the maximum positive difference of precipitation from the long-run mean observed in a city in year $t-l$ with $l \in [0..5]$. α_c are city fixed effects that control for unobservable time-invariant effects that are specific to cities, including their climatic conditions and the associated underlying baseline risk, as well as other unobserved geographic and locational factors (Auffhammer et al. 2013). We include time-fixed effects θ_t to control for time trends and to absorb national shocks that may have occurred during the period of observation. Standard errors are clustered at the city level, accounting for heteroskedasticity across cities.

The key identifying assumption for our specification is that our weather variables are orthogonal to the error term $\epsilon_{c,t}$. Extreme weather events are typically (at least to the current day) unpredictable in time and location, exogenous to growth in the city, and have the potential to push cities out of their expected growth paths. Therefore, controlling for city- and time-specific fixed effects allows for a plausible causal interpretation of the impulse responses to extreme weather events (Dell et al. 2014). The specification is deliberately parsimonious to avoid endogeneity problems that can arise from bad controls (Angrist and Pischke 2009) and over-controlling (Dell et al. 2014). Many factors that are commonly considered determinants of economic activity and growth may themselves be impacted by weather shocks. Including them in our specification could thus bias our impulse responses (Acevedo et al. 2020). To the extent that these factors are time-invariant and city-specific, and therefore not causally linked to the events studied here, they are subsumed in the fixed effects.

The combination of a dynamic panel model with fixed effects potentially introduces "Nickell bias," which describes endogeneity that arises from lags of the dependent variable being included as explanatory variables (Nickell 1981). Given the relatively short length of our panel, this bias may be severe. We apply the bias-corrected method of moments estimator of Breitung et al. (2021) to take care of the potential bias. Under the condition that all regressors besides the lagged dependent variable are strictly exogenous (as is the case for our weather variables), these estimators directly correct the Nickell bias while retaining the small variance of the fixed effects estimator and being more efficient than alternative approaches, such as generalized method of moments (GMM) estimators (Bun and Carree 2005).

Using the fitted values of Eq. 4 as $\hat{y}$ in Eqs. 2 and 3, where resistance and recovery are measured relative to a benchmark level of GDP-growth estimated as the growth rate we would expect for city c affected by an extreme weather event of type p and intensity D in year t, we obtain our dependent variables for our primary analysis.

4.2 Local financial structure and extreme weather resilience

In the second step, we assess whether the resistance to and recovery from extreme weather events can be explained, at least in part, by differences in cities' local financial structures. To this end, we treat our measures of resistance (*Resis*) and recoverability (*Recov*) as the dependent variables in regression models in which variables that capture heterogeneity in financial structure are the primary variables of interest. As outlined in Sect. 3.3, we consider observations above the 92nd percentile in physical wind intensity and the 95th percentile in precipitation intensity as treated by extreme events in our baseline sample. We thus use pooled cross-sectional data in this part of the analysis (as in Schüwer et al. (2019) and Baltas et al. (2021), for instance).

Building on our discussion in Sect. 2.2, we explore whether the configuration of the local financial system has an effect on local resistance and recoverability. Specifically, we consider the level of pre-event indebtedness and the structure of the local banking market as explanatory variables in these regressions. In line with previous literature, we measure the former as the ratio of loans to GDP at the city level (Levine 2005), while we use the share of "Big 4" SOC bank branches to capture the latter. Consequently, we specify

$$Resis_{i,t} = \beta_0 + \beta_1 log(Loans_{i,t-1}) + \beta_2 log(Big4_{i,t-1}) + \beta_3 X_{i,t-1} + \tau_t + \epsilon_{i,t} \tag{5}$$

and

$$Recov^k_{i,t} = \gamma_0 + \gamma_1 Resis_{i,t} + \gamma_2 log(Loans_{i,t-1}) + \gamma_3 log(Big4_{i,t-1}) + \gamma_4 X_{i,t-1} + \tau_t + e_{i,t} \tag{6}$$

with $Loans_{i,t-1}$ as the city-level loans-to-GDP ratio, and $Big4_{i,t-1}$ as the share of bank branches of the "Big 4" SOC banks in the total number of bank branches at the city-level. Besides that, we control for covariates that we select based on the previous literature on the economic effects of extreme weather events and which allow us to hold constant known determinants of economic resilience and exposure to such events (see Sect. 2.2). The set of control variables $X_{i,t-1}$ includes the level of GDP per capita, population density, past experience of extreme weather events, the degree of urbanization, the level of related variety in industrial structure, the shares of primary and secondary sectors in local output, and the share of state employed in total employment. τ_t represent year dummies.

As disaster preparedness is typically difficult to measure, we rely on the relative homogeneity in institutional factors driving disaster preparedness within our sample and do not include explicit controls for disaster preparedness. In China, the management of natural hazard-related disasters and extreme weather events falls under the central body of the National Disaster Reduction Committee which is responsible for drafting the 5-year National Comprehensive Disaster Prevention and Mitigation Plans, which coordinate disaster mitigation efforts across the whole country (Shi et al. 2016; World Bank and GFDRR 2020). Furthermore, while increasing exposure to natural hazards has recently led to a growth in insurance markets in China (Elliott et al. 2015), damages from floods and tropical cyclones are still considerably underinsured, with only around 2% of economic losses covered by insurance in recent years (MunichRe 2021). This suggests a more important role for other actors in

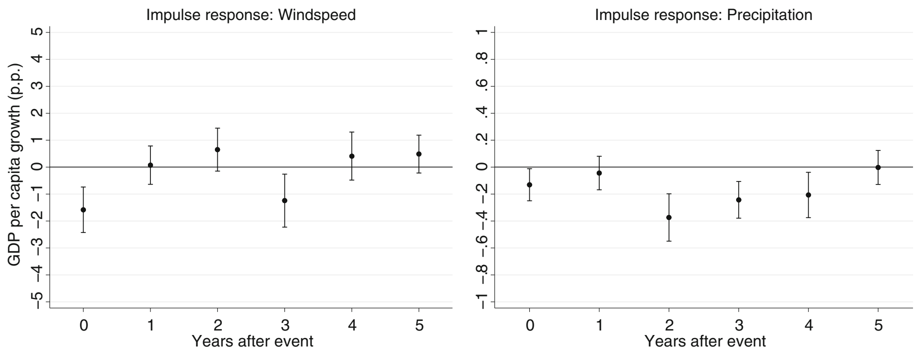

Fig. 1 Temporal effects of extreme weather events on GDP per capita growth. Note: The sample period is 2004–2013. Bars represent 90% confidence intervals. Year "0" on the x-axis is the year of the event

the economy, such as the government and the banking sector, to insure against these adverse shocks, at least implicitly.

Note that we select the pre-event realizations of our explanatory variables (period *t-1*) in Eqs. 5 and 6. These are unaffected by the event occurring in period *t*, such that we can reasonably assume that they are exogenous and OLS estimation yields unbiased results. Furthermore, note that we use dependent variables that are based on estimates. Following Lewis and Linzer (2005), we use Eicker-White standard errors in our baseline OLS regressions to account for the heteroskedasticity associated with estimated dependent variable models.[14] Since our sample now consists of only those city-year observations that experienced extreme weather of a certain intensity, we are using data from multiple years in which some cities appear only once, while other cities have experienced multiple events. To accommodate this feature of our data, we cluster standard errors at the city level in additional robustness checks.

5 Results

5.1 Local economic impacts of extreme weather events

The estimation results for the impulse response functions outlined in Sect. 4.1 are presented in Table 2 and illustrated in Fig. 1. Column (3) of Table 2 presents our baseline specification. Note that because of the way the variables are constructed, effect sizes are not directly comparable and have to be interpreted carefully.

First, consider the results on wind, as they are shown in the left panel of Fig. 1 and in column (3) of Table 2. The coefficients estimated for the contemporaneous and the lagged effects of the maximum sustained wind speeds measured in a city in a given year represent the average effect of wind speeds across prefecture-level cities on real GDP per capita growth. Extreme winds appear to have a significant effect only in the year of their occurrence but not thereafter. To get a sense of the magnitude of this effect, it makes sense to compare the measured wind speeds with a classification system of storm severity. For instance, according

[14] Lewis and Linzer (2005) show that the common approach to setting up estimated dependent variables models, weighted least squares, performs worse than OLS with Eicker-White heteroskedasticity consistent standard errors. As an additional alternative, they propose a feasible GLS estimator. Existing empirical evidence supports the use of OLS with Eicker-White standard errors in an estimated dependent variable setting (e.g., Caron et al. 2014).

Table 2 Impact of extreme wind and precipitation on GDP per capita growth

	(1) Δ log GDP p.c.	(2) Δ log GDP p.c.	(3) Δ log GDP p.c.
L.Δ log GDP p.c	0.21907*** (0.053)	0.20976*** (0.051)	0.20866*** (0.051)
Wind speed	−0.00016*** (0.000)		−0.00016*** (0.000)
L.Wind speed	0.00002 (0.000)		0.00001 (0.000)
L2.Wind speed	0.00004 (0.000)		0.00006 (0.000)
L3.Wind speed	−0.00009 (0.000)		−0.00012** (0.000)
L4.Wind speed	0.00004 (0.000)		0.00004 (0.000)
L5.Wind speed	0.00005 (0.000)		0.00005 (0.000)
Positive Δ rain		−0.00112 (0.001)	−0.00131* (0.001)
L.Positive Δ rain		−0.00053 (0.001)	−0.00044 (0.001)
L2.Positive Δ rain		−0.00360*** (0.001)	−0.00374*** (0.001)
L3.Positive Δ rain		−0.00228*** (0.001)	−0.00243*** (0.001)
L4.Positive Δ rain		−0.00201** (0.001)	−0.00207** (0.001)
L5.Positive Δ rain		0.00014 (0.001)	−0.00002 (0.001)
Constant	0.10062*** (0.009)	0.12375*** (0.012)	0.12849*** (0.015)
Observations	2556	2556	2556
Cities	284	284	284
City FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The sample period is 2004–2013. Time- and city-fixed effects included. Standard errors clustered at the city level. Sections C.1 and C.2 in the online supplementary material present additional analyses, alternative specifications, and robustness checks

to the Cyclone Intensity Scale of the Regional Specialized Meteorological Center (RSMC) Tokyo,[15] a typhoon is defined as exhibiting a minimum sustained wind speed of 64 knots while a violent typhoon registers at least 105 knots. Storms of these intensities would result in a reduction of GDP per capita growth by 1.03 and 1.69 percentage points, respectively. Looking at the coefficient itself, a one standard deviation (15.5 knots) increase in the annual maximum sustained wind speed corresponds with an expected reduction of income growth of 0.25 percentage points. Our results are in line with previous studies by Elliott et al. (2015), Del Valle et al. (2018) and Felbermayr et al. (2022). To put the numbers into perspective, GDP growth in China decreased by around 3–4 percentage points during the Global Financial Crisis (Huang et al. 2011). A violent typhoon thus corresponds with half a financial crisis. Compared to the average GDP per capita growth in our sample of around 12% per year, these reductions suggest that Chinese prefectures are quite resilient in absolute terms.

Turning to extreme precipitation, the right panel of Fig. 1 and column (3) of Table 2 shows that output growth per capita suffers only marginally in the year of the event. At a 90% significance level, a one standard deviation (0.99 local standard deviations above the mean) increase in our precipitation measure, which (as described in Sect. 3.2) captures extreme positive deviations from the long-run mean precipitation in a city, would result in an output growth decline of 0.13 percentage points. Given the average rate of growth in

[15] The Japan Meteorological Agency (JMA/RSMC Tokyo) is responsible for issuing tropical cyclone advisories within the Western Pacific basin, including Mainland China (Japan Meteorological Agency 2022).

Chinese prefecture-level cities this is not an economically large effect. Strong deviations from a region's long-run precipitation mean, however, will have a sizeable effect on growth. For instance, an event located at the 95th percentile of the distribution of our precipitation measure would lead to a 0.57 percentage points decrease in output per capita growth. In terms of economic magnitude, this corresponds roughly with results from related studies, such as Kotz et al. (2022). In contrast to wind, precipitation shows larger long-run impacts, too. In fact, the second to the fourth lag suggests significant negative effects of extreme precipitation events that accumulate to economically considerable impacts. For a 95th percentile extreme precipitation event, the total cumulative loss in GDP per capita growth is estimated to amount to around 6.5 percentage points, or 8.6% of growth, in the 4 years after the event.

Comparing our results again, Felbermayr et al. (2022) present negative effects on grid cell-level night light emissions upon impact, and an instantaneous recovery in the following period. In our case, the recovery does not push the coefficient of the first lag significantly above zero, in spite of the well-documented recovery efforts of the Chinese authorities. Instead, our results suggest that it is important to consider an even longer time frame, as cities can be stunted in their development for years following the event. This finding is in line with the results of, e.g., Hu et al. (2019) who find lasting, cascading effects on economic activity after flood events in China.

We have conducted additional analyses on the reactions of employment growth to extreme weather shocks and on the impacts on output growth in the primary, secondary, and tertiary sectors. Employment growth reacts more sluggish but results are consistent with our main findings. Immediate impacts are concentrated in the tertiary sector, while secondary sector growth is stunted in the aftermath of an event. The presented patterns are robust to a range of alternative modeling decisions and for different choices regarding our event variables. These analyses are discussed in more depth in Section C of the online supplementary material.

5.2 Resilience and local financial structure

We use the results from Sect. 5.1 to construct our measures of resilience as described in Sect. 3.3. Figure 2 and Table 1 describe the resulting distributions of resistance and recoverability. As we would expect, both measures are centered around zero and exhibit a slightly positive skew. Note that the number of observations for recoverability in Table 1 is lower because of data constraints towards the end of the panel. Furthermore, Fig. 2 suggests that resistance and recoverability are not entirely independent of each other. On average, cities that are more resistant seem to have a higher recoverability as well. As explained in Sect. 3.3, these measures represent the relative resistance and recoverability of cities experiencing extreme weather events compared to the sample average effect of extreme weather events, taking into account the severity of the local events and fixed characteristics of the affected city.[16]

In the next step, we associate our measures of resilience with local financial features of prefecture-level cities that were treated by extreme weather events (Sect. 4.2). Table 3 summarizes the main results. Additional robustness checks can be found in Section C.3 of the online supplementary material.

According to our baseline specification for resistance (column (1)), resistance is negatively associated with the level of pre-event debt in a city that is hit by an extreme weather event. This suggests that the available margin for lending is important immediately after the impact of an extreme event. A doubling in the loans-to-GDP ratio (1.4 standard deviation increase

[16] In other words, we compare the actual economic outcome of a city relative to the outcome that would have been expected given the physical intensity of the shock.

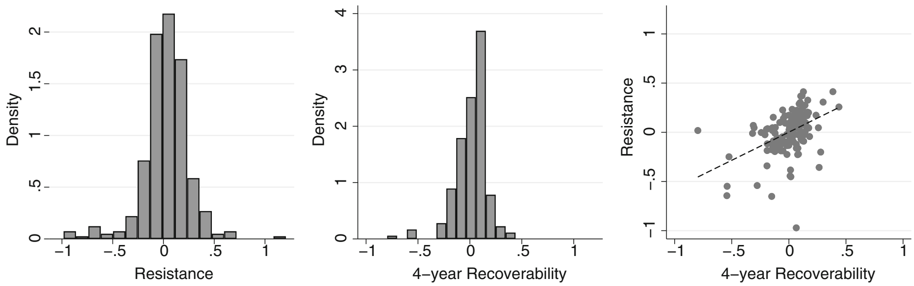

Fig. 2 Distributions of resilience indicators

at the mean) corresponds with a 7.4 percentage point decrease in local resistance. As can be seen from Eq. 2, this implies that GDP per capita growth is indeed 7.4% lower in an otherwise average city with 1.4 standard deviations above mean loans-to-GDP ratio compared to a city with an average level of pre-event indebtedness when faced with a shock of comparable type and intensity. For example, a city that would have expected to have GDP per capita growth of 10% in the year of the shock grows with only 9.26% if, in addition to the shock, its pre-event debt levels were 1.4 standard deviations above the average. Likewise, the level of indebtedness before the event exhibits strong negative effects on the post-event recovery process, as can be seen from column (4) in Table 3. In quantitative terms, a doubling in pre-event indebtedness corresponds with an 11.1 percentage point decrease in recoverability after 4 years. An otherwise average city loses 11.1% of the growth it would have been expected to have in the 4 years after the shock (given the type and intensity of the shock), if its pre-event loans-to-GDP ratio is 1.4 standard deviations above the sample mean.

This suggests that high debt levels carry an externality that reduces resilience to extreme weather events. At first sight, this is in contrast to previous findings that suggest that macroeconomic financial development reduces the economic consequences of such shocks (see Sect. 2). Given the very high levels of debt in the Chinese economy, this may mean that the relationship between financial development and resilience is non-monotonic, in line with recent notions in the finance-growth literature. Arcand et al. (2015), for instance, suggest a "vanishing effect" of financial depth, i.e., a threshold above which financial depth no longer has a positive effect on economic growth in normal times. In our case, the findings signify impaired resilience in the face of extreme weather shocks if pre-event debt levels are (too) high.

The pre-event share of the "Big 4" SOC banks in the local banking market reveals a positive relationship with both resistance and recoverability. This suggests that the increased presence of this type of bank aids in the face of adverse events, i.e., when recovery funds need to be allocated. In quantitative terms, a doubling in the share of the "Big 4" SOC banks in the local banking market (2.5 standard deviation increase at the mean) corresponds with an 8.5 percentage point increase in resistance and a 6.0 percentage point increase in recoverability (columns (1) and (4) in Table 3). For instance, an otherwise average city, in which the share of "Big 4" branches is 20%, is expected to experience 8.5% lower GDP per capita growth in the year of the event, and 6.0% in the 4 years after, compared to a city with a "Big 4" share of 40% that is hit by the same shock. Our results comply with previous findings on the role of state ownership of banks in the post-disaster recovery phase in China (Celil et al. 2022). Furthermore, this is consistent with papers that emphasize the importance of bank size and diversification for the post-shock supply of credit (Cortés and Strahan 2017).

Table 3 Regressions for resistance and recoverability and local finance

	(1) Resistance	(2) Resistance	(3) Resistance	(4) Recoverability	(5) Recoverability	(6) Recoverability
L.Loan/GDP	−0.074**	−0.073**		−0.111***	−0.113***	
	(0.031)	(0.031)		(0.033)	(0.033)	
L.Big 4 share	0.085**		0.084**	0.060*		0.065**
	(0.037)		(0.037)	(0.030)		(0.032)
Resistance				0.250***	0.263***	0.230***
				(0.071)	(0.073)	(0.077)
Observations	336	336	336	153	153	153
Adjusted R^2	0.085	0.076	0.073	0.433	0.421	0.382
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Exposure controls	Yes	Yes	Yes	Yes	Yes	Yes
Vulnerability controls	Yes	Yes	Yes	Yes	Yes	Yes
Industrial structure controls	Yes	Yes	Yes	Yes	Yes	Yes
Other determinants	Yes	Yes	Yes	Yes	Yes	Yes
Eicker-White SE	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The sample period is 2004–2013. Explanatory variables in logs, except resistance. Full regression results are shown in Table D.7 in the online supplementary material. Section C.3 in the online supplementary material presents alternative specifications and robustness checks

Taken together, our results reveal that the local financial structure matters when Chinese prefecture-level cities are hit by extreme weather events. In fact, while financial development and commercial banking are frequently seen as beneficial in overcoming natural hazard-related shocks by alleviating credit constraints, our results show that high pre-shock indebtedness reduces resistance and retards recovery at the local level. A strong presence of “Big 4” SOC banks does seem to alleviate the economic hardship associated with extreme weather events. While commonly associated with lower economic growth because of their high degree of state control and a potential bias towards relatively unproductive state-owned enterprises, they seem to be instrumental in the recovery after a shock in China. With the data at hand, it is not possible to shine a light on the deeper underlying mechanisms. We suspect that these banks both gear up the recovery funding after a shock because of their state-controlled objective function and that a higher presence of these banks facilitates the rapid dispersion of such funds into the local economy. In addition, and in comparison to smaller, and more local banks, such as city commercial or rural commercial banks, the “Big 4” SOC banks can draw on “deep pockets” to reallocate funds from other parts of the country to affected areas. This benefits both public authorities and enterprises in the local economy, as well as the private banking sector. For future research, this would suggest a closer inspection of both the bank-level and borrower-level effects of extreme weather events in China. In such an exercise, further emphasis should be placed on the differentiation between private and public banks and firms, and whether these different types of agents reveal different degrees of resistance and recoverability.

6 Conclusion

We study the indirect economic impacts of exogenous extreme weather events on prefecture-level cities in China between 2004 and 2013. In addition, we present one of the first investigations into the role of local finance in resilience towards extreme weather shocks in China. For this purpose, we combine a dataset that comprises detailed information about local weather intensities with disaggregated socio-economic and banking structure information.

Utilizing bias-corrected impulse response functions, we find that high wind speeds cause short-term downward pressure on the local economic growth path. Cities that experience extreme precipitation events suffer several years from the economic consequences of such events. Using these results, we construct event-based resilience measures that show us the relative resistance and recoverability of cities for a given event intensity. We find that characteristics of the local financial market are significantly related to economic resilience to extreme weather events. First, high levels of pre-event debt strongly correspond with reduced resilience, both in terms of resistance and especially in terms of recoverability. Second, contrary to the notion that state-owned banks are associated with worse economic performance, cities with a higher pre-event market share of the “Big 4” SOC banks show stronger economic resistance and more rapid post-event economic recovery. Our results comprise important implications for the discourse on extreme weather resilience in the face of climate change. First, the economic effects of extreme weather events are not merely short-lived, even in China, where there is substantial recovery spending after extreme weather events. A closer look at the root causes of such “scarring effects” is advised to complement the assessment of economic resilience to extreme weather events. Second, although access to credit helps in the recovery, a modern, market-based financial system may imply an externality in the sense that it leads to excessive pre-event leverage and debt, making economic agents more vulnerable. This vulnerability amplifies the adverse effects of exogenous extreme weather shocks. Third, climate change may affect the trade-off between privatization and localization of the Chinese banking system on the one hand, and having large, diversified, state-owned banks with a societal objective function on the other. While the former may be conducive to economic growth and local development in normal times, being able to fall back on the latter in times of crisis may be beneficial. These insights have relevance for macroprudential policy and bank regulation in the face of physical climate risk.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s10584-023-03599-w.

Acknowledgements We thank two anonymous referees, Maryann Feldman, Scott Langford, Karsten Mau, Huub Meijers, Vincent Schippers, Stefan Straetmans, participants at the GCEG 2022 in Dublin, the 2022 Workshop on Environmental Time Series Analysis at Maastricht University, the KVS New Paper Sessions 2022 at Leiden University, the 10th IWCEE in Rome, the EPSF 2022 in Graz, and seminars at Maastricht University and Aston University, Birmingham, for useful comments and suggestions. We are grateful to our colleagues Vincent Schippers (Netherlands Bureau for Economic Policy Analysis (CPB)) for the preparation of the meteorological data and Sibo Liu (Hong Kong Baptist University) for generously sharing his data on Chinese bank branches.

Author contribution Author 1 contributed to the study conception and design, material preparation, data collection and analysis, preparation of the original draft, and review and editing. Author 2 contributed to the study conception and design, material preparation, and data collection. Author 3 contributed to the study conception and design, material preparation, and review and editing. All authors read and approved the final manuscript.

Funding Open access funding is provided by Maastricht University.

Data availability The datasets generated during the current study are available from the corresponding author upon reasonable request.

Declarations

Conflict of interest The authors declare no competing interests.

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