Fintech Development and Small Business Resilience: Evidence from China

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Abstract

We examine the effect of fintech development on promoting small business resilience in response to natural disasters through the lens of credit access expansion. Exploiting an innovation policy in China as an identification strategy, we find that fintech development has a positive effect on SMEs' business activities and performance, which persists in the aftermath of disaster shocks. More importantly, the fintech development increases the fintech credit access, allowing small business to increase their debt capacity and substitute short-term bank loans with long-term fintech loans. Our analysis of fintech credit quality shows that successful fintech loans exhibit lower delinquency and interest rates after disaster shocks, with accepted borrowers having higher credit ratings, highlighting the role of fintech development in identifying creditworthy borrowers. We further find that there is a significant decrease in the unemployment rate after fintech development in the times of disaster shocks. These findings underscore the contribution of fintech development in enhancing financial inclusion and improving small business resilience to natural disasters.

Keywords: fintech development, SMEs, small business resilience, credit access, natural disasters, China

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1 Introduction

The breakneck speed of climate change has increased the frequency and intensity of natural disasters, disrupting businesses globally, particularly small businesses.[1] Evidence has been uncovered in various countries worldwide, namely Japan, the United States, Pakistan, Indonesia, and China.[2,3] Compared to large organizations, small and medium-sized enterprises (SMEs) are more susceptible to bankruptcy after severe weather events due to their limited resources, smaller size, weaker financial position, and reduced access to government recovery programs (Abdulsaleh and Worthington, 2013; Freel et al., 2012; Vos et al., 2007; United Nations Development Programme (UNDP), 2018). Reviving SMEs is now a significant concern for academics and practitioners given their invaluable role in generating employment, driving the national economy, and promoting the creation of social capital within local communities (Bernstein et al., 2022).[4] Previous studies have emphasized the importance of insurance and governmental emergency management in bolstering SMEs' resilience (e.g., Asai, 2019; Williams and Shepherd, 2016). However, the potential underservicing of SMEs by traditional financial services, especially in developing countries, may result in heightened credit constraints and a surge in demand for funds.[5,6] This can create challenges for insurance and governmental recovery management in fulfilling their roles (Agarwal and Hauswald, 2010; Demirgüç-Kunt and Klapper, 2013). The surge of financial technology (fintech) in recent

[1]In 2019, the cost of disaster losses was estimated to be USD 150 billion, with climatological disasters accounting for USD 139.5 billion of the total (IFRC, 2020).

[2]The 2011 Great East Japan Earthquake impacted more than 120,000 micro, small and medium enterprises (MSMEs), representing 99.9% of all enterprises in the affected area. In the event of 2005 Hurricanes Katrina and Rita, 60% of small businesses earned less than pre-disaster levels. 75.4% of surviving MSMEs in 2010 Pakistan Flood were worse off and 25% of the population in Indonesia lost their livelihoods during the 2004 Indian-ocean tsunami, a third of them being MSMEs owners (UNDP, 2018).

[3]China's populace is mostly concentrated in the southeast of a line stretching from Beijing to Sichuan. The entirety of this area experiences significant flooding on an annual basis, with the southern and eastern coastal regions being affected by typhoons and the western and northern margins being prone to major earthquakes. Direct property damage is estimated at USD 15 billion annually on average, but when combined with other immediate economic losses such as business interruption, disaster relief, and related expenses, the total cost is significantly higher (Wang, 2010).

[4]According to the International Finance Corporation (IFC), MSMEs contribute to over 50% of employment and around 90% of businesses globally.

[5]According to IFC's estimates, approximately 65 million firms, or 40% of MSMEs in developing nations, have an unfulfilled financing requirement of USD 5.2 trillion each year. This amount is equal to 1.4 times the present level of global MSME lending (https://www.worldbank.org/en/topic/smefinance).

[6]According to the Federal Reserve Bank of New York's 2015 Joint Small Business Credit Survey, credit access has been a significant hurdle for small businesses (https://www.newyorkfed.org/medialibrary/media/smallbusiness/2015/Report-SBCS-2015.pdf).

years has expanded credit access possibilities for SMEs (e.g., Allen et al., 2020; Qi et al., 2021). Nevertheless, studies that link fintech development and small business resilience to natural disasters are limited. This paper aims to provide insights into the real effects of fintech development on small business resilience through the lens of credit constraints.

Natural disasters can hinder SMEs' access to traditional finance, especially bank loans, due to three factors. First, the physical damage caused by these events reduces collateral value, decreasing firms' creditworthiness and borrowing capacity (Zhang et al., 2009). Second, the need to invest in restoring assets can result in a surge of loan requests, while banks may face deposit withdrawals as affected individuals and businesses attempt to compensate for economic losses and increased expenses. As such, banks may reduce lending in affected regions (Breiling et al., 2020; Nguyen and Wilson, 2020). Third, SMEs anticipate receiving prompt relief and support after natural disasters, but traditional finance may struggle to meet their needs due to costly fees, long settlement times, and difficulties managing small transactions efficiently (Eggers, 2020; Piette et al., 2015).

Fintech development can enhance SMEs' resilience by filling the credit gap in two ways. First, fintech lenders offer collateral-free or alternative-collateral lending products, enabling SMBs to access finance during natural disasters (Schweitzer and Barkley, 2017). Compared to traditional banks, fintech lenders offer loans that are smaller, have shorter durations, and are typically utilized for operational needs rather than long-term investments (Huang et al., 2020). Second, leveraging extensive banking and accounting data along with advanced credit risk models, fintech lenders can creditworthy SMEs and process their loans promptly, thereby lowering the cost of borrowing (e.g., Balyuk et al., 2020; Berg et al., 2020; Fuster et al., 2019). Specifically, Gambacorta et al. (2019) show that fintech lenders can gather and leverage a significant amount of information and extract non-linear information by utilizing machine learning techniques, resulting in improved predictive models.

Out of the 125 million SMEs worldwide, 71.2 percent are located in developing countries with the percentage peaking at 80 percent in China (Kushinir et al., 2010). SMEs play a crucial role in China's economy, with over 140 million SMEs in China in 2020 contributing over 60% of total GDP (OECD, 2022). Fintech credit has also witnessed significant growth in China, accounting for approximately 3% of the outstanding credit in the non-bank sector by the end of 2017 (BIS, 2019). Fintech has embraced significant development due to the innovation and adoption of network and mobile communication technologies. Specifically, internet-based loan distribution is one of the fastest-growing segments of the country's financial sector, with outstanding loans increasing from USD 4 billion in 2013 to USD 156 billion in 2016.[7] Approximately 40% of the online loan market comprises loans to SMEs, while consumer lending makes up the remaining portion (Hau et al., 2020).

We employ three different identification strategies to examine the effect of fintech development on small business resilience. First, we use the staggered difference-in-differences (DID) method by treating an innovation policy issued by the authorities as en exogenous shock. Technological innovation is emerging as the driving force in fintech development. Conceptually, greater attention to innovation, particularly in communication technology, can facilitate rapid progress and development in fintech (Ding et al., 2022). China's national independent innovation demonstration zone (NIDZ) policy selects representative cities at different levels of development to serve as pilot projects. It creates policies and measures aimed at encouraging these cities to enhance their independent innovation levels and capabilities. Liu et al. (2022) use the NIDZ policy as an identification strategy for technological innovation. Second, we utilize broadband services as an exogenous shock as the growth of broadband network and infrastructure can provide fundamental support for fintech development (Wan et al., 2021; Zhaohui et al., 2022). Similarly, Ding et al. (2022) use 4G services as an identification strategy. Third, we adopt the two-stage lease square (2SLS) approach by using the distance to Hangzhou as instrumental variables. This city is considered to be the fintech center in China. Hangzhou is home to the headquarters of Alibaba Group - one of the largest fintech service providers in China. As a result, fintech development in these areas is expected to be more should be more advanced (Ding et al., 2022; Hong et al., 2020). We use the first identification strategy as our baseline model. The broadband and 2SLS results are inline with the baseline results, which are further elaborated in the additional tests.

We examine SMEs' resilience using two distinct measures. Our first measure focuses on business

[7]The statistics are sourced from a report titled "Future of Finance: The Rise of China FinTech" by Goldman Sachs Global Investment Research, published on August 7, 2017.

activities, including the rate of new business entries and net business growth. Net business growth serves as a proxy for survivorship. Second, we examine SMEs' financial performance by measuring their return on equity (ROE) and return on assets (ROA). Following Suri et al. (2021), we include two stages in our empirical analysis. The first stage explores the effect of fintech development on small business activities and financial performance. In the second stage of our design, we restrict our samples to cities having faced disaster shocks during the sample period, which is 85% of the full sample. The following outcome we examine is whether the positive effect of fintech development on SME's business activities and performance sustains in the face of disaster shocks. We find that the NIDZ policy has a significantly positive effect on SMEs' business activities and performance. Theses effects persist in regions that have faced disaster shocks.

Next, we explore the economic explanations by focusing on the second-stage results. Initially, given that disasters may impact SMEs in various sectors differently, we ask whether particular industries are responsible for the positive impact of fintech development on small business activities. We find that industries that typically experience slower recovery under traditional financial services or require prompt recovery strategies, such as manufacturing and service, can benefit from the fintech development. Our channel analysis indicates that fintech development increases SMEs' fintech credit access in the wake of natural disasters. Specifically, successful fintech loans are long-term loans with a large size after the fintech development in the wake of disasters. However, the fintech development has a negative impact on SMEs' leverage, particularly short-term leverage. These results are consistent with previous studies (Ferreira et al., 2022). In times of natural disasters where indicates a surge of uncertainties, SMEs may prefer to finance their growth with long-term debt to avoid the refinancing risks and increased borrowing costs. Access to fintech credit empowered by fintech development allows small business to increase their debt capacity and substitute short-term bank loans with long-term fintech loans.

We also examine the fintech credit quality after the fintech development in the aftermath of natural disasters. Previous studies document a high delinquency rate of fintech loans after stressed times, indicating a low credit quality (e.g., Bao and Huang, 2021). Natural disasters may increase the risks that are neither observable nor fully captured by interest rates. Our analysis of the ex-post performance of fintech loans suggest that successful fintech loans after fintech development experience lower delinquency rates and have borrowers with higher credit ratings and lower interest rates. As such, fintech development can allow lenders to identify creditworthy borrowers and increase fintech credit quality in the face of disasters.

Lastly, we look at the real impact of fintech development and ask whether fintech development helps the recovery of the local economy in the face of natural disasters. We find that there is a significant decrease in the unemployment rate after NIDZ policy compared to unaffected cities in the face of disaster shocks. More importantly, such a decrease in unemployment could be enhanced in regions where the use of fintech loans is prevalent. In that sense, fintech development helps restore job loss in the face of disaster shocks. Our results remain robust in various robustness tests, including parallel trend assumption, alternative estimators, alternative control groups, and placebo test.

Our paper contributes to burgeoning literature on fintech development in the developing world. Focusing on the fintech credit in China, our results echo the recent work by Suri et al. (2021), who study digital loans in Kenya and find that proving access to digital banking to households improves their resilience in the face of adverse shocks. Lee et al. (2021) provide evidence that mobile banking to poor households and migrants in Bangladesh improves consumption during the lean season. Our paper complements this area by adding evidence of fintech loans in a Chinese context. Recent work of fintech industry in China focuses primarily on expanding credit and promoting innovation (e.g., Ding et al., 2022; Hau et al., 2020). Our paper differs from these existing studies by providing evidence of fintech development in promoting small business resilience. We extend the work by showing that fintech development also increases enterprise growth and preserves SMEs' financial flexibility amid natural disasters.

Our paper complements the existing fintech literature in several aspects. First, we contribute to understanding the role of fintech development in SMEs' access to finance in the aftermath of adverse shocks. During times of high uncertainties and tighter capacity constraints, traditional banks may tighten their credit standards to reduce processing costs and limit associated credit risks (Bedayo et al., 2020; Jagtiani and Lemieux, 2019). In contrast, the algorithm-driven approaches may enable fintech lenders to identify creditworthy borrowers who are perceived to be riskier by banks without tightening underwriting standards (e.g., Beaumont et al.; Cornelli et al.; Gopal and Schnabl).

Second, this study connects to the literature on behavioral features of fintech lending. Bao and Huang (2021) are the first to evaluate the performance of post-disaster fintech loans. They document a high delinquency rate of fintech loans after the COVID-19 outbreak. In contrast, Allen et al. (2020) and Qi et al. (2021) find that fintech lenders do not experience higher delinquency rates or interest rates in the aftermath of natural disasters. We add to the area demonstrating a decrease in delinquency rate fintech loans amid disaster shocks. Our results also speak to the work studying the fintech credit quality (Gambacorta et al., 2019; Iyer et al., 2016; Vallee and Zeng, 2019). The empirical setting of NIDZ establishment enables us to directly examine the effect of fintech development on the behavioral features of fintech lending. With the fintech development, the algorithm-driven approaches enable fintech lenders to retrieve borrower information and identify creditworthy borrowers, thereby decreasing the delinquency rate of fintech loans.

Third, our paper extends the literature on financial inclusion (e.g., Berg et al. (2020); Buchak et al. (2018); Erel and Liebersohn (2020); Tang (2019)). We add nuance to the literature by demonstrating that fintech development can lower the financial access barriers created by traditional banks, especially during the highly uncertain times. Additionally, fintech development increases service affordability by enabling fintech lenders to identify creditworthy borrowers through advanced approaches (Bedayo et al., 2020; Gambacorta et al., 2019; Jagtiani and Lemieux, 2019).

Our analysis of business establishment offers us an opportunity to examine the drivers of firm entry. Important work in the area of competition and finance demonstrates the role of cash holdings (Boutin et al., 2013), derivatives (Giambona et al., 2021), and access to the public market (Phillips and Sertsios, 2017) in enterprise growth. Our results add to this area by proposing that fintech development can drive firm entry in the face of disaster shocks. The increased access to fintech credit provides a novel financing to new entrants.

Finally, our study is policy relevant to mitigate climate change risks. Climate change has become a pressing global issue. Due to the increasing frequency and severity of disasters, emergency management attempts by government agencies and response organizations struggle to fulfill community needs in the aftermath of natural disasters due to the increasing frequency and severity of disasters (Williams and Shepherd, 2016). Additionally, authorities offer a series of capital and other regulations to ensure the resilience of banks in the aftermath of disasters. Nevertheless, there still exists significant credit demand. In this paper, we suggest a new disaster mitigation strategy. Our results argue that entrepreneurs may better understand when and how they can seize new business opportunities in the aftermath of natural disasters. Promoting fintech development can enhance access to fintech loans, encouraging the business establishment and benefiting vulnerable inhabitants by creating more jobs. Better still, fintech development can improve the performance of fintech loans and benefit fintech lenders, resulting in a more sustainable financial system amid disaster shocks.

The remainder of this paper proceeds as follows. In Section 2, we discuss the background and develop the hypothesis. We describe the data, sample selection procedure, and variable definitions in Section 3. We report the baseline analysis in Section 4. We report the economic explanations in Section 5. We describe the robustness results in Section 6. We conclude in Section 7.

2 Background and Hypothesis Development

2.1 SME financing in China

There were more than 140 million SMEs and self-employed individuals in China in 2020. These SMEs make up over 60% of the total GDP, 50% of the tax income, 79% of job creation, and 68% of the country's exports. In the same year, there were around 2.52 million new companies established, with an average of 22,000 newly registered enterprises per day (OECD, 2022).

China is gradually fostering a business environment that is favorable for SMEs, leading to an increase in their financing needs. The outstanding business loans for SMEs rose by 10.17% in 2019 to CNY 36,900 billion, but credit constraints still exist. SMEs face extra fees during loan application, with an average charge of 2.47% of the loan value in 2019. Collateral requirements were also a constraint from 2016-2019 (OECD, 2022). In response, the Chinese government called for more credit support for SMEs. As a result, SMEs pursue alternative financing source, including venture capital, leasing and factoring, online lending and crowdfunding.

2.2 Fintech development in China

Historically, capital investment has been the driving force behind economic growth in China, leading to a traditional financial system that primarily caters to the needs of large corporations. This leaves significant potential for growth and development in the areas of payment systems, wealth management, financing, insurance, and credit rating services for both retail customers and SMEs. China's shift from an investment-driven to a consumption-driven growth model underscores the increasing importance of providing better services to consumers and SMEs (Chen, 2016).

In recent years, the fintech advancement in China has garnered significant attention within the finance industry, where it has progressed across various finance fields, including online payment, financing, wealth management, and online insurance. The rapid development of internet finance was driven by the explosive growth of the Chinese mobile internet from 2013 to 2015, resulting in 343 operating lending platforms in 2019, with an outstanding volume of online lending amounted to CNY 236.48 billion (OECD, 2022). Examples of fintech unicorns include Ant Financial, Lufax, Zhongan, and Du Xiaoman Financial. Ant Financial, a subsidiary of the Chinese e-commerce giant Alibaba Group, has emerged as the world's largest fintech company in the top 100 global fintech companies in 2019. Ant Financial started to provide loans and short-term working capital financing in 2010. Between 2010 and 2016, Ant financial has provided over CNY 700 billion (equivalent to over USD 100 billion) in loans to SMEs (Chen, 2016).

2.3 Fintech development and SMEs

In this section, we develop a hypothesis that explores how fintech development impacts small business resilience in response to natural disasters by examining the expansion of credit access as an economic mechanism. Fintech signifies a novel dimension of financial development, wherein the fundamental objective of finance remains to serve the real economy. Therefore, the better developed fintech means greater financial inclusion and better developed financial markets, which creates a more favorable environment for SMEs to sustain their business activities and performance in the aftermath disaster shocks.

SMEs heavily rely on commercial banks for debt finance (Coleman and Cohn, 2000). Traditional banks possess unique advantages and incentives that enable them to increase credit supply to SMEs in disaster situations. Their creditworthiness allows for inter-temporal credit smoothing, utilizing low deposit rates to gain a larger net interest spread and implicitly guarantee credit supply during times of uncertainty (Berger et al., 2022; Bolton et al., 2016). Local or community banks with established customer relationships and access to soft information can provide stable access to bank loans during good and bad times (Berger and Udell, 2006; Nguyen, 2019). Furthermore, regulatory relief measures are available to traditional banks to aid in post-disaster recovery (Allen et al., 2020).

However, SMEs' lack of financial data results in information asymmetry and credit rationing (Stiglitz and Weiss, 1981), leading to unmet loan demand despite their willingness to comply with the contract terms. This issue is exacerbated during disaster crises. First, smaller businesses often have limited financial and technical resources to mitigate and manage risks. During times of high uncertainties and tighter capacity constraints after natural disasters, traditional banks may tighten their credit standards to reduce processing costs and limit associated credit risks (Bedayo et al., 2020; Jagtiani and Lemieux, 2019). Second, disasters tend to have a broader negative impact on the communities where SMEs operate and SMEs are more dependent on community recovery compared to larger firms (UNDP, 2018). Consequently, natural disasters could have a significant impact on SMEs' performance and business activities.

Fintech development lowers financial access barriers classified by the World Bank (Beck et al., 2008), including physical barriers, appropriate product availability, and service affordability. Compared to traditional financial institutions that rely on physical branches to expand their services, fintech development provides digital access to financial services, overcoming coverage limitations and reaching customers in impoverished regions where physical branches are costly. Fintech distributes financial resources more directly and widely than traditional institutions that focus on densely populated and commercial areas. Therefore, fintech development promotes greater financial inclusion in the local areas. Additionally, algorithm-driven approaches enable fintech lenders to identify creditworthy borrowers perceived as riskier by banks without tightening underwriting standards (Balyuk et al., 2020; Berg et al., 2020; Fuster et al., 2022), boosting credit access for SMEs after natural disasters.

These arguments suggest that fintech development promotes SMEs resilience in response to natural disasters by expanding their credit access, which leads to our hypothesis.

Hypothesis 1. Fintech development has a positive effect on SMEs' business activities and financial performance in the aftermath of natural disaster.

3 Data and Descriptive Statistics

3.1 National Innovation Demonstration Zone in China

China has implemented various innovation policies to boost technological advancement in recent years, and the national innovation demonstration zone (NIDZ) policy is a noteworthy regional innovation policy among them. Since 2009, the Chinese authority has designated representative cities at different levels of development as pilot projects and implemented policies and measures to stimulate these cities' independent innovation capacity. In March 2009, China established the first Zhongguancun NIDZ in Beijing. As of August 2019, a total of 21 NIDZs had been established, spanning 56 cities. The establishment of a NIDZ can enhance the technological innovation system, expedite the growth of high-tech industries, and achieve a shift in economic development mode in the affected areas (Huang et al., 2013). We construct the variable $NIDZ_{i,t}$ to be a dichotomous treatment variable for the group of NIDZ cities. It takes the value of 1 for cities approved to be a NIDZ in year t; this term is set to zero for control cities in any t.[8]

Technological innovation can enable the empowerment of fintech development. Most financial institutions' primary competencies lie in their capability to efficiently and securely reach a diverse customer base and to understand and manage risk through assessing their customers. Technological

[8] We use the NIDZ policy released date as the approval date and the year of treatment in our empirical analysis. See http://english.www.gov.cn/policies/latest_releases/2016/06/20/content_281475376072953.htm as an example.

advancement has played a critical role in advancing progress in both areas. For instance, the accessibility and convenience of financial services are improved by mobile internet technology, big data is redefining the efficiency of information collection and processing, leading to an increased ability to assess risks, and cloud computing is significantly changing the cost and efficiency of financial services (Chen, 2016). Therefore, we argue that this shock can directly bring about the development of fintech as the NIDZ innovation policy can increase the innovation capacity and promote the technological innovation system in the affected regions. Similarly, Liu et al. (2022) use the NIDZ policy as an exogenous shock to regional technology innovation and study its effect on haze control.

3.2 Data on business registry and financial performance

The business registry data are from the State Administration for Industry and Commerce (SAIC). We collect information for all registered SME entities available until 2018.[9] For each entity, we retrieve information on the date of incorporation, date of liquidation, current trading status, industry (tabulation categories identified by letters - China's Industrial Classification for National Economic Activities (CISIC)),[10] and the administrative division codes of the place of incorporation. The sample selection procedure is based on data availability, resulting in the maximum number of observations.[11] Our sample comprises 33,725,816 entities in 339 cities. Based on the available data on business registry, it is impossible to assess the impact of the NIDZ on business activities in 2019. Therefore, we exclude these cities from our sample. Finally, we summarize the full business registry data to 2,384 city-year observations from 2008 to 2018. We construct two business activities measures at the city levels Bermejo et al. (2020). *Entry rate (%)* denotes the number of new entities in year t divided by the number of established entities in year $t-1$ in city i. *Survival rate (%)* represents the growth of survived entities from year $t-1$ to year t in city i. Survived entities are

[9] The classification of SMEs in China varies across different industry sectors and SAIC provides information on whether registered entities fall under this category.

[10] The current industry classification standard in China is the Industrial Classification for National Economic Activities (CISIC) (http://www.stats.gov.cn/tjsj/tjbz/201709/t20170929_1539288.html), generally adapted from the International Standard Industrial Classification of All Economic Activities (ISIC) issued by the United Nations. (https://unstats.un.org/unsd/publication/seriesm/seriesm_4rev4e.pdf)

[11] Hong Kong SAR, Macao SAR, and Taiwan are excluded from our analysis due to the lack of data.

defined as the sum of established entities and new entities, minus liquidated entities.

Since the information on firm-level financial performance is not available from SAIC, we augment the business registry data with financial performance data obtained from the Chinese Industrial Enterprise Database (CIED). This database is also known as the Chinese Industry Business Performance Database (CIBPD) and has been widely used in the literature (Hau et al., 2020; Hsieh and Klenow, 2009; Liu et al., 2021; Song et al., 2011). It covers all establishments from 2008 to 2015, including firm-level information on physical addresses, ownership structure, and basic financial data. Although we cannot match individual business registries with CIED data, we exclude listed firms in the database and collect financial data for private SMEs. Our sample comprises 1,400,907 enterprises in 361 cities. Based on the data availability, we exclude NIDZ cities after 2015 from our sample and summarize the financial data to 890,573 firm-year observations from 2008 to 2015. We construct the following performance variables that are widely used in the literature (Kim, 2020). *ROE (%)* is operating income before depreciation and amortization scaled by lagged equity. *ROA (%)* is operating income before depreciation and amortization scaled by lagged assets.

Panel A of Table 1 provides descriptive statistics on the business activities variables at the city-year level and performance variables at the firm-year level. Figure 1 presents the heat map of business establishment density measured as the average number of new entities established between 2008 and 2018.

[Insert Table 1 here]

3.3 City-level control variables

Local credit demand and borrower credit risk can be impacted by the local socioeconomic and demographic characteristics and the presence of traditional banks. We obtained city-level census data from the City Statistical Yearbook issued by the National Bureau of Statistics of China (NBS). We construct the following city-level variables: GDP per capita (*GDPpc*), population (*Population*), city area (*Area*), deposit per capita (*Deposit pc*), bank loan balance per capita (*BL pc*), and tax revenue *(TAX)*. We also include the innovation variables for each city: the number of R&D staff

(*R&Dpp*) and the number of granted patents (*Grant*).[12,13] Variable definitions are provided in Appendix A.1. We match the city-level variables with business activities and performance data.[14] Panel B of Table 1 provides descriptive statistics on the local variables at the city-year level.

3.4 Natural disasters

We collect data on natural disasters from the National Disaster Reduction Centre of China (NDRCC), a national disaster database established in 2002. The NDRCC provides the declaration date of the disaster, location of the incident (county, city, and province), disaster type, and measures of impact (economic loss, deaths, and injured population). Our sample covers the period from 2014 through 2018. The total number of disasters is 6,866 in 340 cities. We observed 16 types of disasters during the sample period, including floods, typhoons, heavy rains, fires, droughts, cold waves, hailstorms, landslides, earthquakes, and others.

Panel C of Table 1 provides descriptive statistics on the number of incidents per year in each city from 2014 to 2018. The lowest number of incidents is one per year, while the largest number of incidents per year is 138. Figure 2 presents a map of city-level natural disaster intensity. It shows that 68 out of 340 cities (20%) are classified as high-risk areas in terms of the total number of incidents between 2014 and 2018. Each of these cities had more than 32 natural disaster occurrences (the value of the 80^{th} percentile) over the sample period.

Panel C of Table 1 also reports the descriptive statistics on disaster types from 2014 to 2019. Floods, heavy rain, hailstorm, high wind, and typhoons were ranked as the top five declared major disaster types based on the number of occurrences.

[12]All monetary variables are reported in Chinese yuan (CNY), where the exchange rate was 6.77 CNY to one USD at the beginning of our sample period.

[13]All monetary variables are adjusted for the consumer price inflation (Year 2008=100). The consumer price index is obtained from the World Bank https://data.worldbank.org/indicator/FP.CPI.TOTL?locations=CN

[14]We use the latest administrative division codes issued in 2019 as a reference to account for any alternation of administrative names or boundaries during our sample period.

4 Empirical Analysis: Dose NIDZ policy affect small business resilience?

We use a staggered difference-in-differences (DiD) framework that compares SMEs' business activities and performance in NIDZ cities relative to unaffected cities:

$$Y_{i,t} = \delta_i + \delta_t + \beta_1 NIDZ_{i,t} + \gamma Z_{i,t} + \varepsilon_{i,t}, \tag{1}$$

where i indexes city and t year; δ_i is the city fixed effect; and δ_t is the year fixed effect. $NIDZ_{i,t}$ is a dichotomous treatment variable equal to one if city i has been approved to be an innovation demonstration zone in year t; this term is set to zero for control cities in any t. $Y_{i,t}$ can be one of the business activities and performance variables described in Section 3.2: *Entry rate (%)*, *Survival rate (%), ROE (%),* or *ROA (%)*. $Z_{i,t}$ is a vector of city-level time-variant local socioeconomic and demographic control variables described in Section 3.3. The coefficient of interest β_1 measures the average difference in business activities and performance between the treatment (*NIDZ*=1) and control cities (*NIDZ*=0). Standard errors are clustered at the city level to address any common unobserved random shock that may lead to correlations in our baseline results.

Panel A of Table 2 presents estimation results for Equation 1. Following Suri et al. (2021), we include two stages in our empirical analysis. Columns (1) and (2) focus on the analysis of our full sample that we refer to as "first stage" outcomes. Column (1) shows the estimate on *NIDZ* that is significantly positive at the 1% level, indicating that the entry rate of new business increases by about 1.726 percentage points after a NIDZ establishment relative to that in the unaffected cities. Column (2) indicate that the survival rate increases significantly at the 1% level by about 0.017 percentage points. Overall, fintech development has a positive effect on small business activities.

In the second stage, we restrict our samples to cities having faced disaster shocks during the sample period, which is 85% of the full sample, and investigate whether the positive effects of fintech development on small business activities persist. Columns (3) and (6) present the "second stage" outcomes. The estimates on *NIDZ* in columns (3) and (4) show that the NIDZ policy has positive effect on new business entry rate and survival rate in the aftermath of natural disasters.

Notably, the magnitude of *NIDZ* in restricted samples is greater than that in the full sample, indicating a stronger effect of fintech development on business activities. Additionally, the effects of fintech development are marginal in the sample of cities that have no disaster shocks during the sample period. In summary, these results are consistent with our hypothesis that fintech development has a positive effect on small business activities in the wake of natural disasters.

Next, we examine the small business performance using the model of Equation 1. Panel B of Table 2 presents estimation results. Columns (1) and (2) show that NIDZ policy has a significantly positive effect on ROE and ROA at the 5% and 1% levels, respectively. Columns (3) and (4) include $Industry \times year$ fixed effects and the estimates on *NIDZ* remain significantly positive. When we restrict our samples to cities having faced disaster shocks during the sample period in the second stage, columns (3) and (4) show that the positive effects persist after disaster shocks. Columns (5) and (6) include $Industry \times year$ fixed effects and the estimates on *NIDZ* remain significantly positive at the 5% levels. Notably, the effects of fintech development are insignificant in the sample of cities that have no disaster shocks (columns (9) to (11)). Overall, our results suggest that fintech development has a positive effect on small business performance in the aftermath of natural disasters.

[Insert Table 2 here]

5 Empirical Analysis: Economic Explanations

Our results in Section 4 demonstrate our hypothesis that fintech development can improve small business resilience. Next, we focus on the second-stage results and explore the economic explanations.

5.1 Firm-level heterogeneity by industry

First, we examine whether specific industries are accountable for the positive impact of fintech development on small business activities. Disasters may affect SMEs in various sectors differently. Studies indicate that SMEs operating in the retail industry can recuperate at a faster pace than those in other industries. The construction sector may gain temporary advantages from reconstruction initiatives following disasters. However, SMEs in the manufacturing sector may experience prolonged periods of closure and business disruption due to the loss of essential resources and personnel. Furthermore, SMEs in the tourism and service industries can recover swiftly from short-term collapses if they adopt prompt recovery strategies (UNDP, 2018). As a result, industries that typically experience slower recovery under traditional financial services may benefit more significantly from the positive impact of fintech development on business activities.

We partition the sample into subsamples of industries and re-estimate Equation 1. The information on business industry classification (CISIC) is obtained from SAIC. Panel A of Table 3 presents the new business distribution from 2008 to 2018 according to the CISIC categories by descending order of the number of new entities. All 18 industries are presented based on affected and non-affected cities. The most frequent industry for both affected (31.314%) and non-affected (31.070%) cities is wholesale and retail. Four of the five most frequent industries (wholesale and retail., manufacturing, commercial service, and construction) in affected cities are also four of the five most frequent industries for non-affected cities. However, it is noticeable that scientific research is the third most frequent industry in affected cities that have the fintech development while agriculture is the second most frequent industry in control cities.

Next, we exploit the differential effect of NIDZ policy on business activities in different industries amidst disaster shocks. Table 3, Panel B presents the positive regression estimates of *NIDZ* from Equation 1. The NIDZ policy increases new business entry rate and survival rate in manufacturing, real estate, resident service, and education in response to natural disasters. Consistent with previous studies, our results suggest that industries that typically experience slower recovery under traditional financial services or require proper recovery strategies, such as manufacturing and service, can benefit significantly from the fintech development.

[Insert Table 3 here]

5.2 Mechanism: credit access expansion

The innovative services and advanced technologies under fintech development aim to expand credit access. Specifically, fintech lenders utilizing the fully-automated algorithm to process credit information have a competitive advantage in providing credit (Balyuk et al., 2020; Berg et al., 2020; Fuster et al., 2022). Therefore, the positive effect of fintech development on SMEs' resilience can be explained by the credit access expansion. In this section, we investigate whether fintech development increases SMEs' credit access in the wake of natural disasters.

5.2.1 Access to fintech credit

We measure credit access in two aspects. Initially, we examine the use to fintech loans. Fintech development powered by enhanced innovation system can increase online lending in the regions, leading to a expansion of access to fintech credit. We obtain fintech loans data from all loan listings posted on Renrendai and Eloancn, two leading Chinese peer-to-peer (P2P) lending platforms, between 2010 and 2018. Founded in 2010, Renrendai is one of the most popular P2P lending platforms in China. It now has over 2 million members located in more than 2000 areas. Up to 2020, Renrendai has originated loans of more than CNY 116 billion. Moreover, Renrendai has been widely used in the literature on fintech loans.[15] To mitigate the confounding impact of one specific lending platform, we augment the Renrendai data with loan listings from Eloancn, an online P2P lending platform with a focus on micro and small enterprises. Founded in 2007, Eloancn has completed 952,330 loans with a cumulative credit amount of more than CNY 65 billion by 2020. It has gained its market share promptly by offering credits to small businesses, such as farmers (Liu et al., 2022).

These two P2P platforms work similarly. First, borrowers are required to provide an ID card for verification. The platform provides verification services on ID cards and credit reports. It assigns a credit score to each borrower based on their borrowing or lending history and the amount of verified information, such as the repayment source, income, job title, or ownership of other properties. Second, borrowers post loan listings with the required information, including loan title, residence

[15] See examples: Chen et al. (2020); Li et al. (2020); Song and Zhang (2020)

city, borrowing amount, interest rate, and description of loan usage. When creating loan listings, borrowers are encouraged to disclose additional information concerning the purpose of the loan and other personal information. Finally, once a loan listing is posted, lenders can place bids on the amount they are willing to fund. A listing typically requires multiple bids to become fully funded and it is called a successful listing. Otherwise, the listing fails and the borrowers receive zero funding (Chen et al., 2020). Given that the verification and credit rating provided by the platform is limited, it is of utmost importance for lenders to determine the creditworthiness of borrowers from the information disclosed on the platform (Iyer et al., 2016; Michels, 2012).

Our sample comprises 1,524,061 loan applications in 357 cities between 2010 and 2018. Based on the data availability, we exclude NIDZ cities before 2010 from our sample and summarize the fintech loans data to 2,384 city-year observations from 2010 to 2018. We include the following variables that measure the use of fintech credit: *FTL Number (thousand)*, defined as the number of successful fintech loan applications in city i in year t and *FTL Amount (CNY million)*, defined as the total loan amount of successful fintech loans in city i in year t. We use the same regression model setup as in Equation 1 but use *FTL Number* and *FTL Amount* as dependent variables.

Table 4, Panel A presents the estimation results for *NIDZ*. Columns (1) and (2) show that the NIDZ policy has a significantly positive effect on the use of fintech credit at the 1% level in the aftermath of natural disasters. We also include an additional interaction term $NIDZ \times Intensity$ in Equation 1. *Intensity* is defined as the total number of disaster incidents that occurred during 2010-2018 in city i. Moreover, column (3) shows that the estimate of $NIDZ \times Intensity$ is 0.064 and statistically significant at the 1% level. Thus, in regions with higher disaster densities, the number of successful fintech loans increases by 64 after the NIDZ policy relative to regions with lower disaster densities. Overall, our results support that fintech development can increase access to fintech credit in the wake of disaster shocks. Additionally, the use of fintech loans is more pronounced in regions with high disaster densities.

We supplement the analysis of access to fintech loans by analyzing the heterogeneous characteristics of successful fintech loans. First, we examine the successful loan size and loan term in our baseline results. We partition the loan samples into subsamples of loan size and loan term.

A short-term loan is defined as the number of successful fintech loans with a repayment period of less than or equal to 12 months in city i in year t. A long-term loan is defined as the number of successful fintech loans with a repayment period of more than 12 months in city i in year t. A small (large) loan is defined as the number of successful fintech loans with a loan amount less than or equal to (more than) the median of loan amount across all applications in city i in year t.

Panel B of Table 4 presents the estimation results for Equation 1 using the subsample of loan term and loan size. Columns (2) and (4) show the estimates on *NIDZ* are significantly positive at the 1% levels. Our results demonstrate that successful fintech loans are long-term loans with a large size after the fintech development in the wake of disaster.

[Insert Table 4 here]

5.2.2 Access to bank loans

The use of fintech credit is not reflected in firms' balance sheet, while the leverage can be employed to gauge the use of bank loans. Thus, we use the leverage to explore SMES' credit access in the wake of natural disasters. Utilizing the financial performance data in Section 3.2, we include the following leverage variables: *Leverage (%)*, defined as the debt-to-capital ration defined as total debt (long-term plus short-term debt) divided by the sum of total debt and the book value of equity in percentage. *LT Leverage (%)*, denoted as long-term debt divided by the sum of long-term debt and the book value of equity in percentage. *ST Leverage (%)*, defined as short-term debt divided by the sum of short-term debt and the book value of equity in percentage. We use the same regression model setup as in Equation 1 but use leverage as dependent variables.

Table 4, Panel B reports the estimation results for *NIDZ*. Columns (2), (4), and (6) include $Industry \times year$ fixed effects in the regression models. The estimates on NIDZ show that the NIDZ policy has a negative effect on firms' leverage (columns (1) and (2)). Specifically, the negative effect of NIDZ policy is more pronounced on short-term leverage (columns (5) and (6)). Overall, SMEs reduce their short-term leverage after the fintech development in the aftermath of natural disasters. Combined with results in Section 5.2.1 that successful fintech loans are long-term loans with a large size after the fintech development in the face of disaster, small businesses reduce their leverage in our setting and substitute short-term bank loans with long-term fintech loans. In times of natural disasters, banks may face increased uncertainty. Hence, SMEs may be concerned that banks would tighten underwriting standards in the face of uncertainties, thereby increasing their refinancing risks. As a result, SMEs may prefer to finance their growth with long-term debt to avoid the refinancing risks (Ferreira et al., 2022). Access to fintech credit empowered by fintech development allows small business to increase their debt capacity and substitute short-term bank loans with long-term fintech loans.

5.3 Fintech credit quality

Natural disasters may adversely increase the risks that are neither observable nor fully captured by interest rates, indicating a low credit quality. In contrast to traditional banks, fintech lenders harness a vast amount of data points provided by borrowers and produce a snapshot for each borrower's creditworthiness and probability of repaying the loan. Accordingly, we investigate the ex-post performance of fintech loans to provide insights into whether the fintech development empowered by innovation policy allow fintech lenders to identify creditworthy borrowers, thereby reducing the delinquency rates of fintech loans.

First, we partition both the loan samples into subsamples of loan delinquency and summarize the number of delinquent (non-delinquent) fintech loans in city i in year t. We also construct a delinquency variable: *Delinquency rate,* defined as the ratio of delinquent fintech loan numbers to all fintech loan numbers in city i in year t. Table 5, Panel A reports the estimation results for Equation 1. Columns (2) shows the estimates on *NIDZ* that are significantly positive at the 1% level, suggesting that the successful fintech loans after NIDZ policy are non-delinquent in the aftermath of disasters. Similarly, column (3) shows that successful fintech loans after fintech development experience lower delinquency rates than those in unaffected cities.

We supplement the analysis of ex-post performance of fintech loans by examining the borrowers' characteristics in the face natural disasters. Renrendai and Eloancn platforms will assign a credit rating to each borrower based on the amount of verified information. The current ratings range from the lowest HR to the highest AA. Typically, a borrower with a higher credit rating can enjoy a higher success rate of getting a loan. Moreover, borrowers with high credit ratings can ask for lower interest rates when posting loan listings. We construct two credit risk variables: an indicator variable for the credit rating of fintech borrowers across successful fintech loan applications (*FTL Score*) and the annual interest rate for fintech borrowers across successful fintech loan applications (*FTL Interest Rate*). We address this research question by estimating Equation 1, where *FTL Score* and *FTL Interest Rate* are the dependent variables using the loan listing samples. We also include the borrower's fixed effect and borrower-level control variables: age (*Age*), gender (*Gender*), educational level (*Education*), profession (*Job*), ownership of a house (*House*), and ownership of a car (*Car*).[16]

Panel B of Table 5 presents the estimation results for Equation 1. Columns (1) and (2) show the estimates on *NIDZ* that are significantly positive at the 1% levels. These outcomes suggest that the successful fintech loans after NIDZ policy have borrowers with higher credit ratings and lower interest rates than those in unaffected cities in the wake of disaster. Consistent with previous studies, fintech development can allow lenders to identify creditworthy borrowers and lower the delinquency rates of fintech loans.

[Insert Table 5 here]

5.4 Real impact of fintech development

The last question we ask is whether fintech development helps the recovery of the local economy in the face of natural disasters. We examine the real impact of fintech development by looking at the annual unemployment rate in the region, determining whether more intensive use of fintech loans could help alleviate the adverse effect of disaster shocks on local unemployment. Following Qi et al. (2021), we construct the following two variables measuring the use of fintech loans in the region: *Fintech Loan_ Pre*, defined as the number of successful fintech loan applications per 1,000 population pre-disaster in city i in year t; *Fintech Loan_ Post*, defined as the number of successful fintech loan applications per 1,000 population post-disaster in city i in year t. We include year and disaster-year fixed effects in the specification from Equation 1.

[16] See Appendix 7 for the definition.

The results are presented in Table 6. We find that there is a significant decrease in the unemployment rate after NIDZ policy compared to unaffected cities in the face of disaster shocks. Columns (2) and (3) further suggest that the decrease in the unemployment rate could be enhanced in regions where the use of fintech loans is prevalent. In that sense, fintech development helps restore job loss due to disaster shocks, thereby eventually promoting recovery of catastrophes.

[Insert Table 6 here]

6 Additional Tests

6.1 Different estimation windows

In this section, we examine the effect of fintech development on SMEs' business activities after disasters from Equation 1 using two different estimation windows. The first estimation window is three years before and after the approval of a NIDZ ([-three years, three years]). The second estimation window is three years before and six years after the approval of a NIDZ ([-three years, six years]). We use the second-stage sample comprising 2,024 city-year observations from 2008 to 2018. We include dependent variables examining small business activities (*Entry rate (%)* and *Survival rate (%)*).

The results are presented in Table 7. We find that the estimate on *NIDZ* is significantly positive at the 5% level in [-three years, six years] estimation windows. In that sense, NIDZ policy has an impact on SMEs' business activities after three years in the face of disasters.

[Insert Table 7 here]

6.2 Dynamic effects and parallel trend assumption

Our identification strategy employs the staggered difference-indifferences framework. The validity of the framework depends on the parallel trends assumption. To test, we examine the dynamic effects of fintech development on SMEs' business activities in the face of disaster shocks, using the following specification:

$$Y_{i,t} = \delta_i + \delta_t + \beta_k \sum_{k=-3}^{-2} Zone_{i,t} \times d[t+k]_t + \beta_k \sum_{k=0}^{6} Zone_{i,t} \times d[t+k]_t + \gamma Z_{i,t} + \varepsilon_{i,t} \qquad (2)$$

This specification is similar to that in Equation 1, with the exception that the indicator variable *NIDZ* is replaced with the nine indicator variables *d[t+k]*, $-3 \leq k \leq -2$ or $0 \leq k \leq 6$, which are equal to one for city i in three years before and after establishing NIDZ and zero otherwise. [17, 18] We use the second-stage sample comprising 2,024 city-year observations from 2008 to 2018. We include dependent variables examining small business activities (*Entry rate (%)* and *Survival rate (%)*).

Table 8 presents the estimation results from Equation 2. The coefficients on *Zone* × *d[t+k]* ($-3 \leq k \leq -2$) show that there exists no significant pattern of SMEs' business activities before establishing NIDZ ("year t-1" is the baseline year, and thus d[t-1] is set to zero by construction), which satisfies the parallel trend assumption and bolsters our inferences stemming from the baseline specification. In contrast, the coefficients on *Zone* × *d[t+k]* ($0 \leq k \leq 6$) show that access to fintech loans starts to increase from the year of incidents ("year t") and peaks at year four("year t+4"). Specifically, four years after establishing NIDZ, the entry and survival rates of small business increase on average at the 1% significance level compared to one year before the NIDZ establishment. We do not find a significant change in entry and survival rates three years following the NIDZ establishment ("year t+3"). These results are consist with the results in Section 6.1. **??** and **??** depict the dynamic effects based on the estimates in **??** and corresponding 95% confidence intervals. The figures display the same pattern in coefficient estimates as those in **??**. Specifically, there was an increase in the number of fintech loans after establishing NIDZ and a sharp spike in four years (Panel A of **??**).

the number of fintech loans increased by 2,010 on average at the 1% significance level, compared to one year before the NIDZ establishment. However, we do not find a significant change in entry and net entry rate three years following the NIDZ establishment ("year t+3"). Notable, the exit

[17] $\{\beta_k\}$ are estimated relative to β_{-1}, which is omitted. Thus all event time indicators represent enterprise growth relative to one year before the occurrence of natural disasters.

[18] The estimation window is consistent in Section **??**.

rate starts to decrease first two years after the NIDZ establishment ("year t+2"). In that sense, establishing NIDZ creates an opportunity for existing small businesses to survive first, lowering the exit rate and promoting the business establishment afterward. Additionally, Figure 3 depicts the dynamic effects based on the estimates in Table 8 and corresponding 95% confidence intervals. The figures display the same pattern in coefficient estimates as those in Table 8. Specifically, there was an increase in the SMEs' business activities after NIDZ policy and a sharp spike in four years.

[Insert Table 8 here]

6.3 Alternative identification strategies

We use two other identification strategies to address any potential endogeneity issues. First, we employ the "Broadband China" pilot program (BCP) as another policy shock and re-estimate Equation 1 using samples restricted to cities having faced disaster shocks. To promote the development of broadband infrastructure in China, State Council issued the "Broadband China" pilot program on August 16, 2013. 117 cities were selected in three batches in 2014, 2015, and 2016. The use of BCP as an exogenous shock to fintech development has been justified in previous studies (Wan et al., 2021; Zhaohui et al., 2022). The development of broadband network and infrastructure can provide fundamental support for fintech development.

Panel A, Table 9 presents the estimation results from Equation 1 using BCP as an exogenous shock. Columns (1) and (2) show that the broadband development has a significantly positive effect on credit access expansion. Columns (3) and (4) indicate the satisfaction of parallel trends assumption of our identification strategy.

Second, we employ an instrumental variable approach (2SLS). We utilize the Peking University Digital Financial Inclusion Index of China (PKU-DFIIC) (*DFI*) as a proxy for fintech development in a city.[19] Innovative fintech is a significant impetus behind the current growth of financial inclusion in China. From this perspective, this index quantifies China's digital financial inclusion practices. It establishes an indicator system that measures all social classes and groups' access to

[19]PKU-DFIIC exploits Ant Financial's massive dataset on digital financial inclusion. Financial inclusion refers to offering financial services to all socioeconomic classes and groups with an effective and comprehensive financial system. See details: https://en.idf.pku.edu.cn/docs/20190610145822397835.pdf.

financial services and the achievements of financial development in various areas. A greater index indicates a more substantial development of fintech in the area. This index covers the city level from 2011 to 2018. Li et al. (2020) utilize the PKU-DFIIC as a measure of fintech development and conclude that inclusive fintech could promote household consumption.

Following Hong et al. (2020), we use the natural logarithm of a city's geographic distance to Hangzhou as an instrument variable (*Log(Distance_HZ)*) to measure the intensity fintech adoption across different cities. Over past decades, Hangzhou has adopted policies to support high-tech industries and become the hub of sci-tech advancement. For example, Hangzhou is the headquarter of Alibaba, the leading Chinese multinational technology company. Thus, the expansion of fintech is believed to center around Hangzhou and gradually penetrate other cities (Hong et al., 2020). In the second stage, we examine the effect of instrumented *DFI* on access to fintech loans.

Table 9, Panels B and C report the IV test estimations. Panel B presents the results in the first stage regression where *DFI* is regressed on *Log(Distance_HZ)*. We include the full sample and subsamples of cities with 500km, 1000km, and 2000km radius from Hangzhou. The results confirm our conjecture that cities that are closer to Hangzhou have a higher level of fintech development. Panel B of Table 3 presents the results in the second stage regression using cities within a small circle around Hangzhou (500km) and all cities. We find that the instrumented DFI has a significantly positive effect on the number of fintech loans and fintech loan amounts ($p<0.01$) in both cities within 500 kilometers around Hangzhou and all cities. Overall, these results corroborate our hypothesis that fintech development promotes access to fintech loans.

[Insert Table 9 here]

6.4 Alternative Estimators

In light of Baker et al. (2022), staggered DiD estimates often do not provide valid estimates of the casual estimands of interest, even under the random treatment assignment. Following Baker et al. (2022), we construct three alternative estimators for the average treatment effect on the treated (ATT). We use the second-stage sample comprising 2,024 city-year observations from 2008 to 2018. We also include dependent variables examining business establishment (*Entry rate*) and financial performance (*ROA* and *Leverage*).

The first two estimators (CS and SA) are developed by Callaway and Sant'Anna (2021) and Sun and Abraham (2021). Each depends on first estimating the individual cohort-time-specific treatment effects. We use not-yet-treated as control groups in the CS estimator, while the SA estimator allows for last-treated controls. A "stacked regression" approach is used to develop the third ATT estimator (SR). We build event-specific "clean 2×2" datasets, including dependent variables and other city-level controls for the affected cohort and all other observations that are "clean" controls within the treatment window.[20] These even-specific data sets are then stacked together for an ATT estimate. We re-estimate the regression from Equation 1. Panel A of Table 10 shows that except for the CS estimator for *Entry rate (%)* , the statistical significance is consistent across three alternative estimators. In that sense, our baseline results from staggered DiD specification provide valid estimates of the causal interpretation.

[Insert Table 10 here]

6.5 Alternative Control Group

The significance and strength of the staggered DiD approach manifest in the fact that the establishment of a national innovation demonstration zone, conditional on time and city fixed effects, are random exogenous shocks. One concern with the NIDZ establishment is that normally these demonstration zones are first- or second-tier cities with high economic growth. For example, the first NIDZ is Beijing, which is the capital of China. Therefore, our baseline results could be driven by a pre-event difference in access to fintech loans due to the difference in economic growth.

We address this concern using one-to-one nearest neighbor propensity score matching (PSM) approach to identify an alternative control group. The identification strategy based on the PSM approach is proposed by Rosenbaum and Rubin (1983), which allows for further reduction of the unobserved heterogeneity between affected and unaffected cities. In particular, the matching procedure identifies a comparable counterfactual group of unaffected cities that is identical to the treatment group on average, thus achieving pseudo-randomization (Caliendo and Kopeinig,

[20] We use not-yet-treated as "clean" controls in this specification.

2008; Imbens, 2004). We match affected with control cities by a set of city-level socioeconomic and demographic variables (Z) observed in 2009 (*GDP pc*, *Population,Area,BL pc,* and *Deposit pc*).The matching algorithm adopted to identify a control group is the nearest neighbor approach that matches each affected county with one control county (Li, 2013).

Columns (1) and (2) of Panel B, Table 10 presents the estimation results from Equation 1 using alternative control groups. The coefficient estimates on *NIDZ* remain statistically significant at the 1% level for *FTL Number* and *FTL Amount.* This result bolsters the inference that fintech development promotes access to fintech loans.

6.6 Placebo Test

To further examine whether our baseline results are biased due to the omitted or unobservable variables, we conduct a placebo test by randomly assigning NIDZ to cities (Cai et al., 2016). In particular, there are 52 treatment cities in our sample. We first randomly select 52 cities from the total 297 cities and assign them with a random year as their treatment year, with the remaining being unaffected cities. Next, we construct a false treatment variable $NIDZ^{false}$ and re-estimate Equation 1 using *FTL Number* and *FTL Amount* as the dependent variable. The randomization ensures that $NIDZ^{false}$ has no effect on access to fintech loans. If our results are robust and not biased, we should observe an insignificant zero coefficient estimate on $NIDZ^{false}$ We conduct this random assignment-generating process 10,000 times to prevent contamination from any uncommon events.

Columns (3) and (4) of Panel B, Table 10 report the mean values of the estimates from the 10,000 random assignments. We find that the mean values are close to zero. Figure 4 depicts the distribution of 10,000 estimated coefficients and their associated p-values. The distributions center around zero with p-values equal to 1. Moreover, the red dashed lines in the figures represent the true estimate from our baseline analysis. Notably, our baseline estimates are clear outliers in the placebo tests. Overall, these findings confirm that our estimates are not significantly biased due to omitted variables.

7 Conclusion

Natural disasters can disrupt SMEs' business activities and financial performance, especially in developing countries. Although the development of insurance and governmental recovery management may fulfill their needs for funds. Fintech development can promote SMEs' resilience by filling the credit gap from traditional financial services. In this study, we examine the effect of fintech development on promoting SMEs' resilience in the aftermath of natural disasters through the lens of credit access expansion.

To answer the question, we exploit the innovation policy - NIDZ policy in China as an identification strategy and include small business activities and performance as measures for resilience. Following Suri et al. (2021), we include two stages in our empirical design. The first-stage results suggest that fintech development has a positive effect on SMEs' business activities and performance. The second-stage results demonstrate that the positive effects of fintech development persist in the cities that have faced natural disasters, indicating an increase in SMEs' resilience. Additionally, we find that fintech development has a more pronounced effect on industries that typically experience slower recovery under traditional financial services or require prompt recovery strategies, such as manufacturing and service. Our mechanism analysis indicates that fintech development increases SMEs' fintech credit access in the wake of natural disasters. Notably, successful fintech loans are longterm loans with a large size after the fintech development. Moreover, access to fintech credit empowered by fintech development allows small business to increase their debt capacity and substitute short-term bank loans with long-term fintech loans.

Lastly, we examine the fintech credit quality after fintech development in the wake of disasters. Our results suggest that successful fintech loans after fintech development experience lower delinquency rates and have borrowers with higher credit ratings and lower interest rates. From this perspective, fintech development can allow lenders to identify creditworthy borrowers and increase fintech credit quality in the face of disasters. We also find that there is a significant decrease in the unemployment rate after NIDZ policy.

Our results underline the significance of fintech development in enhancing SMEs' resilience in the face of disaster shocks. The potential under-serving of SMEs by traditional finance may result in more credit-constrained, leading to substantial loss and business discontinuity in stressed times. Insurance and disaster risk management may struggle to fulfill the needs of SMEs. The financial and banking sectors are undergoing profound change. Fintech is reshaping the sectors in transformative ways. We argue that fintech development can also serve to be transformative in bolstering SMEs resilience in the times disaster shocks.

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Figures and Tables

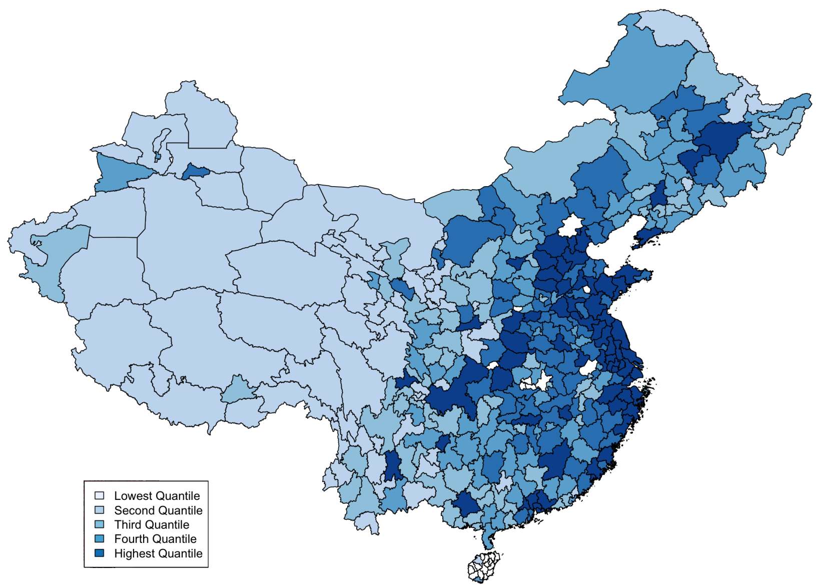


Figure 1. Distribution of Business Establishment

This figure shows the heat map of business establishment density measured as the average number of new entities established in each city between 2010 and 2018. The darker shade represents more business establishments. The unshaded area has no available data.

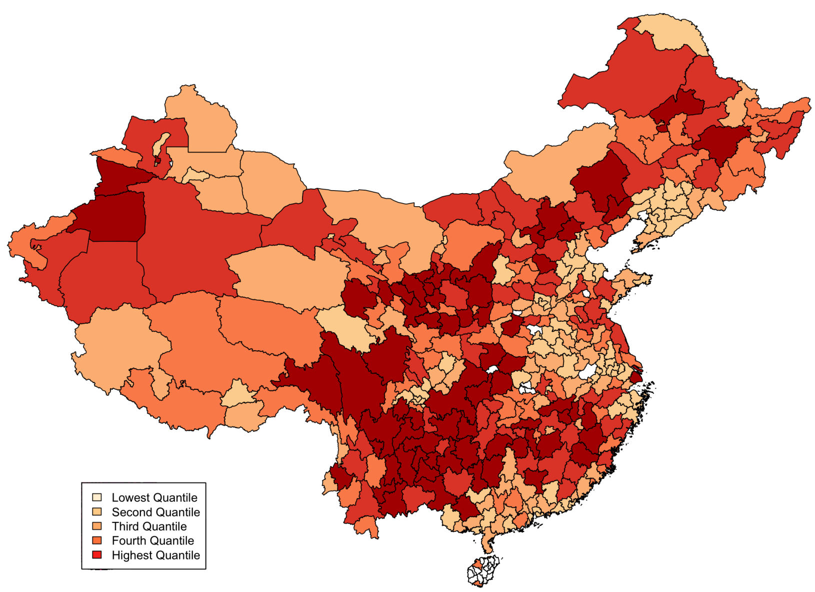
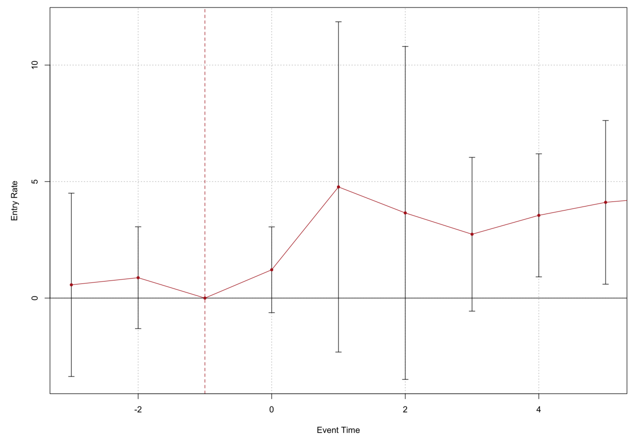
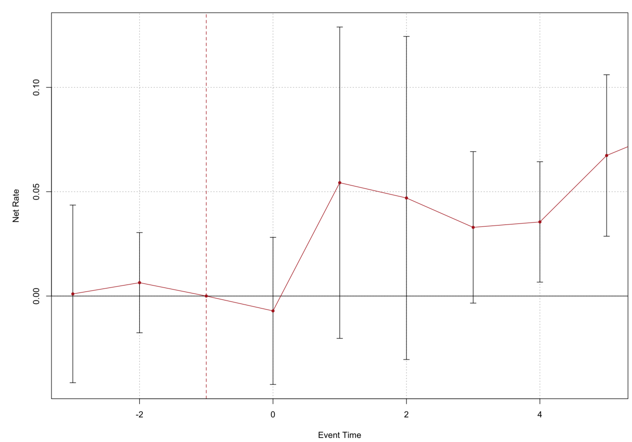


Figure 2. Natural Disaster Exposure

This figure shows the natural disaster exposure measured as the total number of incidents between 2014 and 2018 in each city. The darker shade represents more incidents. The unshaded area has no available data.



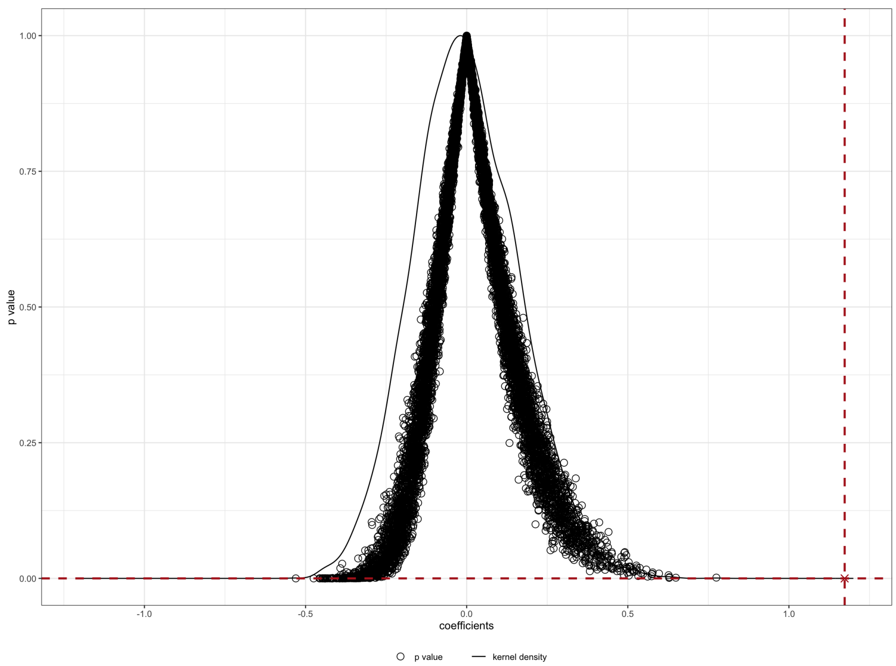
Panel A: Entry Rate (%)



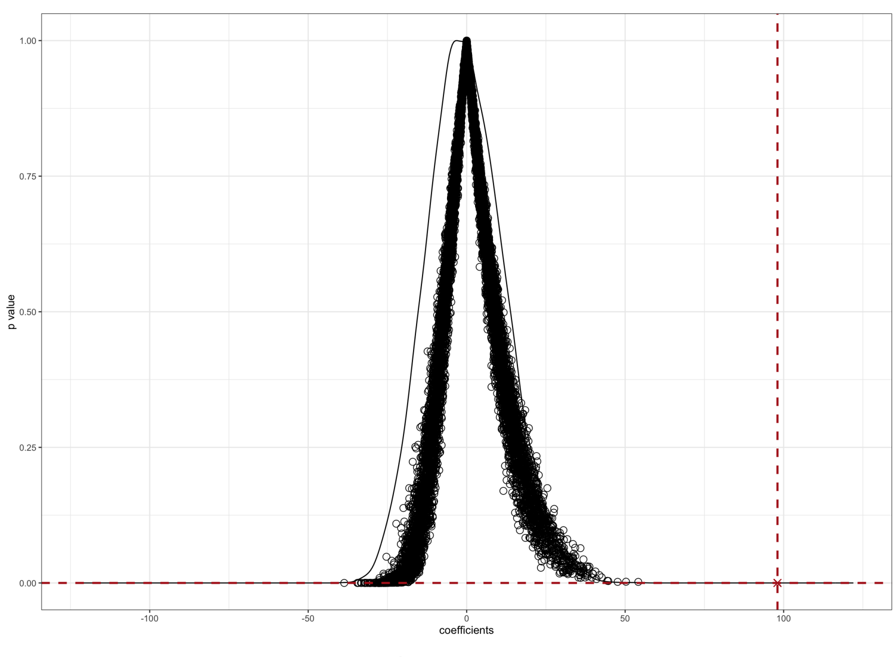
Panel C: Survival Rate (%)

Figure 3. Dynamic Effect on Enterprise Growth

This figure shows the dynamic effect of fintech development on SMEs' business activities from three years before and six years after the approval of an innovation demonstration zone in the aftermath of disasters. In Panel A, $Y_{i,t}$ measures the *Entry rate (%)*. In Panel B, $Y_{i,t}$ measures the *Exit rate (%)*. The bands around the coefficient estimates show 95% confidence intervals.



Panel A: Loan Number (FTL Number)



Panel B: Loan Amount (FTL Amount)

Figure 4. Placebo Test

This figure shows the Kernel density of 10,000 estimates. In Panel A, $Y_{i,t}$ measures the number of successful fintech loan applications in city i in year t (*FTL Number (thousand)*). The X-axis presents the estimated coefficients of *Zone* from the 10,000 randomized assignment exercises. The curve is the kernel density distribution of the estimates, whereas the dots are associated *p-values*. The red dashed lines represent the true estimate with the associated *p-value*. In Panel B, $Y_{i,t}$ measures the total loan amount of successful fintech loans in city i in year t (*FTL Amount (CNY million)*). The X-axis presents the estimated coefficients of *Zone* from the 10,000 randomized assignment exercises. The curve is the kernel density distribution of the estimates, whereas the dots are associated *p-values*. The red dashed lines represent the true estimate with the associated *p-value*.

Table 1
Summary Statistics

This table reports the descriptive statistics for each variable. All monetary variables are reported in the Chinese yuan (CNY) and adjusted for the consumer price inflation (Year 2008=100). The sample covers the period 2010-2019. Panel A shows the business variables. Business activities variables are presented at the city-year levels covering the period 2008-2018. Performance variables are presented at the firm-year levels covering period 2008-2015. Panel B reports the local macroeconomic variables at the city-year levels. Panel C details the number and types of disasters by each affected city in each year covering the period 2014-2018. All variables are defined in Appendix A.1.

Panel A: Business Variables

	N	Mean	Std.	Median	Min.	Max.
Entry rate (%)	2,384	18.600	11.900	19.500	0	171.900
Survival rate (%)	2,384	0.165	0.118	0.173	-0.187	1.718
Log sales	1,400,907	3.692	1.921	3.727	-4.605	7.987
Log assets	1,400,907	3.943	1.901	3.897	-3.324	8.926
Leverage	1,400,907	61.860	41.820	61.920	-13.130	316.670
Interest coverage	1,400,907	48.200	241.600	2.800	-291.600	1,934
Zscore	1,400,907	2.345	5.529	1.317	-4.023	73.274
Cash holdings	1,400,907	0.114	0.147	0.061	0	0.997

Panel B: Macroeconomic Variables

	N	Mean	Std.	Median	Min.	Max.
GDP pc (CNY thousand)	2,384	0.826	10.538	10.446	8.675	19.501
Population (thousand)	2,384	15.013	0.893	15.125	5.992	17.343
Area (km^2)	2,384	9.392	0.967	9.418	2.565	12.917
BL pc (CNY thousand)	2,384	54.320	78.610	25.930	2.470	1,351.460
Deposit pc (CNY thousand)	2,384	75.800	108.780	40.610	6.950	1,416.550
Tax (CNY billion)	2,384	5.134	9.655	1.749	0.000	109.679
R&Dpp (thousand)	2,384	3.772	18.589	0.000	0.000	397.281
Grant	2,384	0.3107	0.758	0.000	0.000	4.950

Panel C: Disaster Variables

	N	Mean	Std.	Median	Min.	Max.
Disaster Intensity	1,381	4.800	5.800	3	1	138
Flood	873	2.700	3.300	2	1	73
Heavy rain/Mountain torrent	487	2.300	3.300	1	1	57
Hailstorm	393	2.190	1.650	2	1	10
High wind	305	1.830	1.220	1	1	8
Typhoon	241	2.200	2.500	1	1	28
Cold wave	155	1.800	1.400	1	1	9
Snow	154	2	1.600	1.500	1	10
Earthquake	126	1.900	1.500	1	1	9
Mud/Lands	107	1.500	1.200	1	1	8
Drought	84	1.230	0.550	1	1	4
Hail	21	1.100	0.300	1	1	2
Thunder-strike	18	1.110	0.320	1	1	2
Freezing	7	1.400	0.800	1	1	3
Sand Storm	3	1	0	1	1	1

Table 2
Effect of fintech development on SMEs' resilience

This table presents the effect of fintech development on SMEs' resilience. Panel A reports the effect of fintech development on SMEs' business activities from 2008 to 2018 concerning nine affected cities and 241 control cities. Columns (1) and (2) report the results in the first stage. Columns (3) to (6) reports the results in the second stage in the sample restricted to 250 cities with natural disaster shocks (85% of the full sample). The sample of cities that have faced natural disasters consists of 2,024 city-year observations and the sample of cities with no disasters consists of 360 city-year observations. Panel B reports the effect of fintech development on SMEs' performance from 2008 to 2015 concerning nine affected cities and 229 control cities. Columns (1) and (2) report the results in the first stage. Columns (3) to (6) reports the results in the second stage in the sample restricted to 248 cities with natural disaster shocks (85% of the full sample). The sample of cities that have faced natural disasters consists of 584,521 city-year observations and the sample of cities with no disasters consists of 306,052 city-year observations. Column headings indicate the dependent variables. All dependent variables are winsorized at 1% and 99%. All monetary variables are reported in Chinese yuan (CNY), where the exchange rate was 6.77 CNY to one USD at the beginning of our sample period in 2008. All monetary variables are adjusted for the consumer price inflation. All variables are defined in Appendix A.1. Robust t-statistics clustered at the city level are shown in parentheses. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively (two-tailed test).

Panel A: Analysis of small business activities

	(1)	(2)	(3)	(4)	(5)	(6)
	First stage		Second stage			
Sample	Full		Disaster		Non-disaster	
Dependent variable	Entry rate (%)	Survival rate (%)	Entry rate (%)	Survival rate (%)	Entry rate (%)	Survival rate (%)
NIDZ	1.726***	0.017***	2.901**	0.029**	2.697*	0.027*
	(0.655)	(0.007)	(1.397)	(0.014)	(1.428)	(0.014)
GDPpc	5.014**	0.050**	5.133**	0.051**	4.202	0.042
	(2.099)	(0.021)	(2.218)	(0.022)	(8.703)	(0.087)
Population	-10.090***	-0.101***	-9.692***	-0.097***	-9.718	-0.097
	(2.833)	(0.028)	(3.287)	(0.033)	(7.151)	(0.072)
Area	7.967**	0.080**	7.459*	0.075*	27.215**	0.272**
	(3.707)	(0.037)	(4.013)	(0.040)	(12.183)	(0.122)
Deposit pc	0.015***	0.0001***	0.015***	0.0002***	0.031**	0.0003**
	(0.004)	(0.00004)	(0.005)	(0.00005)	(0.013)	(0.0001)
BL pc	-0.010**	-0.0001**	-0.008*	-0.0001*	-0.051**	-0.001**
	(0.004)	(0.00004)	(0.005)	(0.00005)	(0.022)	(0.0002)
Tax	0.004	0.000	-0.031	-0.0003	0.067*	0.001*
	(0.034)	(0.0003)	(0.031)	(0.0003)	(0.036)	(0.0004)
R&Dpp	-0.000	-0.000	0.000	0.000	0.002	0.000
	(0.006)	(0.0001)	(0.008)	(0.0001)	(0.008)	(0.0001)
Grant	-0.056	-0.001	0.215	0.002	-0.088	-0.001
	(0.296)	(0.003)	(0.370)	(0.004)	(0.694)	(0.007)
City fixed effects	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y
Observations	2,384	2,384	2,024	2,024	360	360
R^2	0.729	0.729	0.720	0.720	0.771	0.771

Table 2
Continued

Panel B: Analysis of small business performance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	First stage				Second stage							
Sample	Full				Disaster				Non-disaster			
Dependent variable	ROE (%)	ROA (%)	ROE (%)	ROA (%)	ROE (%)	ROA (%)	ROE (%)	ROA (%)	ROE (%)	ROA (%)	ROE (%)	ROA (%)
NIDZ	1.428***	0.064**	1.236***	0.047**	1.539**	0.075***	1.245**	0.049**	1.640	0.050	1.719	0.053
	(0.497)	(0.028)	(0.418)	(0.020)	(0.646)	(0.028)	(0.582)	(0.024)	(0.624)	(0.049)	(0.685)	(0.039)
SOE	-0.722	-0.015	-0.768	-0.023	-0.526	0.004	-0.594	-0.005	-1.163	-0.060	-1.213	-0.066
	(0.755)	(0.027)	(0.755)	(0.026)	(0.935)	(0.033)	(0.932)	(0.031)	(1.299)	(0.048)	(1.315)	(0.048)
Log assets	0.525	-0.108***	0.466	-0.112***	0.258	-0.121***	0.207	-0.123***	1.004	0.085**	0.931	-0.092**
	(0.422)	(0.023)	(0.417)	(0.023)	(0.559)	(0.028)	(0.551)	(0.028)	(0.634)	(0.039)	(0.627)	(0.039)
Tangibility	0.445	0.014	0.600	0.031	0.428	-0.011	0.578	0.007	0.479	0.067	0.670	0.086
	(1.243)	(0.048)	(1.234)	(0.049)	(1.466)	(0.056)	(1.449)	(0.056)	(2.322)	(0.091)	(2.299)	(0.095)
Zscore	1.661***	0.311***	1.640***	0.308***	1.682***	0.310***	1.660***	0.307***	1.616***	0.313***	1.598***	0.311***
	(0.083)	(0.010)	(0.084)	(0.010)	(0.099)	(0.014)	(0.100)	(0.014)	(0.159)	(0.011)	(0.161)	(0.011)
Cash holdings	-0.077	0.237***	-0.241	0.211***	0.660	0.228***	0.519	0.197***	-1.472	0.260***	-1.628	0.246**
	(1.204)	(0.061)	(1.197)	(0.059)	(1.442)	(0.076)	(1.441)	(0.074)	(2.086)	(0.100)	(2.040)	(0.097)
City fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y			Y	Y			Y	Y		
Industry × year fixed effects			Y	Y			Y	Y			Y	Y
Observations	890,573	890,573	890,573	890,573	584,521	584,521	584,521	584,521	306,052	306,052	306,052	306,052
R^2	0.736	0.948	0.736	0.948	0.730	0.947	0.730	0.947	0.748	0.948	0.748	0.948

Table 3
Firm-level heterogeneity by industry

This table presents the effect of fintech development on business activities by industry in the sample restricted to 250 cities with natural disaster shocks (85% of the full sample). Panel A presents the new business distribution from 2008 to 2018 according to the China Industry Classification National Standard (CISIC) by descending order of the number of new entities. The full sample is split into two groups: 3,560,082 new entities incorporated in affected cities and 11,782,405 new entities incorporated in control cities counties. Panel B re-estimates the model in Table 2 from Equation 1 based on the subsamples of industries and reports the positive regression estimates. All dependent variables are winsorized at 1% and 99%. All monetary variables are reported in Chinese yuan (CNY), where the exchange rate was 6.77 CNY to one USD at the beginning of our sample period in 2008. All monetary variables are adjusted for the consumer price inflation. All control variables from Table 2 are included but are not shown for parsimony. All variables are defined in Appendix A.1. Robust t-statistics clustered at the city level are shown in parentheses. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively (two-tailed test).

Panel A: New entities distribution by industry							
Affected cities ($Zone = 1$)				Non-affected cities ($Zone = 0$)			
	Industry	N	%		Industry	N	%
F	Wholesale and retail	1,114,867	31.314	F	Wholesale and retail	3,661,194	31.070
L	Commercial service	840,862	23.618	A	Agriculture, forestry and fishing	2,464,257	20.913
M	Scientific research and technical service	498,371	13.998	C	Manufacturing	1,263,139	10.719
C	Manufacturing	261,496	7.345	L	Commercial service	1,247,860	10.590
E	Construction	214,036	6.012	E	Construction	750,014	6.365
I	Information technology	137,560	3.864	M	Scientific research and technical service	508,924	4.319
G	Transportation and storage	97,450	2.737	I	Information technology	377,003	3.199
R	Arts, entertainment and recreation	87,722	2.464	K	Real estate	297,624	2.526
K	Real estate	81,738	2.296	G	Transportation and storage	294,909	2.503
A	Agriculture, forestry and fishing	68,469	1.923	O	Resident service	287,690	2.441
O	Resident service	54,651	1.535	H	Accommodation and food service activities	159,456	1.353
H	Accommodation and food service activities	49,257	1.384	R	Arts, entertainment and recreation	156,930	1.332
J	Finance	29,188	0.820	J	Finance	112,633	0.956
N	Water supply	8,318	0.234	D	Electric power and water production	71,744	0.609
P	Education	7,142	0.201	N	Water supply	49,880	0.423
Q	Health and social work	4,824	0.135	P	Education	29,633	0.251
D	Electric power and water production	3,832	0.108	B	Mining	28,100	0.238
B	Mining	299	0.008	Q	Health and social work	21,415	0.182
	Total	3,560,082	100		Total	11,782,405	100

Table 3
Continued

Panel B: Positive effect on business activities

	(1)	(3)	(4)	(6)	(7)	(9)	(10)	(12)
Industry code	Industry_C		Industry_K		Industry_O		Industry_P	
Industry name	Manufacturing		Real estate		Resident service		Education	
Dependent variable	Entry rate (%)	Survival rate (%)	Entry rate (%)	Survival rate (%)	Entry rate (%)	Survival rate (%)	Entry rate (%)	Survival rate (%)
NIDZ	2.602***	0.034***	5.335***	0.051***	2.866***	0.032***	18.649**	0.185**
	(0.815)	(0.010)	(0.748)	(0.007)	(0.823)	(0.009)	(8.118)	(0.081)
Control variables	Y	Y	Y	Y	Y	Y	Y	Y
City fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	2,008	2,008	2,008	2,008	2,008	2,008	1,992	1,992
R^2	0.608	0.576	0.588	0.574	0.521	0.464	0.417	0.383

Table 4
Resilience: Effect of innovation demonstration zones on credit access

This table presents the effect of fintech development on credit access in the sample restricted to 250 cities with natural disaster shocks (85% of the full sample). Panel A reports the effect of fintech development on the use of fintech loans. The sample consists of 2,024 city-year observations from 2010 to 2018 concerning nine affected cities and 241 control cities. Panel B reports the heterogeneity of fintech loans. Panel C reports the effect of fintech development on the use of bank loans. Column headings indicate the dependent variables. All dependent variables are winsorized at 1% and 99%. All monetary variables are reported in Chinese yuan (CNY), where the exchange rate was 6.77 CNY to one USD at the beginning of our sample period. All monetary variables are adjusted for the consumer price inflation. All control variables from Table 2 are included but are not shown for parsimony. All variables are defined in Appendix A.1. Robust t-statistics clustered at the city level are shown in parentheses. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively (two-tailed test).

Panel A: Use of fintech loans

	(1)	(2)	(3)	(4)
Dependent variable	FTL Number	FTL Amount	FTL Number	FTL Amount
NIDZ	1.156***	107.630***	0.650**	100.891***
	(0.314)	(23.094)	(0.327)	(29.545)
NIDZ × Intensity			0.064***	0.850
			(0.013)	(1.453)
Control variables	Y	Y	Y	Y
City fixed effects	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y
Observations	2,024	2,024	2,024	2,024
R^2	0.674	0.647	0.677	0.648

Panel B: Heterogeneity of fintech loans

	(1)	(2)	(3)	(4)
	Size		Loan term	
Dependent variable	Short-term	Long-term	Small	Large
NIDZ	-0.091	1.160***	-0.106	1.290***
	(0.262)	(0.343)	(0.275)	(0.349)
Control variables	Y	Y	Y	Y
City fixed effects	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y
Observations	1,958	1,674	1,963	1,473
R^2	0.557	0.685	0.566	0.690

Panel C: Use of bank loans

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Leverage		LT Leverage		ST Leverage	
NIDZ	-1.946**	-2.006***	-0.208	-0.309	-1.748**	-1.765**
	(0.762)	(0.751)	(0.438)	(0.461)	(0.703)	(0.689)
Control variables	Y	Y	Y	Y	Y	Y
City fixed effects	Y	Y	Y	Y	Y	Y
Year fixed effects	Y		Y		Y	
Industry × year fixed effects		Y		Y		Y
Observations	565,033	565,033	565,033	565,033	565,033	565,033
R^2	0.845	0.845	0.832	0.832	0.854	0.854

Table 5
Ex-post performance of fintech loan

This table presents the ex-post performance of fintech loans in the sample restricted to 250 cities with natural disaster shocks (85% of the full sample). The full sample comprises 2,024 city-year observations from 2010 to 2018. Panel A reports the results on loan delinquency and Panel C reports the estimates on the heterogeneity of credit standards. All dependent variables are winsorized at 1% and 99%. All monetary variables are reported in Chinese yuan (CNY), where the exchange rate was 6.77 CNY to one USD at the beginning of our sample period. All monetary variables are adjusted for the consumer price inflation. All control variables from Table 2 are included but are not shown for parsimony. All variables are defined in Appendix A.1. Robust t-statistics clustered at the city level are shown in parentheses. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively (two-tailed test).

Panel A: Loan delinquency

	(1)	(2)	(3)
Dependent variable	FTL Number		Delinquency rate
Group	Delinquency	Non-delinquency	
NIDZ	0.010	1.393***	-0.063**
	(0.054)	(0.314)	(0.030)
Controls	Y	Y	Y
City fixed effects	Y	Y	Y
Year fixed effects	Y	Y	Y
Observations	1,197	2,001	2,024
R^2	0.584	0.650	0.436

Panel B: Credit standard

	(1)	(2)
Dependent variable	FTL Score	FTL Interest Rate
NIDZ	0.277***	-0.387***
	(0.129)	(0.139)
Age	0.015***	0.016***
	(0.001)	(0.002)
Gender	-0.264***	0.194***
	(0.020)	(0.033)
Education	0.032***	-0.021**
	(0.006)	(0.009)
Job	0.005	-0.174***
	(0.017)	(0.023)
House	0.503***	-1.037***
	(0.075)	(0.097)
Car	0.355***	-0.839***
	(0.044)	(0.072)
City-level controls	Y	Y
Borrower fixed effects	Y	Y
Year fixed effects	Y	Y
Observations	899,001	899,001
R^2	0.911	0.853

Table 6
Effect of innovation demonstration zones and fintech lending on unemployment

This table presents the effect of NIDZ policy on unemployment in the sample restricted to 250 cities with natural disaster shocks (85% of the full sample). *Fintech Loan_ Pre* is defined as the number of successful fintech loan applications per 1,000 population pre-disaster in city i in year t. *Fintech Loan_ Post* is defined as the number of successful fintech loan applications per 1,000 population post-disaster in city i in year t. City-disaster and time fixed effects are included. All dependent variables are winsorized at 1% and 99%. All monetary variables are reported in Chinese yuan (CNY), where the exchange rate was 6.77 CNY to one USD at the beginning of our sample period. All monetary variables are adjusted for the consumer price inflation. All control variables from Table 2 are included but are not shown for parsimony. All variables are defined in Appendix A.1. Robust t-statistics clustered at the city level are shown in parentheses. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively (two-tailed test).

	(1)	(2)	(3)
Dependent variable		Unemployment rate (%)	
NIDZ	-0.057**	-0.009	0.102
	(0.026)	(0.047)	(0.075)
NIDZ × Fintech Loan_Pre		-0.185*	
		(0.113)	
NIDZ × Fintech Loan_Post			-0.308**
			(0.120)
Control variables			
City-disaster fixed effects	Y	Y	Y
Year fixed effects	Y	Y	Y
Observations	9,441	9,418	7,623
R^2	0.832	0.832	0.833

Table 7
Effect of fintech development on SMEs' business activities: Different estimation windows

This table presents regression estimates from Equation 1 using different estimation windows. The first estimation window is three years before and after the approval of an innovation zone ([-three years, three years]). The second estimation window is three years before and six years after the approval of an innovation zone ([-three years, six years]). The sample is the same as that in Table 2. All dependent variables are winsorized at 1% and 99%. All monetary variables are reported in Chinese yuan (CNY), where the exchange rate was 6.77 CNY to one USD at the beginning of our sample period. All monetary variables are adjusted for the consumer price inflation. All control variables from Table 2 are included but are not shown for parsimony. All variables are defined in Appendix A.1. Robust t-statistics clustered at the city level are shown in parentheses. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively (two-tailed test).

	(1)	(2)	(3)	(4)
Estimation window	[-three years, three years]		[-three years, six years]	
Dependent variable	Entry rate (%)	Survival rate (%)	Entry rate (%)	Survival rate (%)
NIDZ	2.624	0.029	2.659**	0.029**
	(1.774)	(0.020)	(1.494)	(0.017)
Controls	Y	Y	Y	Y
City fixed effects	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y
Observations	2,007	2,007	2,019	2,019
R^2	0.719	0.675	0.722	0.678

Table 8
Dynamic effect of innovation demonstration zones

This table presents the dynamic effect of fintech development on SMEs' business activities in the aftermath of disasters. The sample is the same as that in Table 2 . *d[t+k]*, -3≤k≤6, is an indicator variable equal to one if the city is in three years before or six years after the approval of an innovation zone, and zero otherwise. *d[t+k]* is set to zero for the control cities. *d[t-1]* is zero by construction. Column headings indicate the dependent variables. All dependent variables are winsorized at 1% and 99%. All monetary variables are reported in Chinese yuan (CNY), where the exchange rate was 6.77 CNY to one USD at the beginning of our sample period. All monetary variables are adjusted for the consumer price inflation. All control variables from Table 2 are included but are not shown for parsimony. All variables are defined in Appendix A.1. Robust t-statistics clustered at the city level are shown in parentheses. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively (two-tailed test).

	(1)	(2)
Dependent variable	Entry rate (%)	Survival rate (%)
d[t-3]	0.569	0.001
	(2.007)	(0.022)
d[t-2]	0.874	0.006
	(1.115)	(0.012)
d[t-1]	0.000	0.000
	-	-
d[t]	1.215	-0.007
	(0.939)	(0.018)
d[t+1]	4.770	0.054
	(3.616)	(0.038)
d[t+2]	3.654	0.0467
	(3.645)	(0.040)
d[t+3]	2.740	0.033*
	(1.684)	(0.019)
d[t+4]	3.550***	0.035**
	(1.347)	(0.05)
d[t+5]	4.109**	0.067***
	(1.792)	(0.020)
d[t+6]	4.363**	0.080***
	(1.828)	(0.020)
Control variables	Y	Y
City fixed effects	Y	Y
Year fixed effects	Y	Y
Observations	2,024	2,024
R^2	0.717	0.675

Table 9
Alternative identification strategies

This table presents regression estimates from Equation 1 using alternative identification strategies. Panel A reports the results employing Broadband China program as an exogenous shock. Panes B and C reports the 2SLS results using the distance to Hangzhou as an instrumental variable. All dependent variables are winsorized at 1% and 99%. All monetary variables are reported in Chinese yuan (CNY), where the exchange rate was 6.77 CNY to one USD at the beginning of our sample period. All monetary variables are adjusted for the consumer price inflation. All control variables from Table 2 are included but are not shown for parsimony. All variables are defined in Appendix A.1. Robust t-statistics clustered at the city level are shown in parentheses. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively (two-tailed test).

Panel A: Alternative estimators

	(1)	(2)	(3)	(4)
	Broadband		Broadband (Parallel trend)	
	FTL Number	FTL Amount	FTL Number	FTL Amount
NIDZ	0.766**	71.193**		
	(0.245)	(22.195)		
d[t-3]			-0.2602	-18.98
			(0.2710)	(25.90)
d[t-2]			-0.2750	-16.55
			(0.2787)	(24.11)
Control variables	Y	Y	Y	Y
City fixed effects	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y
Observations	1,953	1,953	1,953	1,953
R^2	0.702	0.654	0.725	0.678

Panel B: First stage: DFI on Log(Distance_HZ)

	(1)	(2)	(3)	(4)
Sample	≤500km	≤1,000km	≤2,000km	All
Log(Distance_HZ)	-2.524***	-8.120***	-6.652***	-6.402***
	(0.785)	(0.466)	(0.367)	(0.356)
Controls	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y
Observations	391	1,118	2,236	2,373
R^2	0.987	0.983	0.976	0.974

Panel C: Second stage: Log(Distance_HZ) as IV for DFI

	(1)	(2)	(3)	(4)
Dependent variable	FTL Number		FTL Amount	
	≤500km	All	≤500km	All
DFI	0.035***	0.022***	0.032***	0.020***
	(0.006)	(0.005)	(0.006)	(0.004)
Controls	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y
Observations	391	2,373	391	2,373
R^2	0.439	0.274	0.437	0.276

Table 10
Robustness tests

This table presents several robustness tests using regression estimates from Equation 1. Panel A reports the results using alternative DiD estimates of the average treatment effect on the treated (ATT). The sample is the same as that in Table 2. CS and SA estimators are developed by Callaway and Sant'Anna (2021) and Sun and Abraham (2021). Not-yet-treated is used as control groups in the CS estimator, while the SA estimator allows for last-treated controls. A "stacked regression" approach is used to develop the third estimator (SR) with not-yet-control as "clean" controls. Panel B reports the results for PSM control group and placebo test. All dependent variables are winsorized at 1% and 99%. All monetary variables are reported in Chinese yuan (CNY), where the exchange rate was 6.77 CNY to one USD at the beginning of our sample period. All monetary variables are adjusted for the consumer price inflation. All control variables from Table 2 are included but are not shown for parsimony. All variables are defined in Appendix A.1. Robust t-statistics clustered at the city level are shown in parentheses. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively (two-tailed test).

Panel A: Alternative estimators

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Entry rate			ROA		
Estimator	CS	SA	SR	CS	SA	SR
ATT	4.3854	3.929**	1.862**	0.111**	0.054**	0.107***
	(2.3848)	(1.614)	(0.766)	(0.022)	(0.027)	(0.028)
Control variables	Y	Y	Y	Y	Y	Y
City fixed effect	Y	Y	Y	Y	Y	Y
Year fixed effect	Y	Y	Y	Y	Y	Y
Observations	2,024	2,024	2,024	584,521	584,521	584,521

Panel B: Alternative control group and placebo test,

	(1)	(2)	(3)	(84)
Robustness tests	PSM control group		Placebo test	
Dependent variable	FTL Number	FTL Amount	FTL Number	FTL Amount
Zone	0.650***	56.000***	-0.0003	-0.069
	(0.206)	(15.219)	(0.157)	(11.567)
Control variables	Y	Y	Y	Y
City fixed effects	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y
Observations	918	918	2,432	2,432
R^2	0.741	0.714	-	-

Appendix Tables

Table A.1
Variable definitions

Variable	Definitions
Panel A: Indenpendent variables	
NIDZ	a dichotomous treatment variable equal to one if city i has been approved to be an innovation demonstration zone in year t; this term is set to zero for control cities in any t.
Log(Distance_HZ)	the natural logarithm of a city's geographic distance to Hangzhou
Log(Distance_SH)	the natural logarithm of a city's geographic distance to Shanghai
DFI	the Peking University Digital Financial Inclusion Index of China (PKU-DFIIC)
Intensity	the number of disaster incidents that occurred during 2010-2019 in city i.
Diff	the difference in years between the disaster year and the NIDZ establishment year in city i.
Panel B: Business registry and financial performance	
Entry rate (%)	the number of established entities in year $t-1$ in city i
Survived Entry (%)	the growth of survived entities from year $t-1$ to year t in city i. Survived entities are defined as the sum of established entities and new entities, minus liquidated entities.
ROE (%)	operating income before depreciation and amortization scaled by lagged equity
ROA (%)	operating income before depreciation and amortization scaled by lagged assets
Log sales	the natural logarithm of sales in million CNY
Leverage (%)	the debt-to-capital ration defined as total debt (long-term plus short-term debt) divided by the sum of total debt and the book value of equity in percentage
LT Leverage (%)	long-term debt divided by the sum of long-term debt and the book value of equity in percentage
ST Leverage (%)	short-term debt divided by the sum of short-term debt and the book value of equity in percentage
SOE	a dichotomous variable equal to one if the firm is a state-owned enterprise and zero otherwise
Log assets	the natural logarithm of book assets in million CNY
Tangibility	net value of plant, property, and equipment divided by total assets
Zscore	modified Altman Z-score applicable to emerging market companies (Altman et al., 2017) $= 3.3(EBIT \div Asset_{t-1}) + 1.0(Sales \div Asset_{t-1}) + 1.4(Retained\,earnings \div Asset_{t-1}) + 1.2(Working\,capital \div Asset_{t-1})$
Cash holdings	cash and equivalents divided by total assets
Panel C: City-level macroeconomic data	

GDPpc	the logarithm of gross domestic product (GDP) per capita measured in CNY thousand
Population	the logarithm of the population measured in thousand
Area	the logarithm of city area measured in km 2
BL Amount (CNY billion)	the total bank loan balance in city i in year t
BL pc (CNY thousand)	the total bank loan balance divided by the total population in city i in year t
Deposit pc (CNY thousand)	the total bank deposit balance divided by the total population in city i in year t
Tax (CNY billion)	the total tax revenue in city i in year t
R&Dpp (thousand)	the number of R&D staff in city i in year t
Grant	the logarithm of one plus the number of granted patents in city i in year t
Bank Density	the number of bank branches per 1,000 population in city i in year t
Local Bank Density	the share of local branches in city i in year t
Local Bank	a time-invariant local finance indicator variable for each city that equals one if the city falls into the top terciles of the share of local branches across all sample cities in at least half of the years before 2010 and 0 otherwise.
Unemployment (%)	the unemployment rate in city i in year t
Panel D: Fintech loan data	
FTL Number (thousand)	the number of successful fintech loan applications in city i in year t
FTL Amount (CNY million)	the total loan amount of successful fintech loans in city i in year t
FTL Average (CNY thousand)	the total loan amount of fintech loans divided by the number of successful fintech loan applications in city i in year t.
FTL Interest Rate (%)	the interest rate of each loan listing
FTL Score	an indicator variable equals to 1 if the borrower's credit rating is HR, equals to 2 if the borrower's credit rating is E, equals to 3 if the borrower's credit rating is D, equals to 4 if the borrower's credit rating is C, equals to 5 if the borrower's credit rating is B, equals to 6 if the borrower's credit rating is BB, equals to 7 if the borrower's credit rating is BBB, equals to 8 if the borrower's credit rating is A and 9 otherwise.
Delinquency rate	the ratio of delinquent fintech loan numbers to all fintech loan numbers in city i in year
Age	the fintech borrower's age
Gender	the fintech borrower's gender
Education	the fintech borrower's educational level
Job	the fintech borrower's profession
House	the fintech borrower's ownership of a house
Car	the fintech borrower's ownership of a car
Info	the number of data fields that contain relevant information for each borrower
Info_DD	the number of data fields with drop-down lists that have relevant information

Info_DS	the number of empty data fields that include relevant information
Fintech Loan_Pre	the number of successful fintech loan applications per 1,000 population pre-disaster in city i in year t
Fintech Loan_Post	the number of successful fintech loan applications per 1,000 population post-disaster in city i in year t
High_Fintech Loan	a dichotomous variable equal to one if the number of successful fintech loan applications per 1,000 population in city i is more than the number of successful fintech loan applications per 1,000 population across all cities in year t and zero otherwise.