Pacific-Basin Finance Journal 74 (2022) 101791

Contents lists available at ScienceDirect

Pacific-Basin Finance Journal

journal homepage: www.elsevier.com/locate/pacfin

Corporate resilience to the COVID-19 pandemic: The role of digital finance

Yanchun Xia [a], Zhilin Qiao [b], Guanghua Xie [c,*]

[a] School of Economics and Business Administration, Chongqing University, Chongqing, China
[b] School of Economics and Finance, Xi'an Jiaotong University, Xi'an, China
[c] School of Management, Northwestern Polytechnical University, Xi'an, China

ARTICLE INFO

JEL classification:
G30
G34
J16

Keywords:
Digital finance
Corporate resilience
Financing frictions
The COVID-19 pandemic

ABSTRACT

This paper studies the role of digital finance in shaping corporate resilience to the COVID-19 pandemic by analyzing the stock prices of Chinese listed firms. We find that firms located in regions with higher levels of digital finance experience fewer losses and recover more quickly from the COVID-19 pandemic. Further analysis shows that digital finance helps build corporate resilience by facilitating firms' access to external financing and reducing financing costs. We further document that the positive effects of digital finance on corporate resilience are more pronounced for small firms, non-state-owned enterprises, and low cash holding firms. Overall, these findings suggest that digital finance improves corporate resilience by mitigating financing frictions.

1. Introduction

Recent social and economic environments have dramatically changed the world and significantly impacted firm survival and growth. The sudden outbreak of coronavirus disease 2019 (COVID-19) pandemic has caused a severe public health crisis and devastated the global economy (Arora et al., 2020; Ding et al., 2021). Because of travel restrictions and social distancing requirements, the pandemic has led to large drops in consumer demand, disruption of production, and the deterioration of financial conditions. Under these conditions, business survival is heavily threatened (Miyakawa et al., 2021). As adverse events are generally inevitable and have lasting impacts, corporate resilience, defined as a firm's ability to recover from shocks and adapt to disruptions (Roundy et al., 2017), is playing an increasingly large role in the survival of organizations. Accordingly, it is worthwhile to investigate the determinants of resilience at the organizational level in the context of large disruptive incidents such as the COVID-19 pandemic. Therefore, this research aims to understand the role of digital finance, which is neglected by academics compared to other factors, in shaping corporate resilience.

Given that liquidity support is essential to the functioning of firms, access to external financial resources plays an important role in the survival and growth of firms (Musso and Schiavo, 2008). Due to the various lockdown measures triggered by the COVID-19 shock, many firms have experienced a sharp plunge in operating revenues while their costs continue to accrue (Carletti et al., 2020), thereby increasing the likelihood of corporate insolvencies. Consequently, difficulties in obtaining external finance may adversely influence corporate resilience. Information asymmetry and agency problems often cause financial markets to experience a variety of frictions

* Corresponding author at: 127 West Youyi Road, Beilin District, Xi'an Shaanxi 710072, P.R. China.
E-mail address: guanghuaxie@foxmail.com (G. Xie).

https://doi.org/10.1016/j.pacfin.2022.101791
Received 7 July 2021; Received in revised form 25 April 2022; Accepted 27 May 2022
Available online 2 June 2022
0927-538X/

that significantly constrain firms' access to bank credit (La Porta et al., 1998; O'Connor et al., 2013; Benmelech et al., 2019). Moreover, as banks are more likely to penalize firms that experience difficulties, the COVID-19 pandemic lockdown can amplify financing frictions (Ding et al., 2021), thereby pushing many firms toward bankruptcy. Considering such an extreme financial situation, the role of digital finance has been emphasized in helping firms to tide over the COVID-19 pandemic.

Digital finance integrates digital information technology with traditional financial services, enabling businesses to access financial services through digital channels. The COVID-19 pandemic lockdowns hinder firms' access to loans through in-person contact with banks. However, lending to businesses through digital and contactless methods can help maintain social distancing and thereby reduce the spread of COVID-19. Hence, the adoption of digital finance that promotes remote interactions can be particularly valuable in improving the penetrability and scope of financing services during the COVID-19 pandemic. Furthermore, empowered by big data and algorithms, digital finance is conducive to enhancing the information availability and accuracy of the traditional financial intermediaries, thereby lowering the threshold for corporate financing (Demertzis et al., 2018; Berg et al., 2020). Additionally, when obtaining bank financing has become more difficult in a crisis, fintech companies can also provide alternative financing sources for firms (Gomber et al., 2017; Galema, 2020; Gambacorta et al., 2022). As a result, digital finance might broaden firms' access to finance during the COVID-19 pandemic.

On the other hand, digital finance also offers new technologies and innovative services to the financial market (Tang, 2019; Bollaert et al., 2021; Hornuf et al., 2021), which improves the efficiency of credit allocation. Specifically, digital finance can more efficiently deal with demand shocks and process mortgage applications, thus accelerating lending processes (Buchak et al., 2018; Fuster et al., 2019). Moreover, based on alternative data such as third-party assessments or social network information, digital finance enables lenders to achieve a more accurate portrait of the borrowers, thereby reducing the costs of credit risk assessment (Iyer et al., 2016; Jagtiani and Lemieux, 2019). Prior literature suggests that compared to traditional financial channels, the interest rates provided by digital finance are lower (Wei and Lin, 2016; De Roure et al., 2021). Given the poor corporate information transparency and depressed revenues during the COVID-19 pandemic, digital finance would be beneficial for lenders to assess borrower risk more accurately, thus decreasing the financing costs of firms. Levine et al. (2018) find that available funds can improve corporate resilience during systemic crises. Based on the above considerations, we argue that digital finance may play an important role in shaping corporate resilience during the COVID-19 pandemic.

China provides a convenient and ideal setting in which to examine this issue. First, unlike previous studies that generally use cross-country settings, we focus on a single country to analyze the effects of cross-region digital finance on corporate resilience. Although digital finance has expanded considerably in China over the last decade, the levels of implementation vary significantly across regions (Guo et al., 2016; Song et al., 2021). Therefore, our approach allows us to eliminate cross-country confounding factors and obtain more detailed regional and firm-level information on the impacts of digital finance. Second, banks are the primary liquidity providers for Chinese firms, which are thus particularly sensitive to bank loans when facing liquidity risk. Because of the strict prevention and control measures implemented by the Chinese government, the COVID-19 pandemic is more likely to have adverse effects on traditional financial systems' ability to meet firms' funding needs. In such scenarios, the role of digital finance in shaping corporate resilience by mitigating financing frictions is likely to be amplified.

Based on a sample of Chinese listed firms at the end of 2019, this study examines the effects of digital finance on corporate resilience during the COVID-19 pandemic. We document that firms located in regions with higher levels of digital finance experience fewer losses in stock price and recover more quickly, indicating that digital finance can enhance corporate resilience to the COVID-19 pandemic.

Our primary analysis is subject to the concern that firms located in richer provinces are more resilient to the COVID-19 pandemic and that the levels of digital finance are higher in richer provinces. Although we explicitly control for the levels of regional economic development in our regressions, we use the following approaches to further address this potential endogeneity concern. First, we separately examine the relationship between digital finance and corporate resilience in regions whose gross domestic product (GDP) per capita is above and below the median. Second, we conduct a propensity score matching (PSM) analysis to control for differences in the firm characteristics and levels of regional economic development and identify the treatment group that is most similar to the control group. Finally, the potential endogeneity issue may be more severe for firms from high-tech industries. To alleviate this concern, we exclude such firms. The association between digital finance and corporate resilience is robust to all of these procedures, supporting our conjecture of a causal relationship between digital finance and corporate resilience during the COVID-19 pandemic.

To understand the possible channels through which digital finance improves corporate resilience, we investigate whether digital finance can mitigate financing frictions. First, we examine the relationship between digital finance and corporate debt financing during the COVID-19 pandemic. We find that firms located in regions with higher levels of digital finance are more likely to obtain loans, indicating that digital finance improves firms' access to external financing. Second, as the pandemic depresses corporate sales and increases firms' business risks, the provision of more credit by banks can increase the risk of loan default, leading to higher costs of debt financing for firms. However, digital finance can enhance the efficiency of lending markets (Iyer et al., 2016; Buchak et al., 2018; Bollaert et al., 2021). Indeed, financing costs represent another form of financing friction. Therefore, we also examine the effects of digital finance on firms' financing costs. We further find that the cost of debt financing is lower for firms located in regions with higher levels of digital finance. Improving access to external financing through digital finance does not increase the costs of debt financing. This evidence supports the interpretation that digital finance improves corporate resilience to the COVID-19 pandemic by mitigating financing frictions.

The extent to which firms need digital finance to mitigate financing frictions for survival and growth varies significantly across financial conditions and liquidity needs. We expect the role of digital finance in improving corporate resilience to the COVID-19 pandemic to be particularly important for firms with worse financial conditions and higher liquidity needs (Ding et al., 2021), which are general characteristics of smaller firms. As China's financial system is still controlled by the government, banks prefer lending to state-owned enterprises (SOEs) over non-SOEs (Brandt and Li, 2003; Allen et al., 2017). Additionally, firms' cash reserves decrease their dependence on external financing demands during the COVID-19 pandemic. Consistent with our predictions, we find that the positive effects of digital finance on corporate resilience are more pronounced for smaller firms, non-SOEs, and firms with lower cash reserves.

Our paper contributes to the literature in several ways. First, the existing literature suggests that the financial market environment plays an important role in determining corporate resilience (Carmeli and Markman, 2011; DesJardine et al., 2019). However, it is not clear whether digital finance affects corporate resilience. Our paper presents fresh evidence that digital finance can shape firms' ability to obtain external financing, which in turn improves corporate resilience to the COVID-19 pandemic. Second, this paper contributes to our knowledge of the economic consequences of digital finance. Previous studies focus on the impacts of digital finance on bank behaviors (Norden et al., 2014), investment decisions (Lin and Viswanathan, 2016; Lee and Shin, 2018), and corporate innovation (Fisch, 2019; Block et al., 2021). Our study complements these by examining the effects of digital finance on corporate resilience. Third, our findings add to a growing body of evidence on the determinants of corporate resilience to crises. A recent study by Ding et al. (2021) finds that firms that implemented stronger corporate social responsibility policies and activities prior to the COVID-19 pandemic are more resilient to the pandemic. Levine et al. (2018) focus on systemic banking crises and find that social trust can improve corporate resilience. Our results show that cross-region differences in digital finance shape differences in corporate resilience by mitigating financing frictions during the pandemic. Thus, we identify a new determinant of corporate resilience that is uniquely adapted to the COVID-19 pandemic.

The rest of this paper is organized as follows. Section 2 describes sample selection and model designs. Section 3 discusses regression results. Section 4 summarizes and concludes.

2. Data and descriptive statistics

2.1. Sample and data

Our sample consists of all Chinese firms listed on the Shanghai and Shenzhen stock securities exchanges at the end of 2019. We identify January 20, 2020 as the start of the COVID-19 pandemic, which is when the news of human-to-human transmission of the disease became public in China. We collect data from three sources. First, we obtain digital finance data, firm-level corporate governance data, and financial data from the China Stock Market and Accounting Research (CSMAR) database. Second, we obtain traditional financial development data and GDP statistics from the China Statistical Yearbook. Third, we obtain digital finance index data from the Institute of Digital Finance of Peking University. The initial sample consists of 3963 firm observations. We exclude 100 financial firms (e.g., banks, insurance companies, and investment trusts) whose financial statements are more likely to be influenced by factors specific to their industries, 584 observations with missing stock price data, and 196 firm observations with missing financial data. This process yields 3083 observations for our baseline regression.

2.2. Variable measurement

2.2.1. Corporate resilience

Corporate resilience refers to a firm's ability to recover from shocks and adapt to disruptions (Roundy et al., 2017). Corporate resilience is a latent variable that cannot be observed directly, and researchers address this measurement challenge in two ways (Gittell et al., 2006; Levine et al., 2018; DesJardine et al., 2019). One approach is to measure the firm's performance or volatility in terms of financial performance, financial volatility, growth, and employment (Markman and Venzin, 2014; Ortiz-de-Mandojana and Bansal, 2016; Levine et al., 2018). Another approach is to investigate the firm's reaction to environmental shocks, such as the recovery of stock prices and the loss in stock prices (Gittell et al., 2006; DesJardine et al., 2019; Sajko et al., 2021).

For our primary analysis, consistent with DesJardine et al. (2019) and Sajko et al. (2021), we take the second approach and measure resilience in terms of stock price reactions. The efficient market hypothesis states that market valuations reflect all relevant and new information about companies (Sajko et al., 2021). More importantly, the idea is broadly accepted by academics (Gittell et al., 2006; DesJardine et al., 2019). Therefore, we measure corporate resilience based on how stock prices respond to the COVID-19 pandemic in terms of the severity of loss and the time to recovery (Gittell et al., 2006; DesJardine et al., 2019; Sajko et al., 2021). These two indicators reflect the ability of a company to preserve its core functions and recover from a crisis. It is easier for firms to recover from a pandemic when their losses are small, with faster recovery consistently protecting firms from ongoing damage.

The severity of loss is the maximum economic loss suffered by a company in a crisis and represents the stability of resilience. Less severe losses indicate greater stability of corporate systems, which improves their ability to absorb disturbances. We evaluate the severity of loss by the magnitude of the drops in stock price immediately following the onset of the COVID-19 pandemic. Specifically, we calculate the severity of loss as the percentage drop in a firm's stock price between the closing price preceding the COVID-19 pandemic (i.e., on January 20, 2020) and the minimum stock price in the 12 months after January 20, 2020. Given that the severity of loss in the stock price is closely linked to the industry, this parameter is adjusted based on industry median values. A higher value implies a greater loss in stock price.

We assess time to recovery by the time taken for the firm to return to its pre-shock levels. Time to recovery represents the flexibility of resilience, which helps firms adapt to environmental changes and recover more quickly from shocks (Brand and Jax, 2007). Time to recovery is measured as the number of days that the firm's stock price takes to reach its pre-COVID-19 levels. Shorter recovery times suggest greater corporate resilience.

For robustness tests, following Ortiz-de-Mandojana and Bansal (2016), and Levine et al. (2018), we take the first approach and use earnings before interest and taxes (EBIT) and employment as alternative measures of corporate resilience.

2.2.2. Digital finance

The Financial Stability Board (FSB) defines digital finance as "*technologically enabled financial innovation that could result in new business models, applications, processes, or products with an associated material effect on financial markets, and the provision of financial services*" (Financial Stability Board, 2017, pp.7). By providing services such as data processing, cloud computing, delivery platforms, and crowd-funding, fintech companies enable and complement traditional financial intermediaries.

In our primary analysis, following Song et al. (2021), we measure digital finance as the natural logarithm of the number of provincial fintech companies plus one. We use this approach for several reasons. First, the number of regional fintech companies represents the levels of service they provide to traditional financial institutions. In general, there are two ways in which traditional financial institutions can interact with digital finance: cooperating with fintech companies and setting up fintech departments (Song et al., 2021). Given the technology-intensive and high-investment nature of digital finance, traditional financial institutions usually choose to cooperate with fintech companies. The likelihood of more regional fintech companies collaborating with traditional financial institutions is also higher, indicating that the enabling effects of digital finance on traditional financial intermediaries are more prominent. In addition, more regional fintech companies foster competition, causing the companies to provide higher levels of service to traditional financial institutions to avoid elimination. This can provide more effective methods for firms to interact with banks directly under lockdowns and social distancing regulations during the COVID-19 pandemic, thereby improving firms' access to finance.

Second, the number of regional fintech companies represents the ability of each province to provide alternative financing sources during the COVID-19 pandemic. As it is more difficult for firms to obtain bank financing during a pandemic, fintech companies can provide alternative financing sources for firms, especially for those in financial distress. Even in digital finance platforms, geography can still play a role because of informational frictions (Senney, 2019). Greater distance implies that lenders make fewer direct observations of borrowers' information, thereby hindering lenders' ability to monitor and manage risk. Therefore, informational frictions associated with geography reduce transactional efficiency. In addition, China's financial system is characterized by administrative hierarchy and geographical boundaries (Allen et al., 2005; Allen et al., 2017). This strict regulation of the financial system implies that there still exist barriers to the free flow of financial resources across regions in China (Brandt and Li, 2003; Allen et al., 2017). However, geographical proximity enhances ex-ante information collection and ex-post monitoring, thus decreasing information asymmetry. Moreover, geographical proximity alone can generate trust in transaction partners or opportunities in the same areas, even without any tangible economic benefits (Lai and Teo, 2008). Therefore, digital finance transactions are more likely to occur between parties in the same geographical area rather than across regions (Hortaçsu et al., 2009; Burtch et al., 2014; Lin and Viswanathan, 2016; Senney, 2019). Under such circumstances, firms in regions with more fintech companies are more likely to acquire alternative financing sources during the COVID-19 pandemic.

As digital finance may be correlated with the level of regional economic development, we use the provincial number of fintech companies scaled by provincial GDP (*Fintech/GDP*) as an alternative measure of digital finance in our robustness tests. Following Guo et al. (2020) and Chen and Zhang (2021), we also use the natural logarithm digital finance index, provided by the Institute of Digital Finance of Peking University, to measure digital finance. Digital finance index, based on data provided by Ant Group, captures cross-province variations in digital finance. The performance of Ant Group, the money market product of the Alibaba Group, is indicative of the growth of digital finance in China (Guo et al., 2016; Guo et al., 2020). The digital finance index includes payment, investment, insurance, money fund, and credit service business, which also consists of three dimensions: coverage, usage depth, and the degree of digitalization. Thus, the digital finance index reflects the levels of digital finance in China.

2.3. Model specifications

To evaluate how digital finance shapes corporate resilience in response to the COVID-19 pandemic, we carry out separate regressions for the severity of loss and the time to recovery based on the following specification:

$$\text{Resilience} = \beta_0 + \beta_1 \text{Fintech} + \text{Controls} + \text{Industry} + \varepsilon \tag{1}$$

where *Resilience* is the dependent variable, measured as the severity of loss (*Loss_Severity*) or time to recovery (*Recovery_Time*). *Fintech* is the natural logarithm of the number of provincial fintech companies plus one, which is our main variable of interest. The coefficient on *Fintech*, β_1, is designed to capture the relationship between digital finance and corporate resilience. Specifically, we employ ordinary least squares (OLS) to estimate the coefficients in eq. (1) when corporate resilience is measured as the severity of loss. We apply the negative binomial regression to estimate the coefficients in eq. (1) when we use the time to recovery as the dependent variable. We choose this model specification because the time to recovery is non-continuous, non-normal, and highly skewed, and standard linear regression techniques (e.g., OLS) are not suitable for this data set (Ramaswamy et al., 1994; Sanders, 2001). Poisson regression is our first choice. An important property of the Poisson regression is that the mean is equal to the variance (Greene, 2000). However, the variance of time to recovery is greater than its mean.[1] Based on the Poisson-gamma mixture distribution, negative binomial regression

[1] As shown in Table 1, the mean and standard deviation of time to recovery are 34.829, and 52.419, respectively.

Table 1
Descriptive statistics.

Variable	*N*	*Mean*	*Q1*	*Median*	*Q3*	*S.D.*	*Min*	*Max*
Loss_Severity	3083	−0.023	−0.074	0.000	0.047	0.110	−0.609	0.273
Recovery_Time	3083	34.829	2.000	16.000	32.000	52.419	1.000	317.000
Fintech	3083	4.443	3.135	4.431	6.089	1.651	0.693	6.593
Size	3083	22.358	21.404	22.180	23.096	1.322	18.756	28.341
Lev	3083	0.424	0.272	0.417	0.565	0.195	0.008	1.698
ROA	3083	0.033	0.014	0.036	0.066	0.085	−0.912	0.526
MB	3083	1.841	1.155	1.480	2.053	1.216	0.692	15.490
Growth	3083	0.187	−0.028	0.075	0.204	1.535	−1.309	58.842
SOE	3083	0.318	0.000	0.000	1.000	0.466	0.000	1.000
Findev	3083	1.509	1.236	1.431	1.852	0.429	0.689	3.056
PGDP	3083	11.403	10.977	11.453	11.725	0.405	10.404	12.009

This table reports the descriptive statistics of the variables used in the analyses. All continuous variables are winsorized at the 1% and 99% levels. All variables are defined in Appendix A.

is particularly well suited to handle this problem of overdispersion (Greene, 2000; Sanders, 2001).

Following prior literature (Levine et al., 2018; DesJardine et al., 2019; Ding et al., 2021), we also include a variety of variables in eq. (1) to control for other factors that may impact corporate resilience, such as *Size*, *Lev*, *ROA*, *MB*, *Growth*, *Findev*, and *PGDP*. *Size* equals the natural logarithm of the book value of total assets. *Lev* equals the ratio of total debt divided by total assets. *ROA* is the ratio of earnings to total assets. *MB* is the ratio of market capitalization to net equity of the firm. *Growth* is the sales growth rate. *Findev* represents the levels of regional traditional finance development, measured as the loan balance of financial institutions divided by regional GDP. *PGDP* represents the levels of regional economic development, measured as the natural logarithm of provincial GDP per capita. The control variables represent firm and province characteristics at the end of 2019. We also include industry fixed effects (two digits for the manufacturing industries, and one digit for all the other industries). All continuous variables are winsorized at the top and bottom 1% to mitigate the influence of extreme values. Additionally, we cluster standard errors at the firm level.

2.4. Descriptive statistics and correlation analysis

2.4.1. Descriptive statistics

Table 1 presents the descriptive statistics for the main variables used in our analysis. The average value of industry-adjusted severity of loss (*Loss_Severity*) is −0.023, suggesting that firms experience a significantly large stock price loss during the COVID-19 pandemic. The mean of time to recovery (*Recovery_Time*) is 34.829, and the standard deviation is 52.419, indicating that time to recovery varies significantly across firms. The mean of the natural logarithm of the number of provincial fintech companies (*Fintech*) is 4.443 and the median value is 4.431. Regarding the control variables, the firms in our sample have an average size (*Size*) of 22.358, an average leverage (*Lev*) of 0.424, an average return on total assets (*ROA*) of 0.033, an average market-to-book (*MB*) of 1.841, and an average sales growth (*Growth*) of 0.187. The mean of the levels of regional traditional finance development (*Findev*) is 1.509. The mean of the logarithm of provincial GDP per capita (*PGDP*) is 11.403, and the standard deviation is 0.405, indicating large cross-province variations in the levels of economic development.

2.4.2. Correlation coefficients

Table 2 reports the Pearson (lower-left) and Spearman (upper-right) correlations for the main variables used in our analysis. The correlation between the level of digital finance and the indicator for corporate resilience *Loss_Severity* is significantly negative (−0.066 Pearson; −0.052 Spearman). The correlation between the level of digital finance and the indicator for corporate resilience *Recovery_Time* is also significantly negative (−0.055 Pearson; −0.051 Spearman). These results provide preliminary support for our hypothesis that digital finance is positively associated with corporate resilience during the COVID-19 pandemic. Regarding the control variables, *Loss_Severity* is positively associated with *Size* and *ROA* and is negatively associated with *MB*. *Recovery_Time* is positively associated with *Size* and *Lev* and is negatively associated with *ROA*, *MB*, and *Growth*.

3. Empirical results

3.1. Primary analysis: Effects of digital finance on corporate resilience

In our primary analysis, we estimate the impacts of digital finance on corporate resilience during the COVID-19 pandemic. We measure corporate resilience as the severity of loss (*Loss_Severity*) and time to recovery (*Recovery_Time*). Table 3 reports the regression results. In column (1), the coefficient on *Fintech* is significantly negative (coef. = −0.007, $t = -4.791$) when the dependent variable is *Loss_Severity*, indicating that firms located in regions with higher levels of digital finance experience smaller losses during the COVID-19 pandemic. In column (2), the coefficient on *Fintech* is also negative and significant (coef. = −0.058, z = −2.742) when we use *Recovery_Time* as the dependent variable, suggesting that firms located in regions with higher levels of digital finance recover faster following the COVID-19 pandemic. The results support that digital finance improves the resilience of firms in response to the COVID-

Table 2
Correlation coefficients.

Variable	*Loss_Severity*	*Recovery_Time*	*Fintech*	*Size*	*Lev*	*ROA*	*MB*	*Growth*	*Findev*	*PGDP*
Loss_Severity	1	−0.188***	−0.052***	0.081***	−0.025	0.043**	−0.125***	0.067***	−0.015	−0.017
Recovery_Time	−0.139***	1	−0.051***	0.114***	0.135***	−0.098***	−0.244***	−0.094***	0.007	−0.061***
Fintech	−0.066***	−0.055***	1	−0.066***	−0.045**	0.041**	0.114***	−0.005	0.655***	0.820***
Size	0.086***	0.146***	−0.074***	1	0.507***	−0.069***	−0.558***	0.030*	−0.014	−0.074***
Lev	−0.017	0.129***	−0.040**	0.511***	1	−0.410***	−0.415***	0.035*	−0.032*	−0.057***
ROA	0.060***	−0.040**	0.012	0.033*	−0.290***	1	0.308***	0.333***	0.011	0.059***
MB	−0.086***	−0.169***	0.015	−0.334***	−0.286***	0.170***	1	0.106***	0.049***	0.082***
Growth	−0.003	−0.049***	−0.014	0.035*	0.062***	0.068***	−0.004	1	−0.007	0.002
Findev	0.000	0.004	0.543***	0.020	−0.035**	−0.002	0.029	0.004	1	0.569***
PGDP	−0.021	−0.034*	0.798***	0.027	0.016	−0.017	0.043**	−0.018	0.371***	1

This table reports correlation coefficients among major variables. The lower triangle contains Pearson correlations and the upper triangle contains Spearmen correlations. All variables are defined in Appendix A. The superscripts ***, **, and * indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3
Primary analysis: digital finance and corporate resilience.

Variable	*Loss_Severity*	*Recovery_Time*
	(1)	(2)
Fintech	−0.007***	−0.058***
	(−4.791)	(−2.742)
Size	0.008***	0.081***
	(4.341)	(3.372)
Lev	−0.041***	0.340*
	(−3.081)	(1.828)
ROA	0.084**	−0.039
	(2.400)	(−0.095)
MB	−0.009***	−0.164***
	(−3.719)	(−5.490)
Growth	−0.005	−0.391***
	(−0.643)	(−4.269)
Findev	0.011**	0.238***
	(2.105)	(3.118)
PGDP	0.004	−0.018
	(1.630)	(−0.564)
Constant	−0.187***	1.979***
	(−4.459)	(3.524)
Lnalpha		0.574***
		(34.199)
Industry	Yes	Yes
N	3083	3083
Adj.R^2/Pseudo R^2	0.030	0.014

This table presents the primary regression results for the impacts of digital finance on corporate resilience. The dependent variables are corporate resilience, measured as the severity of loss *(Loss_Severity)* or time to recovery *(Recovery_Time)*. The primary independent variable is *Fintech*, measured as the natural logarithm of the number of provincial fintech companies plus one. Control variables include firm and region characteristics: *Size*, *Lev*, *ROA*, *MB*, *Growth*, *Findev*, and *PGDP*. All variables are defined in Appendix A. Industry fixed effects are included. We cluster standard errors at the company level. T-values or *Z*-values are reported in parentheses below the regression coefficients. The superscripts ***, **, and * indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

19 pandemic. The coefficients of the control variables are consistent with our expectations. For example, the coefficients on *MB* are negative and significant, implying that high-valuation firms are more resilient to the pandemic (Ding et al., 2021).

3.2. Endogeneity issue

There may be a concern that the effects of digital finance on corporate resilience are not exogenous. For example, firms located in richer province are more resilient to the COVID-19 pandemic and the levels of digital finance are higher in richer provinces. It is possible that omitted variables that affect both digital finance and corporate resilience drive our results. Although we explicitly control for the levels of regional economic development in the regressions, we conduct a battery of tests using the following approaches to further address the potential endogeneity issues: (1) separate analyses for provinces at different income levels; (2) propensity score matching (PSM) estimation; and (3) excluding firms from high-tech industries.

3.2.1. Separate analyses for provinces at different income levels

One concern regarding our conclusion is that firms located in richer provinces are more resilient to the COVID-19 pandemic. The levels of digital finance might be also higher in richer provinces, implying that our findings may be a result of different levels of regional economic development. Accordingly, if the effects of digital finance on corporate resilience are driven by the levels of regional economic development, digital finance should have a bigger impact on corporate resilience in richer provinces. Although we control for the levels of regional economic development (i.e., GDP per capita) in our main analysis, we perform the analysis separately on our sample at different income levels to alleviate this concern of omitted variable. Specifically, we separately examine the relationship between digital finance and corporate resilience in regions whose GDP per capita is above and below the median.

The results are reported in Table 4. In columns (1) and (3), for the firms located in provinces whose GDP per capita is above the median, the coefficients on *Fintech* are both negative and statistically significant irrespective of whether the corporate resilience measure is the severity of loss or time to recovery. In columns (2) and (4), for the firms located in provinces whose GDP per capita is below the median, the coefficients on *Fintech* are similarly both negative and statistically significant. However, the difference in the coefficients on *Fintech* between the firms located in rich and poor regions is insignificant. These results do not support the proposition that, in the sub-sample of richer provinces, higher levels of digital finance are associated with better resilience. This suggests that the positive effects of digital finance on corporate resilience are not driven by the levels of regional economic development during the

Table 4
Digital finance and corporate resilience: separate analyses for provinces at different income levels.

Variable	*Loss_Severity*		*Recovery_Time*	
	High-GDP	*Low-GDP*	*High-GDP*	*Low-GDP*
	(1)	(2)	(3)	(4)
Fintech	−0.010***	−0.006***	−0.090*	−0.099***
	(−2.685)	(−3.111)	(−1.952)	(−3.654)
Size	0.011***	0.005*	0.032	0.114***
	(4.281)	(1.783)	(0.936)	(3.305)
Lev	−0.045**	−0.037**	0.532*	0.255
	(−2.217)	(−2.092)	(1.860)	(1.050)
ROA	0.072	0.085*	0.239	−0.146
	(1.418)	(1.778)	(0.404)	(−0.243)
MB	−0.008**	−0.011***	−0.168***	−0.164***
	(−2.161)	(−2.969)	(−4.272)	(−3.729)
Growth	−0.012	0.001	−0.548***	−0.312***
	(−1.020)	(0.122)	(−4.339)	(−2.596)
Findev	0.023**	0.008	0.153	0.264**
	(2.226)	(0.982)	(1.118)	(2.425)
PGDP	−0.003	0.008***	−0.124	0.017
	(−0.491)	(2.740)	(−1.500)	(0.406)
Constant	−0.193***	−0.149**	3.284***	1.119
	(−2.678)	(−2.287)	(3.396)	(1.286)
Lnalpha			0.562***	0.563***
			(23.073)	(23.799)
Industry	Yes	Yes	Yes	Yes
F-statistic (β_ High −β_ Low = 0)	−0.004		0.009	
N	1867	1216	1867	1216
Adj.R^2/Pseudo R^2	0.039	0.043	0.015	0.011

The table presents separate analyses for provinces at different income levels. We divide the sample into two groups based on the median *PGDP*: those with *PGDP* above the median are classified as high-GDP firms and those with *PGDP* below the median are classified as low-GDP firms. The dependent variables are corporate resilience, measured as *Loss_Severity* or *Recovery_Time.* The primary independent variable is *Fintech*, measured as the natural logarithm of the number of provincial fintech companies plus one. Control variables include firm and region characteristics: *Size*, *Lev*, *ROA*, *MB*, *Growth*, *Findev*, and *PGDP*. All variables are defined in Appendix A. Industry fixed effects are included. We cluster standard errors at the company level. T-values or *Z*-values are reported in parentheses below the regression coefficients. The superscripts ***, **, and * indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

COVID-19 pandemic.

3.2.2. PSM estimation

We next use a propensity score matching (PSM) approach to further control for the differences in the levels of regional economic development as well as firm characteristics, as this approach can identify the treatment group that is most similar to the control group. In the first step of the PSM analysis, we estimate the probability of high levels of regional digital finance using a logit model. The dependent variable, *Fintech_High*, is an indicator that equals one if the firm is located in a province with the number of fintech companies above the sample median, and zero otherwise.[2] We also include the control variables, such as *Size*, *Lev*, *ROA*, *MB*, *Growth*, *Findev*, *PGDP*, and industry fixed effects. Column (1) of Table 5 (Panel B) reports the results of the PSM estimation. *Findev* and *PGDP* are positively associated with the probability of high levels of regional digital finance, which is consistent with the view that digital finance fundamentally depends on the real economy and traditional financial sector (Guo et al., 2016).

In the second step, we match each high-level digital finance firm with the low-level digital finance firm that has the closest probability estimate calculated in the first step. Following Lawrence et al. (2011), we impose a restriction that the difference in the estimated probabilities between matched observations should be at most 0.03. The final sample consists of 232 treatment firms with high-level digital finance and 232 matched control firms with low-level digital finance. Panel A of Table 5 compares the characteristics of the two groups of firms. The differences are insignificant, implying that the PSM approach achieves adequate covariate balance between the treatment and control groups. This allows us to control for potential confounding factors, including firm characteristics and levels of regional economic development. In this set-up, it is better to isolate the association between digital finance and corporate resilience. We re-estimate eq. (1) using the matched sample. The regression results of the PSM sample are reported in columns (2) and (3) of Table 5 (Panel B). We continue to find significantly negative coefficients on *Fintech* in eq. (1), indicating that our results are robust after ensuring that high-level digital finance firms are appropriately matched to low-level digital finance firms based on their observable firm characteristics.

[2] The high-level digital finance firms are the treatment group, and the other firms are the control group.

Table 5
Digital finance and corporate resilience: PSM estimation.

Panel A The differences in characteristics between the treat and control firms

Variable	*Fintech_High*		*Fintech_Low*		*t-test*	
	Mean	*N_1*	*Mean*	*N_2*	*Difference*	*T*
Size	22.306	232	22.291	232	0.015	0.124
Lev	0.418	232	0.422	232	−0.004	−0.213
ROA	0.030	232	0.036	232	−0.006	−0.807
MB	1.795	232	1.746	232	0.049	0.556
Growth	0.111	232	0.182	232	−0.071	−1.551
Findev	1.639	232	1.588	232	0.051	1.401
PGDP	11.676	232	11.672	232	0.004	0.066

Panel B Regression results of PSM

Variable	*Full Sample*	*PSM*	
	Fintech_High	*Loss_Severity*	*Recovery_Time*
	(1)	(2)	(3)
Fintech_High		−0.023**	−0.245*
		(−2.105)	(−1.837)
Size	−0.078	0.005	0.032
	(−1.456)	(0.956)	(0.477)
Lev	−0.268	−0.027	−0.332
	(−0.697)	(−0.822)	(−0.807)
ROA	0.202	0.007	−0.414
	(0.304)	(0.094)	(−0.519)
MB	0.008	−0.012	−0.184**
	(0.173)	(−1.343)	(−2.471)
Growth	−0.047	−0.001	0.048
	(−0.739)	(−0.238)	(0.799)
Findev	5.469***	0.016	0.277
	(17.960)	(1.060)	(1.233)
PGDP	0.964***	0.004	−0.136*
	(12.067)	(0.620)	(−1.809)
Constant	−15.063***	−0.023**	−0.245*
	(−9.407)	(−2.105)	(−1.837)
Lnalpha			0.563***
			(12.971)
Industry	Yes	Yes	Yes
N	3083	464	464
Adj.R^2/Pseudo R^2	0.489	0.073	0.019

This table presents the results of PSM estimation. In the first step of the PSM analysis, we estimate the probability of high levels of regional digital finance using a logit model. The dependent variable, *Fintech_High*, is an indicator that equals one if the firm is located in a province with the number of fintech companies above the sample median, and zero otherwise. We also include the control variables, such as *Size*, *Lev*, *ROA*, *MB*, *Growth*, *Findev*, *PGDP*, and industry fixed effects. Column (1) of Panel B reports the regression results of propensity score matching estimation. In the second step, we match each high-level digital finance firm with the low-level digital finance firm that has the closest probability estimate calculated in the first step, in common support, using a caliper distance of 0.03. Panel A reports the differences in characteristics between the treat and control firms of the PSM sample. The results of the matched sample are reported in columns (2) and (3) of Panel B. The dependent variables in the second-stage regression are the two corporate resilience variables *Loss_Severity* and *Recovery_Time*. The primary independent variable is *Fintech_High*. All variables are defined in Appendix A. Industry fixed effects are included. We cluster standard errors at the company level. T-values or *Z*-values are reported in parentheses below the regression coefficients. The superscripts ***, **, and * indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

3.2.3. *Excluding high-tech firms*

There is a concern that the documented relationship between digital finance and corporate resilience is driven by the levels of regional economic development and that this potential endogeneity concern is more severe for firms from high-tech industries. To alleviate this concern, we exclude such firms from our analysis. Our results using samples of non-high-tech industry firms provide stronger evidence for the effects of digital finance on corporate resilience. Table 6 illustrates the regression results for this sample. The coefficients on *Fintech* are significantly negative, implying that the positive effects of digital finance on corporate resilience still hold.

Taken together, our results are robust when controlling for the potential endogeneity issues, indicating that digital finance enhances the resilience of firms to the COVID-19 pandemic.

Table 6
Digital finance and corporate resilience: excluding firms from high-tech industries.

Variable	*Loss_Severity*	*Recovery_Time*
	(1)	(2)
Fintech	−0.007***	−0.060***
	(−4.596)	(−2.705)
Size	0.008***	0.090***
	(4.163)	(3.663)
Lev	−0.044***	0.272
	(−3.248)	(1.423)
ROA	0.089**	−0.256
	(2.489)	(−0.607)
MB	−0.011***	−0.163***
	(−4.012)	(−5.223)
Growth	−0.004	−0.347***
	(−0.534)	(−3.786)
Findev	0.012**	0.245***
	(2.088)	(3.100)
PGDP	0.003	−0.027
	(1.459)	(−0.822)
Constant	−0.176***	1.872***
	(−4.127)	(3.236)
Lnalpha		0.580***
		(33.567)
Industry	Yes	Yes
N	2905	2905
Adj.R^2/Pseudo R^2	0.033	0.011

This table presents the regression results for excluding firms from high-tech industries. The dependent variables are corporate resilience, measured as *Loss_Severity* or *Recovery_Time*. The primary independent variable is *Fintech*, measured as the natural logarithm of the number of provincial fintech companies plus one. Control variables include firm and region characteristics: *Size*, *Lev*, *ROA*, *MB*, *Growth*, *Findev*, and *PGDP*. Industry fixed effects are included. All variables are defined in Appendix A. We cluster standard errors at the company level. T-values or *Z*-values are reported in parentheses below the regression coefficients. The superscripts ***, **, and * indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

3.3. Mechanism test and results

The above analysis suggests that digital finance helps build corporate resilience during the COVID-19 pandemic. To identify the possible channels through which digital finance shapes corporate resilience, we perform a mediation analysis to investigate whether firms' access to finance or financing costs underlie the relationship between digital finance and corporate resilience during the COVID-19 pandemic.

Following the procedure outlined in Baron and Kenny (1986), Preacher and Hayes (2004), Fedaseyeu et al. (2018), Kachelmeier et al. (2019), Sun et al. (2019), and Tan et al. (2020), we use the causal step approach to probe the underlying mechanisms. The first step in our mediation analysis is to establish the effects of digital finance on corporate resilience using eq. (1) in Table 3. The mediator is the variable that may be affected by digital finance and, in turn, may affect the outcome of corporate resilience. The second step is to establish the relationship between digital finance and the mediator variable, which is the firms' access to finance or financing costs. The third step is to establish the relationship between firms' access to finance or financing costs and corporate resilience when controlling for digital finance. When the effects of digital finance on corporate resilience are decreased, partial mediation is considered to have occurred. The mediation analysis model, eqs. (2)–(3), is as follows:

$$\mathrm{Debt/Ddebtcost} = \beta_0 + \beta_1 \mathrm{Fintech} + \mathrm{Controls} + \mathrm{Industry} + \varepsilon \tag{2}$$

$$\mathrm{Resilience} = \beta_0 + \beta_1 \mathrm{Fintech} + \beta_2 \mathrm{Debt/Ddebtcost} + \mathrm{Controls} + \mathrm{Industry} + \varepsilon \tag{3}$$

where eq. (2) is the mediator variable model and eq. (3) examines the effects of both the mediator variable and digital finance on corporate resilience. In this setting, firms' access to finance (*Debt*) or financing costs (*Ddebtcost*) is the mediator. Following prior literature (Pittman and Fortin, 2004; Cull and Xu, 2005; Phan, 2014), we also include a variety of variables in eq. (2) to control for other factors that may have impacts on *Debt* or *Ddebtcost*, such as the log of total assets (*Size*), leverage (*Lev*), return on total assets (*ROA*), market-to-book assets (*MB*), sales growth (*Growth*), current ratio (*CR*), the ownership of the largest shareholder (*FSHR*), property, plant, and equipment ratio (*PPE*), and operating cash flow (*OCF*). All variables are defined in Appendix A. The control variables used in eq. (3) are consistent with those in eq. (1).

3.3.1. Importance of access to finance

First, we investigate how digital finance impacts firms' access to finance. The availability of funds may enhance corporate resilience

Table 7
Mechanism test: digital finance, firms' access to finance, and corporate resilience.

Variable	*Debt*	*Loss_Severity*	*Recover_Time*
	(1)	(2)	(3)
Debt		−0.088***	−1.254***
		(−2.598)	(−2.901)
Fintech	0.002**	−0.006***	−0.054**
	(2.017)	(−4.517)	(−2.567)
Size	0.001	0.008***	0.081***
	(1.482)	(4.430)	(3.405)
Lev	0.011	−0.039***	0.376**
	(1.069)	(−2.905)	(2.023)
ROA	0.061**	0.095***	0.003
	(2.276)	(2.690)	(0.007)
MB	0.001	−0.010***	−0.162***
	(0.663)	(−3.774)	(−5.468)
Growth	0.010**	−0.004	−0.375***
	(2.276)	(−0.529)	(−4.054)
CR	−0.000		
	(−0.731)		
FSHR	0.000		
	(0.844)		
PPE	0.028***		
	(3.027)		
OCF	−0.029***		
	(−2.847)		
Findev		0.011*	0.232***
		(1.912)	(3.034)
PGDP		0.004	−0.021
		(1.612)	(−0.654)
Constant	−0.042*	−0.191***	1.989***
	(−1.923)	(−4.551)	(3.544)
Lnalpha			0.573***
			(34.039)
Industry	Yes	Yes	Yes
N	3083	3083	3083
Adj.R^2/Pseudo R^2	0.218	0.033	0.011

This table presents the regression results of the impacts of digital finance on firms' access to finance and resilience to the COVID-19 pandemic. Firms' access to finance (*Debt*) is the mediator, measured as short-term and long-term debt divided by total assets. Column (1) shows the results for the effects of digital finance on firms' access to finance. The primary independent variable is *Fintech*, measured as the natural logarithm of the number of provincial fintech companies plus one. Control variables include *Size*, *Lev*, *ROA*, *MB*, *Growth*, *CR*, *FSHR*, *PPE*, and *OCF*. Columns (2) and (3) show the results for firms' access to finance on corporate resilience when controlling for digital finance. The dependent variables are corporate resilience, measured as *Loss_Severity* or *Recovery_Time*. Control variables include firm and region characteristics: *Size*, *Lev*, *ROA*, *MB*, *Growth*, *Findev*, and *PGDP*. All variables are defined in Appendix A. Industry fixed effects are included. We cluster standard errors at the company level. T-values or *Z*-values are reported in parentheses below the regression coefficients. The superscripts ***, **, and * indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

to systemic crises (Levine et al., 2018), especially during the COVID-19 pandemic. We predict that digital finance broadens access for firms to obtain external financing during the pandemic, thus helping them cope with negative events. We use debt financing to capture firms' access to finance, which is measured as short-term and long-term debt divided by total assets (Cull and Xu, 2005; Phan, 2014).

Table 7 reports our regression of the impacts of digital finance on firms' access to finance and resilience to the COVID-19 pandemic. In column (1), we regress the mediator, firms' debt financing (*Debt*), on the independent variable, digital finance (*Fintech*), and find that the relationship is significantly positive (coef. =0.002, $t = 2.107$) when firms' access to finance is measured by debt financing. In columns (2) and (3), we regress the dependent variables of corporate resilience on both the independent variable, *Fintech*, and the mediator, *Debt*. The coefficients on *Debt* are negative and statistically significant at the 1% level. In addition, the coefficient on *Fintech* is negative and significant (coef. = − 0.006, $t = -4.517$) when we use *Loss_Severity* as the dependent variable. A Sobel test (Sobel, 1982) reveals that the effect is significantly reduced in the presence of the mediator (z = 2.234, $p = 0.025$). The coefficient on *Fintech* is also negative and significant (coef. = − 0.054, z = −2.567) when we use *Recovery_Time* as the dependent variable. The Sobel (1982) test confirms that a portion of the mediated effect is significant (z = 1.692, $p = 0.09$). In this regression, coefficients on *Fintech* are smaller than in eq. (1) as reported in Table 3,[3] suggesting that firms' access to finance is the partial transmission channel for the impacts of digital finance on corporate resilience. These results indicate that higher levels of digital finance improve access to finance for firms and thereby enhance resilience to the COVID-19 pandemic. The results are consistent with our prediction that digital finance enhances

[3] In Table 3, the coefficients on *Fintech* are 0.007, and 0.058, respectively.

Table 8
Mechanism test: digital finance, financing costs, and corporate resilience.

Variable	*Ddebtcost*	*Loss_Severity*	*Recover_Time*
	(1)	(2)	(3)
Ddebtcost		−0.761***	−3.893*
		(−3.480)	(−1.945)
Fintech	−0.001***	−0.006***	−0.051***
	(−2.601)	(−4.943)	(−2.864)
Size	0.000**	0.008***	0.081***
	(2.046)	(4.470)	(3.373)
Lev	0.013***	−0.031**	0.393**
	(5.114)	(−2.255)	(2.088)
ROA	−0.014***	0.072**	−0.107
	(−5.105)	(2.052)	(−0.259)
MB	0.000	−0.009***	−0.163***
	(0.145)	(−3.692)	(−5.470)
Growth	−0.003***	−0.007	−0.397***
	(−3.210)	(−0.921)	(−4.318)
CR	−0.001		
	(−0.733)		
FSHR	0.000		
	(0.486)		
OCF	−0.134***		
	(−3.283)		
Findev		0.012**	0.247***
		(2.222)	(3.220)
PGDP		0.004	−0.016
		(1.550)	(−0.510)
Constant	−0.007*	−0.190***	1.959***
	(−1.721)	(−4.532)	(3.476)
Lnalpha			0.574***
			(34.176)
Industry	Yes	Yes	Yes
N	3083	3083	3083
Adj.R^2/Pseudo R^2	0.179	0.035	0.015

This table reports the regression results for the decreasing financing costs channel. The change in debt financing costs (*Ddebtcost*) from the year 2019 to 2020 is the mediator. Financing costs are calculated as short-term and long-term debt divided by total assets. Column (1) shows the results for the effects of digital finance on financing costs. The primary independent variable is *Fintech*, measured as the natural logarithm of the number of provincial fintech companies plus one. Control variables include *Size*, *Lev*, *ROA*, *MB*, *Growth*, *CR*, *FSHR*, *PPE*, and *OCF*. Columns (2) and (3) show the results for financing costs on corporate resilience when controlling for digital finance. The dependent variables are corporate resilience, measured as *Loss_Severity* or *Recovery_Time*. Control variables include firm and region characteristics: *Size*, *Lev*, *ROA*, *MB*, *Growth*, *Findev*, and *PGDP*. All variables are defined in Appendix A. Industry fixed effects are included. We cluster standard errors at the company level. T-values or *Z*-values are reported in parentheses below the regression coefficients. The superscripts ***, **, and * indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

corporate resilience by improving access to finance.

3.3.2. Importance of financing costs

The adverse impact of the COVID-19 pandemic on corporate operation risks makes firms' access to external financing more expensive. From this perspective, financing costs might rise during the pandemic. However, digital finance can help lending institutions reduce loan assessment costs and enable them to assess borrowers' risks more accurately. Therefore, it is worth investigating whether digital finance helps build corporate resilience during the COVID-19 pandemic by reducing financing costs. Referring to Pittman and Fortin (2004), financing costs are calculated as the interest expense divided by total short-term and long-term debt. We consider the COVID-19 pandemic and use the change in debt financing costs (*Ddebtcost*) from the year 2019 to 2020 to measure financing costs.

Table 8 presents the regression results for the decreasing financing costs channel. In column (1), the coefficient on *Fintech* is negative and significant at the 1% level when the financing costs are measured by the change in debt financing costs (*Ddebtcost*) from the year 2019 to 2020. In columns (2) and (3) the coefficients on the key variable of interest, *Fintech*, are negative and statistically significant when corporate resilience is measured as *Loss_Severity* and *Recovery_Time*. The coefficients on *Ddebtcost* are also negative and statistically significant. The Sobel (1982) test confirms that a portion of the mediated effect is significant irrespective of whether the corporate resilience is measured by *Loss_Severity* ($z = 2.206$, $p = 0.027$) or *Recovery_Time* ($z = 1.848$, $p = 0.064$). These results suggest that digital finance decreases financing costs for firms, thereby enhancing resilience to the COVID-19 pandemic. This supports our prediction that digital finance improves corporate resilience by decreasing financing costs.

In summary, the regression results in Tables 7 and 8 indicate that digital finance can effectively help firms overcome the

Table 9
Sub-sample analysis: large firms versus small firms.

Variable	*Loss_Severity*		*Recovery_Time*	
	Large Firms	*Small Firms*	*Large Firms*	*Small Firms*
	(1)	(2)	(3)	(4)
Fintech	−0.005	−0.008***	−0.003	−0.089***
	(−1.540)	(−4.500)	(−0.108)	(−2.935)
Size	0.002	0.013***	−0.101	0.266***
	(0.338)	(4.436)	(−1.342)	(6.849)
Lev	−0.034	−0.041***	0.554**	0.089
	(−0.930)	(−2.857)	(2.175)	(0.313)
ROA	0.164	0.084**	−0.274	1.126
	(0.928)	(2.313)	(−0.504)	(1.639)
MB	−0.012	−0.009***	−0.135***	−0.388***
	(−1.388)	(−3.252)	(−3.559)	(−8.248)
Growth	0.008	−0.008	−0.373***	−0.346***
	(0.477)	(−0.873)	(−2.837)	(−2.692)
Findev	−0.001	0.013**	0.148	0.307***
	(−0.122)	(2.092)	(1.347)	(2.872)
PGDP	0.007	0.004	−0.040	−0.019
	(1.333)	(1.386)	(−0.898)	(−0.416)
Constant	−0.082	−0.297***	5.887***	−2.094**
	(−0.641)	(−4.408)	(3.537)	(−2.324)
Lnalpha			0.520***	0.571***
			(20.994)	(23.686)
Industry	Yes	Yes	Yes	Yes
F-statistic (β_Large − β_ Small = 0)	0.003*		0.086**	
N	1542	1541	1542	1541
Adj.R^2/Pseudo R^2	0.028	0.029	0.023	0.011

The table presents the effects of digital finance on corporate resilience across firms of different size. We divide the sample into two groups based on the median firm size: those with firm size above the median are classified as large firms and those with firm size below the median are classified as small firms. The dependent variables are corporate resilience, measured as *Loss_Severity* or *Recovery_Time*. The primary independent variable is *Fintech*, measured as the natural logarithm of the number of provincial fintech companies plus one. Control variables include firm and region characteristics: *Size*, *Lev*, *ROA*, *MB*, *Growth*, *Findev*, and *PGDP*. All variables are defined in Appendix A. Industry fixed effects are included. We cluster standard errors at the company level. T-values or Z-values are reported in parentheses below the regression coefficients. The superscripts ***, **, and * indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

disadvantages of financing frictions by improving firms' access to finance and decreasing financing costs. This, in turn, enhances corporate resilience to the COVID-19 pandemic.

3.4. Sub-sample analysis of primary results: Heterogeneous effects

Having shown that digital finance shapes corporate resilience to the pandemic by mitigating financing frictions, we now deepen our analysis by investigating the role of financial conditions and firms' liquidity needs. The impacts of digital finance on corporate resilience depend on the extent to which firms need digital finance to mitigate financing frictions. In this section, we perform several tests to provide further support for the results of our primary analysis.

3.4.1. Role of firm size

Smaller firms tend to have worse fundamentals and thus are more likely to be vulnerable to shocks (Ding et al., 2021). Given that smaller firms are generally characterized by stronger financial constraints, it is reasonable to expect that the effects of digital finance on corporate resilience will be more pronounced for smaller firms than for larger firms. For our analysis, we divide the sample into two groups based on the median firm size: those with firm size above the median are classified as large firms and those with firm size below the median are classified as small firms.

Table 9 presents the effects of digital finance on corporate resilience across firms of different size. In columns (1) and (2), corporate resilience is measured as severity of loss. In column (1), for large firms, the coefficient on *Fintech* is insignificant. In column (2), for small firms, the coefficient on *Fintech* is negative and significant at the 1% level. In columns (3) and (4), we use time to recovery to capture corporate resilience. In column (3), for large firms, the coefficient on *Fintech* is insignificant. In column (4), for small firms, the coefficient on *Fintech* is negative and significant at the 1% level. In addition, the difference in the coefficients on *Fintech* between the groups with large and small firms is statistically significant at least at the 10% level, as shown in Table 9. Compared to large firms, digital finance helps small firms mitigate their losses and accelerate their time to recovery during the COVID-19 pandemic. These results indicate that the positive effects of digital finance on corporate resilience are more pronounced for small firms, which is consistent with our prediction.

Table 10
Sub-sample analysis: SOEs versus non-SOEs.

Variable	*Loss_Severity*		*Recovery_Time*	
	SOEs	*Non-SOEs*	*SOEs*	*Non-SOEs*
	(1)	(2)	(3)	(4)
Fintech	−0.003	−0.007***	−0.008	−0.074**
	(−1.489)	(−3.212)	(−0.257)	(−2.319)
Size	−0.001	0.007**	−0.074**	0.162***
	(−0.198)	(2.496)	(−1.971)	(4.450)
Lev	−0.043**	−0.034**	0.468*	0.060
	(−2.106)	(−1.981)	(1.905)	(0.210)
ROA	0.233***	0.066*	0.532	−0.706
	(2.918)	(1.703)	(1.116)	(−0.895)
MB	−0.016***	−0.008**	−0.212***	−0.053
	(−3.595)	(−2.484)	(−5.923)	(−0.978)
Growth	0.003	−0.011	−0.459***	−0.139
	(0.229)	(−1.065)	(−3.833)	(−0.989)
Findev	0.007	0.010	0.093	0.365***
	(0.848)	(1.267)	(0.909)	(3.210)
PGDP	0.004	0.003	−0.013	−0.065
	(1.426)	(0.891)	(−0.315)	(−1.343)
Constant	0.014	−0.164***	5.364***	0.434
	(0.234)	(−2.626)	(6.240)	(0.476)
Lnalpha			0.461***	0.589***
			(14.047)	(28.722)
Industry	Yes	Yes	Yes	Yes
F-statistic (β_ SOEs −β_ Non-SOEs = 0)	0.004*		0.066*	
N	979	2104	979	2104
Adj.R^2/Pseudo R^2	0.030	0.007	0.014	0.013

The table presents the effects of digital finance on corporate resilience across firms with different ownership. *SOEs* equals one if a firm's ultimate shareholder is a local or central government, and zero otherwise. The dependent variables are corporate resilience, measured as *Loss_Severity* or *Recovery_Time*. The primary independent variable is *Fintech*, measured as the natural logarithm of the number of provincial fintech companies plus one. Control variables include firm and region characteristics: *Size*, *Lev*, *ROA*, *MB*, *Growth*, *Findev*, and *PGDP*. All variables are defined in Appendix A. Industry fixed effects are included. We cluster standard errors at the company level. T-values or *Z*-values are reported in parentheses below the regression coefficients. The superscripts ***, **, and * indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

3.4.2. *Role of state ownership*

The financial system in China is dominated by a large but underdeveloped banking system controlled by the government (Allen et al., 2005). As state ownership helps firms obtain government benefits, banks have a purely ideological preference for lending to SOEs. The non-SOEs have lower levels of government support and hence might be discriminated against when they attempt to obtain loans from state-owned banks (Brandt and Li, 2003; Allen et al., 2005). Access to finance may therefore not be difficult for SOEs during a pandemic, making them less likely to be vulnerable to liquidity risk and resulting in a smaller role for digital finance in building their corporate resilience.

Table 10 presents the effects of digital finance on corporate resilience across firms with different ownership. *SOEs* equals one if a firm's ultimate shareholder is a local or central government, and zero otherwise. In columns (1) and (2), we use severity of loss (*Loss_Severity*) to capture corporate resilience. In column (1), for SOEs, the coefficient on *Fintech* is insignificant. In column (2), for non-SOEs, the coefficient on *Fintech* is negative and significant at the 1% level. In columns (3) and (4), corporate resilience is measured as time to recovery (*Recovery_Time*). In column (3), for SOEs, the coefficient on *Fintech* is insignificant. In column (4), for non-SOEs, the coefficient on *Fintech* is negative and significant at the 5% level. Moreover, the difference in the coefficients on *Fintech* between the SOEs and non-SOEs groups is statistically significant at the 10% level. These results suggest that the positive effects of digital finance on corporate resilience are more prominent for non-SOEs.

3.4.3. *Role of cash holding*

Considering the adverse effects of the COVID-19 pandemic on cash flow and liquidity, heterogeneity in firms' access to cash can influence corporate resilience (Giroud and Mueller, 2017; Ding et al., 2021). Because the COVID-19 pandemic depresses corporate sales, holding more cash might help firms mitigate their losses and increase the probability of recovery. Therefore, we expect the effects of digital finance on corporate resilience to be less pronounced for firms with high cash holdings than for firms with low cash holdings. We divide the sample into two groups based on the median cash holdings: those with cash holdings above the median are classified as high-cash firms and those with cash holdings below the median are classified as low-cash firms. Cash holdings are measured as cash plus short-term investments divided by total assets.

Table 11 presents the effects of digital finance on corporate resilience across firms with different levels of cash holdings. In columns (1) and (2), corporate resilience is measured as severity of loss (*Loss_Severity*). In column (1), for high-cash firms, the coefficient on *Fintech* is insignificant. In column (2), for low-cash firms, the coefficient on *Fintech* is negative and significant at the 1% level. In columns (3) and (4), we use time to recovery (*Recovery_Time*) as the corporate resilience measure. In column (3), for high-cash firms,

Table 11
Sub-sample analysis: high-cash firms versus low-cash firms.

Variable	*Loss_Severity*		*Recovery_Time*	
	High-cash Firms	*Low-cash Firms*	*High-cash Firms*	*Low-cash Firms*
	(1)	(2)	(3)	(4)
Fintech	−0.006	−0.009***	−0.049	−0.079***
	(−1.470)	(−4.007)	(−1.524)	(−2.768)
Size	0.014***	0.002	−0.044	0.164***
	(5.235)	(0.890)	(−1.247)	(5.057)
Lev	−0.023	−0.047**	1.009***	−0.181
	(−1.239)	(−2.474)	(3.760)	(−0.692)
ROA	−0.028	0.158***	0.677	−0.817
	(−0.532)	(3.425)	(1.043)	(−1.465)
MB	−0.005*	−0.014***	−0.182***	−0.169***
	(−1.770)	(−2.924)	(−5.011)	(−3.188)
Growth	−0.024**	0.009	−0.443***	−0.348***
	(−2.130)	(0.861)	(−3.278)	(−2.656)
Findev	0.014	0.013*	0.128	0.352***
	(1.094)	(1.646)	(1.128)	(3.425)
PGDP	−0.009	0.003	−0.008	−0.026
	(−0.298)	(1.108)	(−0.158)	(−0.609)
Constant	−0.317***	−0.059	4.555***	0.348
	(−3.009)	(−1.007)	(5.567)	(0.451)
Lnalpha			0.557***	0.558***
			(22.819)	(23.418)
Industry	Yes	Yes	Yes	Yes
F-statistic (β_ High −β_ Low = 0)	0.003*		0.030*	
N	1542	1541	1542	1541
Adj.R^2/Pseudo R^2	0.042	0.059	0.014	0.013

The table presents the effects of digital finance on corporate resilience across firms with different levels of cash holdings. Cash holdings are measured as cash plus short-term investments divided by total assets. We divide the sample into two groups based on the median cash holdings: those with cash holdings above the median are classified as high-cash firms and those with cash holdings below the median are classified as low-cash firms. The dependent variables are corporate resilience, measured as *Loss_Severity* or *Recovery_Time*. The primary independent variable is *Fintech*, measured as the natural logarithm of the number of provincial fintech companies plus one. Control variables include firm and region characteristics: *Size*, *Lev*, *ROA*, *MB*, *Growth*, *Findev*, and *PGDP*. All variables are defined in Appendix A. Industry fixed effects are included. We cluster standard errors at the company level. T-values or Z-values are reported in parentheses below the regression coefficients. The superscripts ***, **, and * indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

the coefficient on *Fintech* is insignificant. In column (4), for low-cash firms, the coefficient on *Fintech* is negative and significant at the 1% level. Additionally, the difference in the coefficients on *Fintech* between the firms with high and low cash holdings is statistically significant at the 10% level. These results are in line with our prediction, indicating that the impacts of digital finance on improving corporate resilience are more pronounced for firms with low cash holdings.

3.5. Robustness tests

3.5.1. Corporate profitability and employment

In our primary analysis, we assess resilience in terms of stock behavior. Although stock prices are one of the best measures for capturing corporate resilience in a crisis, capital markets are highly sensitive to firm-specific factors that can interfere with potential outcomes. Our reliance on stock price data may therefore limit the generalizability of our findings. To address this issue, we follow Levine et al. (2018) and use firm profitability and employment as measures of corporate resilience in our robustness tests.

To assess whether firms in regions with higher levels of digital finance perform better during the COVID-19 pandemic than similar firms in other regions, we use the following model:

$$\text{Resilience} = \beta_0 + \beta_1\text{Fintech} + \beta_2\text{Fintech*COVID\_19} + \text{Controls} + \text{Industry} + \text{Year} + \varepsilon \quad (4)$$

where corporate resilience (*Resilience*) reflects superior financial performance and employment (Markman and Venzin, 2014; Levine et al., 2018). We measure corporate resilience as either earnings before interest and taxes (*EBIT*) or employment (*Employment*) (Levine et al., 2018). *EBIT* equals the ratio of earnings before interest and taxes during a period to the book value of total assets. *Employment* equals the natural logarithm of the total number of employees in a firm. The indicator variable *COVID_19* equals one for the year 2020 when the COVID-19 pandemic broke out in China, and zero for the year 2019.[4] The variable of our focus is *Fintech* ×*COVID_19*, which

[4] The sample companies used in this section are those that are publicly listed on the Shanghai and Shenzhen stock exchanges in China during the first quarter of 2019–2020.

Table 12
Robustness tests: corporate profitability and employment.

Variable	*EBIT*			*Employment*		
	All	*High COVID-19 Severity*	*Low COVID-19 Severity*	*All*	*High COVID-19 Severity*	*Low COVID-19 Severity*
	(1)	(2)	(3)	(4)	(5)	(6)
Fintech	−0.005*	−0.012***	0.014**	−0.651***	−0.758***	−0.341
	(−1.802)	(−3.393)	(2.513)	(−3.653)	(−3.587)	(−1.027)
*Fintech*COVID_19*	0.009***	0.013***	0.004	0.282***	0.294***	−0.045
	(3.076)	(3.811)	(0.622)	(3.286)	(2.811)	(−0.288)
Size	0.003***	0.003***	0.003***	0.799***	0.795***	0.815***
	(12.983)	(9.833)	(9.785)	(59.227)	(46.987)	(37.207)
Lev	−0.024***	−0.025***	−0.023***	0.078	0.141	−0.073
	(−17.121)	(−13.637)	(−11.353)	(0.844)	(1.230)	(−0.476)
OCF	0.090***	0.086***	0.098***	0.259	−0.162	0.790
	(11.711)	(8.589)	(8.556)	(0.706)	(−0.361)	(1.241)
MB	0.001***	0.001**	0.002***	0.031***	0.034**	0.023
	(3.242)	(2.169)	(3.552)	(2.794)	(2.524)	(1.219)
Growth	−0.000	−0.000	0.001**	−0.000***	−0.000***	−0.011*
	(−0.783)	(−1.226)	(2.012)	(−20.379)	(−15.659)	(−1.837)
PGDP	0.002***	0.002***	−0.003***	0.117***	0.088***	0.071
	(4.654)	(5.305)	(−2.866)	(5.365)	(3.468)	(1.082)
Constant	−0.037**	−0.003	−0.104***	−8.511***	−7.558***	−9.562***
	(−2.225)	(−0.161)	(−3.005)	(−8.318)	(−6.281)	(−4.850)
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
F-statistic (β_ High −β_ Low = 0)		0.009*			0.339**	
N	6227	2312	3915	6227	2312	3915
Adj.R^2	0.249	0.252	0.268	0.640	0.655	0.620

This table presents the regression results for alternative measures of corporate resilience. We measure corporate resilience in either earnings before interest and taxes (*EBIT*) or employment (*Employment*). *EBIT* equals the ratio of earnings before interest and taxes during a period to the book value of total assets. *Employment* equals the natural logarithm of the total number of employees in a firm. The indicator variable *COVID_19* equals one for the year 2020 when the COVID-19 pandemic broke out, and zero for the year 2019. The variable of focus is *Fintech * COVID_19*. We divide firms into two groups based on the severity of the COVID-19 pandemic in China. Specifically, if the firm is registered in Hubei, Zhejiang, Guangdong, Hunan, and Henan, it is classified as high COVID-19 severity, and as low COVID-19 severity otherwise. *Fintech* is measured as the natural logarithm of the number of provincial fintech companies plus one. Control variables include firm and region characteristics: *Size*, *Lev*, *ROA*, *MB*, *Growth*, *Findev*, and *PGDP*. All variables are defined in Appendix A. Industry and year fixed effects are included. We cluster standard errors at the company level. T-values are reported in parentheses below the regression coefficients. The superscripts ***, **, and * indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

represents the interaction of the digital finance measure and the COVID-19 pandemic dummy variable. The estimated coefficient on the interaction between *Fintech* and *COVID_19*, β_2, measures the differential outcome during the COVID-19 pandemic for firms operating in regions with different levels of digital finance. We include other potential determinants of corporate resilience as control variables following previous studies (Levine et al., 2018; DesJardine et al., 2019; Ding et al., 2021), such as firm size (*Size*), financial leverage (*Lev*), market-to-book ratio (*MB*), sales growth (*Growth*), operating cash flow (*OCF*), the levels of traditional financial development (*Findev*), and the levels of regional economic development (*PGDP*). We also include industry and year fixed effects.

The impact of the COVID-19 pandemic varies across regions in China. Digital finance can more strongly impact corporate resilience in regions heavily affected by the COVID-19 pandemic. To test this prediction, we divide firms into two groups based on the severity of the COVID-19 pandemic in China. Specifically, if the firm is registered in Hubei, Zhejiang, Guangdong, Hunan, and Henan, it is classified as high COVID-19 severity, and as low COVID-19 severity otherwise.

Table 12 reports the regression results of the impacts of digital finance on firm profitability or employment. The dependent variable in columns (1)–(3) is *EBIT*. The coefficients of interaction term *Fintech* ×*COVID_19* are positive and significant in columns (1) and (2), but insignificant in column (3). Moreover, the difference in the coefficients on *Fintech*×*COVID_19* between firms with high and low COVID-19 severity is statistically significant. These results indicate that the positive effects of digital finance on profitability are less pronounced in firms with low COVID-19 severity.

In columns (4)–(6) of Table 12, the dependent variable is *Employment*. As shown in columns (4) and (5) of Table 12, the coefficients of interaction term *Fintech* ×*COVID_19* are positive and significant at the 1% level, but insignificant in column (6), indicating that digital finance helps mitigate the adverse shock of COVID-19 on employment among the regions with high COVID-19 severity. In addition, the difference in the coefficients on *Fintech*×*COVID_19* between column (5) and column (6) is statistically significant. Overall, we find that the positive impacts of digital finance on corporate profitability and employment only hold for the sub-sample of regions that are more heavily affected by the COVID-19 pandemic.

Table 13
Robustness tests: alternative measures of digital finance.

Variable	*Loss_Severity*	*Recovery_Time*	*Loss_Severity*	*Recovery_Time*
	(1)	(2)	(3)	(4)
Fintech/GDP	−0.068***	−0.325*		
	(−4.689)	(−1.741)		
DFI			−0.071**	−1.086***
			(−2.567)	(−2.657)
Size	0.008***	0.088***	0.008***	0.037
	(4.542)	(3.672)	(4.455)	(1.512)
Lev	−0.040***	0.252	−0.040***	0.318*
	(−3.022)	(1.365)	(−2.955)	(1.678)
ROA	0.080**	−0.219	0.085**	0.235
	(2.274)	(−0.525)	(2.406)	(0.568)
MB	−0.009***	−0.156***	−0.010***	−0.161***
	(−3.619)	(−5.217)	(−3.786)	(−5.449)
Growth	−0.005	−0.335***	−0.005	−0.495***
	(−0.620)	(−3.371)	(−0.571)	(−5.513)
Findev	0.013**	0.295***	0.008	0.261***
	(2.200)	(3.736)	(1.462)	(3.055)
PGDP	0.003	−0.085***	0.001	−0.021
	(1.271)	(−2.868)	(0.443)	(−0.667)
Constant	−0.206***	2.166***	0.234	8.779***
	(−4.825)	(3.801)	(1.499)	(3.783)
Lnalpha		0.556***		0.552***
		(32.003)		(32.008)
Industry	Yes	Yes	Yes	Yes
N	3083	3083	3083	3083
Adj.R^2/Pseudo R^2	0.032	0.011	0.015	0.014

This table presents the regression results of the impacts of digital finance on corporate resilience based on the alternative measures of digital finance. The dependent variables are corporate resilience, measured as *Loss_Severity* or *Recovery_Time*. We use *DFI* and *Fintech/GDP* as the digital finance alternative measures. *DFI* is measured as the natural logarithm of the digital financial index, and *Fintech/GDP* is the provincial number of fintech companies scaled by provincial GDP. Control variables include firm and region characteristics: *Size*, *Lev*, *ROA*, *MB*, *Growth*, *Findev*, and *PGDP*. All variables are defined in Appendix A. Industry fixed effects are included. We cluster standard errors at the company level. T-values or *Z*-values are reported in parentheses below the regression coefficients. The superscripts ***, **, and * indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

3.5.2. Alternative measure of digital finance

In the main analysis, we use the natural logarithm of the number of provincial fintech companies to measure digital finance. Two other measures are frequently used in the current literature (Guo et al., 2020; Song et al., 2021; Chen and Zhang, 2021). Accordingly, we construct two new variables to measure digital finance. First, as digital finance may be correlated with the levels of regional economic development, we use the provincial number of fintech companies scaled by provincial GDP (*Fintech/GDP*) as an alternative measure of digital finance. Second, following Guo et al. (2020), and Chen and Zhang (2021), we use the natural logarithm of the digital financial index (*DFI*) to directly measure the levels of digital finance. Higher values of *DFI* indicate higher levels of digital finance. The regression results are reported in Table 13. The coefficients on *Fintech/GDP* and *DFI* are negative and statistically significant across all columns. These results indicate that digital finance shapes corporate resilience to the COVID-19 pandemic, which confirms the robustness of our conclusion.

3.5.3. Controlling for regional spillover effects

Digital finance might have regional spillover effects (Song et al., 2021), which can impact corporate resilience during the COVID-19 pandemic. To alleviate this concern, we repeat our primary analysis by incorporating regional spillover effects of the digital finance variable, *Fintech_Neighbor*, as proxied by the natural logarithm of the mean number of fintech companies in the provinces neighboring the province in which the company is registered. We report the results in Table 14. We find that digital finance continues to have significant positive impacts on corporate resilience after controlling for regional spillover effects and that the regional spillover effect (*Fintech_Neighbor*) is insignificant. These results suggest that the relationship between digital finance and corporate resilience is robust.

3.5.4. Excluding initial public offerings (IPOs)less than one year old

We note that the stock-based performance is volatile in the IPO year, as the corresponding accounting data tend to be heavily manipulated (Fan et al., 2007). As this can confound our findings, we exclude samples of IPOs less than one year old. Table 15 illustrates the regression results. After separately adopting different measures of corporate resilience, we find that the positive effects of digital finance on corporate resilience still hold.

Table 14
Robustness tests: controlling for regional spillover effects.

Variable	*Loss_Severity*	*Recovery_Time*
	(1)	(2)
Fintech	−0.007***	−0.068***
	(−4.325)	(−3.169)
Size	0.008***	0.074***
	(4.367)	(3.049)
Lev	−0.041***	0.336*
	(−3.082)	(1.805)
ROA	0.083**	−0.122
	(2.367)	(−0.292)
MB	−0.009***	−0.144***
	(−3.705)	(−4.743)
Growth	−0.003	−0.408***
	(−0.400)	(−4.462)
Findev	0.008	0.272***
	(1.390)	(3.503)
PGDP	0.003	−0.047
	(1.262)	(−1.494)
Fintech_Neighbor	0.003	−0.021
	(1.645)	(−0.975)
Constant	−0.194***	2.448***
	(−4.488)	(4.252)
Lnalpha		0.574***
		(34.149)
Industry	Yes	Yes
N	3083	3083
Adj.R^2/Pseudo R^2	0.031	0.011

This table presents the regression results after controlling for regional spillover effects. The dependent variables are corporate resilience, measured as *Loss_Severity* or *Recovery_Time*. The primary independent variable is *Fintech*, measured as the natural logarithm of the number of provincial fintech companies plus one. *Fintech_Neighbor* represents regional spillover effects of digital finance, as proxied by the natural logarithm of the mean number of fintech companies in the provinces neighboring the province in which the company is registered. Control variables include firm and region characteristics: *Size*, *Lev*, *ROA*, *MB*, *Growth*, *Findev*, and *PGDP*. All variables are defined in Appendix A. Industry fixed effects are included. We cluster standard errors at the company level. T-values or *Z*-values are reported in parentheses below the regression coefficients. The superscripts ***, **, and * indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

4. Conclusions

Are firms more resilient to the COVID-19 pandemic if they have higher levels of digital finance? Although there are enormous bodies of research on both crises and corporate resilience, we are unable to present any previous research on the role of digital finance in affecting the response of firms to the COVID-19 pandemic. Based on a sample of Chinese listed firms at the end of 2019, we investigate whether digital finance improves corporate resilience to the COVID-19 pandemic.

We document that digital finance helps firms recover from the pandemic by lessening the severity of loss and accelerating recovery times. Namely, firms are more resilient to the COVID-19 pandemic with higher levels of digital finance. In addition, we find that firms located in regions with higher levels of digital finance are more likely to obtain external financing and face lower financing costs. This evidence supports the interpretation that digital finance improves corporate resilience to the COVID-19 pandemic by mitigating financing frictions. Moreover, we find that the positive effects of digital finance on corporate resilience are more pronounced for smaller firms, non-SOEs, and firms with lower cash reserves. These results suggest that the role of digital finance in improving the resilience of firms to the COVID-19 pandemic is particularly important for firms with worse financial conditions and higher liquidity needs.

Our paper represents a first step toward understanding the role of digital finance in shaping corporate resilience to the COVID-19 pandemic in a transition economy such as China. We conclude that digital finance is an important factor that enhances corporate resilience to the COVID-19 pandemic. As countries across the world struggle to lessen the prolonged economic contraction, a better understanding of corporate resilience in China would be relevant to many economic decisions both in China and elsewhere. Therefore, it is necessary to develop digital finance globally in the post-pandemic era. Despite our contributions to the literature, our study also contains limitations. In particular, the date range of our sample is relatively short, even without detracting from the current results. As the ongoing COVID-19 pandemic continues to adversely affect public health and the global economy, we may see a broader picture in a few years. Future research may incorporate longer sample periods to further validate the role of digital finance in shaping corporate resilience found in this study.

Table 15
Robustness tests: excluding IPOs less than one year old.

Variable	*Loss_Severity*	*Recovery_Time*
	(1)	(2)
Fintech	−0.008***	−0.058***
	(−4.876)	(−2.735)
Size	0.008***	0.082***
	(4.224)	(3.394)
Lev	−0.043***	0.359*
	(−3.239)	(1.926)
ROA	0.087**	−0.075
	(2.481)	(−0.180)
MB	−0.010***	−0.162***
	(−3.827)	(−5.410)
Growth	−0.005	−0.386***
	(−0.673)	(−4.208)
Findev	0.012**	0.249***
	(2.123)	(3.238)
PGDP	0.004	−0.022
	(1.630)	(−0.693)
Constant	−0.181***	1.971***
	(−4.305)	(3.499)
Lnalpha		0.573***
		(33.977)
Industry	Yes	Yes
N	3065	3065
Adj.R^2/Pseudo R^2	0.031	0.011

This table presents the regression results for excluding IPOs less than one year old. The dependent variables are corporate resilience, measured as *Loss_Severity* or *Recovery_Time*. The primary independent variable is *Fintech*, measured as the natural logarithm of the number of provincial fintech companies plus one. Control variables include firm and region characteristics: *Size*, *Lev*, *ROA*, *MB*, *Growth*, *Findev*, and *PGDP*. All variables are defined in Appendix A. Industry fixed effects are included. We cluster standard errors at the company level. T-values or Z-values are reported in parentheses below the regression coefficients. The superscripts ***, **, and * indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

Author statement

None.

Acknowledgements

This work was supported by the National Natural Science Foundation of China (Grant No. 72172127; 71872022), Humanities and Social Science Research Foundation of Ministry of Education of China (Grant No. 18YJA790064), Shaanxi Province Soft Science Research Fund (Grant No. 2019KRM067), Fundamental Research Funds for the Central Universities (Grant No. 3102020XJS02; 2017CDJSK02PT25), and Doctoral Dissertation Innovation Fund of Northwestern Polytechnical University (Grant No. CX2021094).

Appendix A. Detailed definition of variables

Dependent variables	
Loss_Severity	Severity of loss, percentage loss in stock price in the 12 months following the start of the COVID-19 pandemic: [(minimum stock price between January 20, 2020, and January 20, 2021 – closing stock price on January 20, 2020) / closing stock price on January 20, 2020] – 1, adjusted by the industry median
Recovery_Time	Time to recovery, measured as the number of days that the firm's stock price takes to reach its pre-COVID-19 levels (i.e., the closing price on January 20, 2020)
EBIT	The ratio of earnings before interest and taxes during a period to the book value of total assets
Employment	The natural logarithm of the total number of employees in a firm
Debt	Debt financing, measured as short-term and long-term debt divided by total assets
Ddebtcost	Change in debt financing costs from the year 2019 to 2020, which financing costs are calculated as interest expense divided by total short-term and long-term debt
Independent variables	
Fintech	Digital finance, the natural logarithm of the number of provincial fintech companies plus one

(*continued on next page*)

(*continued*)

Dependent variables	
Fintech_High	An indicator that equals one if the firm is located in a province with the number of fintech companies above the sample median, and zero otherwise
Fintech/GDP	The number of provincial fintech companies divided by provincial GDP
DFI	The natural logarithm of the digital finance index by province
COVID_19	An indicator variable equals one for the year 2020 when the COVID-19 pandemic broke out in China, and zero for the year 2019
Control variables	
Size	Firm size, measured as the natural logarithm of total assets of the firm
Lev	Financial leverage, measured as total debt divided by total assets of the firm
ROA	Return on asset, calculated as net income divided by average total assets
Growth	Sales growth rate, calculated as sales in year *t* minus sales year t-1, divided by sales in year t-1
OCF	Ratio of operating cash flow to total assets
MB	The ratio of market capitalization to book value of equity
Cash holding	Cash plus short-term investments divided by total assets
SOE	An indicator variable equals one if a firm's ultimate shareholder is a local or central government, and zero otherwise
Findev	Traditional financial development, the ratio of loan balance of financial institutions divided by provincial GDP
PGDP	The logarithm of provincial GDP per capita
CR	Current ratio, measured as the ratio of current assets to current liabilities
FSHR	The ownership of the largest shareholder, which is the ratio of the number of shares held by the largest shareholder over the number of total shares of the firm
PPE	Property, plant, and equipment, divided by total assets of the firm
OCF	Operating cash flow divided by total assets of the firm
Fintech_Neighbor	Regional spillover effects, proxied by the natural logarithm of the mean number of fintech companies in the provinces neighboring the province in which the company is registered

References

Allen, F., Qian, J., Qian, M., 2005. Law, finance, and economic growth in China. J. Financ. Econ. 77 (1), 57–116.
Allen, F., Qian, J., Gu, X., 2017. An overview of China's financial system. Ann. Rev. Financ. Econ. 9, 191–231.
Arora, A., Belenzon, S., Patacconi, A., Suh, J., 2020. The changing structure of American innovation: some cautionary remarks for economic growth. NBER Innov. Policy Econ. 20 (1), 39–93.
Baron, R.M., Kenny, D.A., 1986. The moderator-mediator variable distinction in social psychological research: conceptual, strategic, and statistical considerations. J. Pers. Soc. Psychol. 51 (6), 1173–1182.
Benmelech, E., Frydman, C., Papanikolaou, D., 2019. Financial frictions and employment during the great depression. J. Financ. Econ. 133 (3), 541–563.
Berg, T., Burg, V., Gombović, A., Puri, M., 2020. On the rise of FinTechs: credit scoring using digital footprints. Rev. Financ. Stud. 33 (7), 2845–2897.
Block, J.H., Groh, A., Hornuf, L., Vanacker, T., Vismara, S., 2021. The entrepreneurial finance markets of the future: a comparison of crowdfunding and initial coin offerings. Small Bus. Econ. 57 (2), 865–882.
Bollaert, H., Lopez-de-Silanes, F., Schwienbacher, A., 2021. Fintech and access to finance. J. Corp. Finan. 68, 101941.
Brand, F.S., Jax, K., 2007. Focusing the meaning(s) of resilience: resilience as a descriptive concept and a boundary object. Ecol. Soc. 12 (1), 1–16.
Brandt, L., Li, H., 2003. Bank discrimination in transition economies: ideology, information, or incentives? J. Comp. Econ. 31 (3), 387–413.
Buchak, G., Matvos, G., Piskorski, T., Seru, A., 2018. Fintech, regulatory arbitrage, and the rise of shadow banks. J. Financ. Econ. 130 (3), 453–483.
Burtch, G., Ghose, A., Wattal, S., 2014. Cultural differences and geography as determinants of online prosocial lending. MIS Q. Manag. Inf. Syst. 38 (3), 773–794.
Carletti, E., Oliviero, T., Pagano, M., Pelizzon, L., Subrahmanyam, M.G., 2020. The COVID-19 shock and equity shortfall: firm-level evidence from Italy. Rev. Corp. Financ. Stud. 9 (3), 534–568.
Carmeli, A., Markman, G.D., 2011. Capture, governance, and resilience: strategy implications from the history of Rome. Strateg. Manag. J. 32 (3), 322–341.
Chen, S., Zhang, H., 2021. Does digital finance promote manufacturing servitization: Micro evidence from China. Int. Rev. Econ. Financ. 76, 856–869.
Cull, R., Xu, L.C., 2005. Institutions, ownership, and finance: the determinants of profit reinvestment among Chinese firms. J. Financ. Econ. 77 (1), 117–146.
De Roure, C., Pelizzon, L., Thakor, A. V., 2021. P2P Lenders Versus Banks: Cream Skimming or Bottom Fishing? SAFE Working Paper No. 206. Available at SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3174632.
Demertzis, M., Merler, S., Wolff, G.B., 2018. Capital markets union and the Fintech opportunity. J. Financ. Regul. 4 (1), 157–165.
DesJardine, M., Bansal, P., Yang, Y., 2019. Bouncing back: building resilience through social and environmental practices in the context of the 2008 global financial crisis. J. Manag. 45 (4), 1434–1460.
Ding, W., Levine, R., Lin, C., Xie, W., 2021. Corporate immunity to the COVID-19 pandemic. J. Financ. Econ. 141 (2), 802–830.
Fan, J.P.H., Wong, T.J., Zhang, T., 2007. Politically connected CEOs, corporate governance, and post-IPO performance of China's newly partially privatized firms. J. Financ. Econ. 84 (2), 330–357.
Fedaseyeu, V., Linck, J.S., Wagner, H.F., 2018. Do qualifications matter? New evidence on board functions and director compensation. J. Corp. Finan. 48, 816–839.
Financial Stability Board, 2017. Financial Stability Implications from FinTech – Supervisory and Regulatory Issues that Merit Authorities' Attention. Working definition of the Financial Stability Board, 6, p. 7. Available at FinDev Gateway. https://www.findevgateway.org/paper/2017/06/financial-stability-implications-finte-ch-supervisory-and-regulatory-issues-merit.
Fisch, C., 2019. Initial coin offerings (ICOs) to finance new ventures. J. Bus. Ventur. 34 (1), 1–22.
Fuster, A., Plosser, M., Schnabl, P., Vickery, J., 2019. The role of technology in mortgage lending. Rev. Financ. Stud. 32 (5), 1854–1899.
Galema, R., 2020. Credit rationing in P2P lending to SMEs: do lender-borrower relationships matter? J. Corp. Finan. 65, 101742.
Gambacorta, L., Huang, Y., Li, Z., Qiu, H., Chen, S., 2022. Data vs collateral. Rev. Financ. (forthcoming).
Giroud, X., Mueller, H.M., 2017. Firm leverage, consumer demand, and employment losses during the Great Recession. Q. J. Econ. 132 (1), 271–316.
Gittell, J.H., Cameron, K., Lim, S., Rivas, V., 2006. Relationships, layoffs, and organizational resilience. J. Appl. Behav. Sci. 42 (3), 300–329.
Gomber, P., Koch, J., Siering, M., 2017. Digital finance and FinTech: current research and future research directions. J. Bus. Econ. 87 (5), 537–580.
Greene, W.H., 2000. Econometric Analysis. Prentice Hall, Upper Saddle River, NJ.
Guo, F., Kong, S.T., Wang, J., 2016. General patterns and regional disparity of internet finance development in China: evidence from the Peking University Internet Finance Development Index. China Econ. J. 9 (3), 253–271.

Guo, F., Wang, J., Wang, F., Cheng, Z., Kong, T., Zhang, X., 2020. Measuring China's digital financial inclusion: index compilation and spatial characteristics. China Econ. Q. (in Chin.) 19 (4), 1401–1418.
Hornuf, L., Klus, M.F., Lohwasser, T.S., Schwienbacher, A., 2021. How do banks interact with fintech startups? Small Bus. Econ. 57 (3), 1505–1526.
Hortaçsu, A., Martinez-Jerez, F.A., Douglas, J., 2009. The geography of trade in online transactions: evidence from eBay and MercadoLibre. Am. Econ. J. Microeconomics 1 (1), 53–74.
Iyer, R., Khwaja, A.I., Luttmer, E.F., Shue, K., 2016. Screening peers softly: inferring the quality of small borrowers. Mark. Sci. 62 (6), 1554–1577.
Jagtiani, J., Lemieux, C., 2019. The roles of alternative data and machine learning in fintech lending: evidence from the LendingClub consumer platform. Financ. Manag. 48 (4), 1009–1029.
Kachelmeier, S.J., Wang, L.W., Williamson, M.G., 2019. Incentivizing the creative process: from initial quantity to eventual creativity. Account. Rev. 94 (2), 249–266.
La Porta, R., Lopez-de-Silanes, F., Shleifer, A., Vishny, R.W., 1998. Law and finance. J. Polit. Econ. 106 (6), 1113–1155.
Lai, S., Teo, M., 2008. Home-biased analysts in emerging markets. J. Financ. Quant. Anal. 43 (3), 685–716.
Lawrence, A., Minutti-Meza, M., Zhang, P., 2011. Can Big 4 versus non-Big 4 differences in audit-quality proxies be attributed to client characteristics? Account. Rev. 86 (1), 259–286.
Lee, I., Shin, Y.J., 2018. Fintech: ecosystem, business models, investment decisions, and challenges. Bus. Horiz. 61 (1), 35–46.
Levine, R., Lin, C., Xie, W., 2018. Corporate resilience to banking crises: the roles of trust and trade credit. J. Financ. Quant. Anal. 53 (4), 1441–1477.
Lin, M., Viswanathan, S., 2016. Home bias in online investments: an empirical study of an online crowdfunding market. Manag. Sci. 62 (5), 1393–1414.
Markman, G.M., Venzin, M., 2014. Resilience: lessons from banks that have braved the economic crisis-and from those that have not. Int. Bus. Rev. 23 (6), 1096–1107.
Miyakawa, D., Oikawa, K., Ueda, K., 2021. Firm exit during the COVID-19 pandemic: evidence from Japan. J. Jpn. Int. Econ. 59, 101118.
Musso, P., Schiavo, S., 2008. The impact of financial constraints on firm survival and growth. J. Evol. Econ. 18 (2), 135–149.
Norden, L., Buston, C.S., Wagner, W., 2014. Financial innovation and bank behavior: evidence from credit markets. J. Econ. Dyn. Control. 43, 130–145.
O'Connor, M., Rafferty, M., Sheikh, A., 2013. Equity compensation and the sensitivity of research and development to financial market frictions. J. Bank. Financ. 37 (7), 2510–2519.
Ortiz-de-Mandojana, N., Bansal, P., 2016. The long-term benefits of organizational resilience through sustainable business practices. Strateg. Manag. J. 37 (8), 1615–1631.
Phan, H.V., 2014. Inside debt and mergers and acquisitions. J. Financ. Quant. Anal. 49 (5/6), 1365–1401.
Pittman, J.A., Fortin, S., 2004. Auditor choice and the cost of debt capital for newly public firms. J. Account. Econ. 37 (1), 113–136.
Preacher, K.J., Hayes, A.F., 2004. SPSS and SAS procedures for estimating indirect effects in simple mediation models. Behav. Res. Methods Instrum. Comput. 36 (4), 717–731.
Ramaswamy, V., Anderson, E.W., DeSarbo, W.S., 1994. A disaggregate negative binomial regression procedure for count data analysis. Manag. Sci. 40 (3), 405–417.
Roundy, P.T., Brockman, B.K., Bradshaw, M., 2017. The resilience of entrepreneurial ecosystems. J. Bus. Ventur. Insights 8, 99–104.
Sajko, M., Boone, C., Buyl, T., 2021. CEO greed, corporate social responsibility, and organizational resilience to systemic shock. J. Manag. 47 (4), 957–992.
Sanders, W.G., 2001. Behavioral responses of CEOs to stock ownership and stock option pay. Acad. Manag. J. 44 (3), 477–492.
Senney, G.T., 2019. The geography of bidder behavior in peer-to-peer lending markets. J. Ind. Econ. 67 (1), 1–36.
Sobel, M., 1982. Asymptotic confidence intervals for indirect effects in structural equation models. Sociol. Methodol. 13, 290–312.
Song, M., Zhou, P., Si, H., 2021. Financial technology and enterprise total factor productivity-perspective of "enabling" and credit rationing. China Ind. Econ. (in Chin.) 4, 138–155.
Sun, S.L., Habib, A., Huang, H.J., 2019. Tournament incentives and stock price crash risk: evidence from China. Pac. Basin Financ. J. 54, 93–117.
Tan, J., Wang, X., Chan, K.C., 2020. Does a national reform of a logistics system matter in corporate cash management? Evidence from logistics service standardization in China. Pac. Basin Financ. J. 63, 101399.
Tang, H., 2019. Peer-to-peer lenders versus banks: substitutes or complements? Rev. Financ. Stud. 32 (5), 1900–1938.
Wei, Z., Lin, M., 2016. Market mechanisms in online peer-to-peer lending. Manag. Sci. 63 (12), 4236–4257.