Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
COVID-19 and trade credit speed of adjustment

Haowen Luo

Assistant Professor of Finance, Doermer School of Business, Purdue University Fort Wayne,

ABSTRACT

This paper examines the extent to which COVID-19 affects corporate trade credit policy. We find that COVID-19 significantly accelerates US firms’ convergency speed toward the target trade credit. In addition, we find that firms subject to higher ex-ante operational risk tend to adjust trade credit toward the target faster than those with fewer risk exposures. Overall, our evidence is consistent with the risk avoidance explanation for trade credit policy changes in the presence of adverse shocks.

1. Introduction

Trade credit is an important financing source for firms. Financial managers are responsible for deciding how much trade credit to offer under various economic conditions. Previous research (Petersen and Rajan 1997) documented that managers choose optimal trade credit based on firm characteristics. However, due to various frictions, a firm’s observed trade-credit level often deviates from its optimal target. In a recent paper, Luo (2021) uses a dynamic model to show that firms actively move toward the target trade credit over time with the speed of adjustment of around 70% of the gap between actual and target trade credit each year. Such finding has important implications for financial managers that go beyond decisions on the static determinants of trade credit. Nonetheless, it remains unclear how macroeconomic shocks affect the adjustment speed of trade credit.

The unprecedented COVID-19 pandemic has created a sizeable macroeconomic shock to the supply of labor and input, and ultimately firm operations worldwide. As one of the most impacted countries, the US observed an economy shrank of 3.5% in 2020. With no apparent end in sight, the pandemics continue to impose uncertainties on the economy that firms must respond to by changing corporate policies and strategies. Among all financial policies under pressure, trade credit policy is arguably the most affected because the COVID-19 shock directly hit real business activity and strained cash flows for buyers and sellers along a supply chain.

In this paper, we study how COVID-19 affects US firms’ trade credit policy. Specifically, our study attempts to answer the following essential questions: Do economic uncertainty induced by COVID-19 affect a firm’s speed of adjustment toward the target trade credit ratio? If so, how do we quantify the effects? Do all firms with various characteristics affected equally by COVID-19? What is the economic mechanism by which uncertainty affects trade-credit adjustment?

Our results show that, during the economic crisis caused by COVID-19, the estimated adjustment speed of trade credit increased significantly compared with the pre-COVID period. For account receivables (AR), the speed of adjustment increased from 54% per quarter during the pre-COVID period to 64% per quarter during the pandemic. For account payables, the speed of adjustment is even higher, from 61.4% during the pre-COVID period to 78.4% during the pandemic.

One possible channel through which the uncertainty induced by COVID-19 affect firms’ trade-credit adjustment speed is risk avoidance. Previous research (Cook and Tang 2010 and Hackbarth et al. 2006) suggests that the adjustment costs are determined...
mainly by the combining force of both general economic conditions and firm-specific characteristics. As the systematic uncertainty level increases during the pandemic, both the liquidity risk and default risk increase, which in turn affect the trade credit adjustment costs. Consequently, significant deviations from optimal targets expose firms to more risks. Given the higher operational risk and tighter credit during the pandemic, the higher the deviation, the more costly for the firm to adjust trade credit. As a result, firms are motivated to adjust their trade credit faster to not drift too far away from the optimal level. If the increased convergence speed during the COVID-19 period is driven by risk avoidance motivation, we should observe that risky firms adjust trade-credit faster. This is what we find empirically: firms with higher operation risk as measured by alternative variables exhibit higher adjustment speed during the crisis.

Because the observed faster adjustment speed of trade credit depends not only on willingness but also on the firm’s capability to make the adjustment, we also examine whether negotiation power affects the adjustment speed. We conjecture that firms with greater negotiation power can enforce more favorable trade credit terms with trading partners and adjust trade-credit faster. Our empirical findings are consistent with such conjecture. Firms with higher market power as measured by market shares are able to adjust their trade credit faster.

Overall, our study contributes to the literature in the following ways. First, our findings add to the emerging studies on how COVID-19 affects corporate financial policies. To the best of our knowledge, we are the first to study how COVID-19 affects firms trade credit policy in a dynamic setting. Such analysis expands our understanding of trade credit policy under uncertainty. Second, we extend the literature on target trade credit (Choi and Kim 2005; Luo 2021). We show that firms exhibit a faster adjustment speed toward target trade credit during the COVID-19 crisis. More importantly, our cross-sectional analysis shows that firms subject to higher risks and tighter credit during the COVID-19 crisis. More importantly, our cross-sectional analysis shows that firms subject to higher risks and higher negotiation power tend to adjust trade-credit faster, supporting the risk avoidance argument as the underlying mechanism through which COVID-19 affects trade credit policy.

2. Sample data and empirical method

Following previous research (Flannery and Rangan 2006; Luo 2021), we adopt the standard partial-adjustment model to estimate the convergence speed of trade credit:

$$TR_{i,t} - TR_{i,t-1} = \lambda \left( TR_{i,t}^* - TR_{i,t-1}^* \right) + \epsilon_{i,t} \quad (1)$$

Where $TR_{i,t-1}^*$ is the target trade credit of firm $i$ in quarter $t$; $\lambda$ is the unobservable adjustment speed toward the target. $TR_{i,t} - TR_{i,t-1}^*$ is the gap between the target and current trade credit. Therefore, a high value of $\lambda$ suggests a faster convergence speed. $TR_{i,t}^*$ is unobservable, but it can be estimated by the following model:

$$TR_{i,t}^* = \beta X_{i,t-1} \quad (2)$$

where $X_{i,t-1}$ is a vector of explanatory variables that serve as determinants of target trade credit. Previous literature (Petersen and Rajan 1997; Choi and Kim 2005) suggests that different variables determine AR and AP, respectively. For AR, the determinants include sales, sales growth, firm size, inventory stock, retained earnings, age, and short-term debt; For AP, $X_{i,t-1}$ include costs, cost change, firm size, inventory stock, retained earnings, age, and short-term debt. We use the same determinants as suggested by previous research to estimate $TR_{i,t}^*$. Detailed variable definitions are provided in Appendix Table A.1.

Substituting Eqs. (2) to (1) and rearrange the terms gives:

$$TR_{i,t} = (1 - \lambda) TR_{i,t-1} + (\lambda \beta) X_{i,t-1} + \alpha_i + \delta_t + \epsilon_{i,t} \quad (3)$$

where $\alpha_i$ is the firm fixed effects and $\delta_t$ is the time-fixed effects. In this model, we are interested in estimating the coefficient on $TR_{i,t-1}$, based on which we can extract the adjustment speed $\lambda$.

---

Table 1
Descriptive statistics for AR sample

This table reports descriptive statistics of variables from the account receivable (AR) subsample for US firms between 2011 and 2021. The sample includes 68,997 firm-quarter observations from 5961 unique firms. The pre-COVID period includes nine years between 2011 and 2019. The COVID period includes 2020 and 2021. Variable definitions are provided in Appendix Table A.1.

| Variable | Pre-COVID-19 | | | COVID-19 | | | |
|----------|--------------|-------------|-------------|---------------|-------------|-------------|
|          | N  | Mean  | Std.Dev. | Median | Min  | Max  | N  | Mean  | Std.Dev. | Median | Min  | Max  |
| AR       | 56,151 | 0.14 | 0.13 | 0.11 | 0 | 0.67 | 12,846 | 0.11 | 0.09 | 0 | 0.67 |
| Sale     | 56,151 | 0.63 | 0.67 | 0.43 | 0 | 3.67 | 12,846 | 0.42 | 0.5 | 0 | 3.67 |
| ΔSale+   | 56,151 | 0.2 | 0.24 | 0.14 | 0 | 1.23 | 12,846 | 0.12 | 0.18 | 0 | 1.23 |
| ΔSale−   | 56,151 | −0.19 | 0.44 | 0 | −2.29 | 0 | 12,846 | −0.21 | 0.41 | 0 | −2.29 |
| Inventory| 56,151 | 0.11 | 0.14 | 0.06 | 0 | 0.63 | 12,846 | 0.09 | 0.11 | 0 | 0.63 |
| RE       | 56,151 | −4.24 | 10.89 | −0.08 | −44.09 | 0.63 | 12,846 | −1.01 | 8.58 | −0.15 | −44.09 |
| Short-term debt | 56,151 | −3.6 | 2.34 | −3.68 | −9.33 | 3.35 | 12,846 | −3.69 | 1.76 | −3.83 | −9.33 |
| Size     | 56,151 | 5.41 | 3.26 | 5.94 | −4.2 | 11.38 | 12,846 | 6.01 | 2.77 | 6.32 | −4.2 |
| Size^2   | 56,151 | 40.03 | 31.25 | 35.59 | 0.03 | 129.6 | 12,846 | 43.89 | 30.59 | 40.07 | 129.6 |
| Age      | 56,151 | 6.18 | 2.68 | 6 | 1 | 11 | 12,846 | 10.18 | 3.03 | 12 | 13 |
Table 2
Descriptive statistics for AP sample
This table reports descriptive statistics of variables from the account payable (AP) subsample for US firms between 2011 and 2021. The sample includes 68,818 firm-quarter observations from 5987 unique firms. The pre-COVID period includes nine years between 2011 and 2019. The COVID period includes 2020 and 2021. Variable definitions are provided in Appendix Table A.1.

| Variable    | Pre-COVID-19 | COVID-19 |
|-------------|--------------|----------|
|              | Obs. | Mean | Std.Dev. | Median | Min | Max | Obs. | Mean | Std.Dev. | Median | Min | Max |
| AP           | 55,786| 0.4  | 1.67     | 0.07   | 0    | 13.56| 13,032| 0.23 | 1.22     | 0.05   | 0   | 13.56|
| Cost         | 55,786| 0.2  | 0.25     | 0.13   | 0    | 1.62 | 13,032| 0.15 | 0.18     | 0.1    | 0   | 1.62 |
| ∆Cost+       | 55,786| 0.02 | 0.05     | 0      | 0    | 0.38 | 13,032| 0.01 | 0.04     | 0      | 0   | 0.38 |
| ∆Cost-       | 55,786| -0.02| 0.05     | 0      | -0.37| 0   | 13,032| -0.01| 0.04     | 0      | -0.37| 0    |
| Inventory    | 55,786| 0.11 | 0.14     | 0.06   | 0    | 0.64 | 13,032| 0.12 | 0.04     | 0      | 0   | 0.64 |
| RE           | 55,786| -4.31| 11.03    | -0.09 | -44.55| 0.63 | 13,032| -3.06| 8.7      | -0.16  | -44.55| 0.63 |
| Short-term debt | 55,786| -3.59| 2.35     | -3.67 | -9.32 | 3.38 | 13,032| -3.68| 1.77     | -3.83  | -9.32| 3.38 |
| Size         | 55,786| 5.4  | 3.27     | 5.93   | -4.2 | 11.38| 13,032| 5.99 | 2.78     | 6.3    | -4.2 | 11.38|
| Size^2       | 55,786| 39.95| 31.28    | 35.43  | 0.03 | 129.5| 13,032| 43.71| 30.56    | 39.78  | 0.03 | 129.5|
| Age          | 55,786| 6.18 | 2.68     | 6      | 1    | 11   | 13,032| 10.16| 3.04     | 12     | 1   | 13   |

Table 3
Effects of COVID on speeds of adjustment to target trade credit
This table reports the baseline results to estimate how COVID-19 affects speeds of adjustment of trade credit toward the target. We regress current values of trade credit on the lagged values of trade credit as well as a set of controls suggested by previous literature (see Eq. (3)). The model is estimated using the Quasi-maximum likelihood (QML) method. The pre-COVID period includes nine years between 2011 and 2019. The COVID period includes 2020 and 2021. Variable definitions are provided in Appendix Table A.1. t-values are shown in parentheses. ***, ** and * represents significance at the 1%, 5%, and 10% levels, respectively.

| Variable    | (1) Pre-COVID-19 | (2) COVID-19 | (3) Pre-COVID-19 | (4) COVID-19 |
|-------------|------------------|--------------|------------------|--------------|
| AR          | 0.460*** (21.20) | 0.358*** (9.26) |                    |              |
| Sale        | 0.006*** (2.81)  | -0.003 (0.74)        |              |              |
| ΔSale+      | -0.003 (-0.27)   | -0.029** (-2.14)    |              |              |
| ΔSale-      | -0.008** (-2.47) | 0.017*** (4.00)     |              |              |
| AP          | 0.386*** (15.77) | 0.216*** (4.67)     |              |              |
| Cost        | -0.279*** (-3.00)| -0.105 (-0.52)      |              |              |
| ∆Cost+      | -0.995 (-0.51)   | 0.328 (1.18)        |              |              |
| ∆Cost-      | 0.182 (1.19)     | -0.246 (-1.14)      |              |              |
| Inventory   | 0.094*** (5.19)  | 0.102*** (3.15)     | 0.432** (2.26)|              |
| RE          | -0.000 (-1.55)   | -0.001 (-1.57)      | 0.007 (1.39)  |              |
| Short-term debt | -0.001** (-2.39)| -0.000 (-2.14)     | 0.005 (2.17)  |              |
| Size        | -0.018*** (-6.15)| -0.021*** (-3.26)   | -1.115*** (-14.33)| -1.470*** (-6.96) |
| Size^2      | -0.000 (-0.98)   | -0.002*** (-3.48)   | 0.089*** (16.41)| 0.118*** (6.25) |
| Age         | 0.001** (2.58)   | 0.009*** (8.08)     | -0.001 (8.09)  | 0.013 (1.39)  |
| Constant    | 0.168*** (12.44) | 0.174*** (6.01)     | 2.806*** (9.97)| 3.859*** (6.94) |
| Firm fixed effect | Yes         | Yes                   | Yes             | Yes          |
| Time fixed effect | Yes        | Yes                   | Yes             | Yes          |
| N           | 56,151 | 12,846       | 55,786 | 13,032 |
| Estimated Speed | 0.540  | 0.642       | 0.614  | 0.784  |
| Speed difference | 0.162*** | 0.17***    |              |              |
| Empirical P-value | 0.00  | 0.00       |              |              |
Table 4
Cross-sectional heterogeneity in the effect of COVID on AR adjustment speed
This table reports the results of how cross-sectional heterogeneity of operational risk moderates the effect of COVID-19 on speeds of adjustment of AR toward the target. We use sales volatility, operating leverage, and firm size to measure a firm’s operating risk. Sales volatility is the standard deviation of a firm’s quarterly net sales over a rolling five-quarter period prior to each sample quarter. Operating leverage is measured by the inverse of the quarterly operating costs divided by assets, where operating costs are the cost of goods sold plus selling, general, and administrative expenses. For firms during the pandemic period, we define high(low) risk firms as those with sales volatility (operating leverage) above(below) their cross-sectional median at time t. Firm size is calculated as the natural logarithm of the quarterly sales. Small firms are expected to have higher operational risks than large firms. For both high-risk and low-risk groups, we regress current values of trade credit on the lagged values of trade credit and a set of controls suggested by previous literature. The model is estimated using the Quasi-maximum likelihood (QML) method. The pre-COVID period includes nine years between 2011 and 2019. The COVID period includes 2020 and 2021. Control variable definitions are provided in Appendix Table A.1. t-values are shown in parentheses. ***, ** and * represents significance at the 1%, 5%, and 10% levels, respectively.

|                  | (1) | (2) | (3) | (4) | (5) | (6) |
|------------------|-----|-----|-----|-----|-----|-----|
|                  | Pre-COVID-19 | COVID-19 | Pre-COVID-19 | COVID-19 | Pre-COVID-19 | COVID-19 |
| AR               | 0.314*** | 0.458*** | 0.345*** | 0.456*** | 0.408*** | 0.329*** |
|                  | (7.20) | (5.84) | (5.13) | (5.64) | (5.30) | (6.72) |
| Sales            | −0.001 | −0.014 | −0.044** | 0.005 | 0.006*** | −0.013 |
|                  | (−0.20) | (−1.10) | (−2.14) | (1.27) | (2.78) | (−1.35) |
| ΔSales+          | −0.030*** | −0.058* | 0.032 | −0.054** | −0.071*** | −0.012 |
|                  | (−2.04) | (−1.95) | (1.39) | (−2.51) | (−5.69) | (−0.53) |
| ΔSales−          | 0.018*** | 0.041*** | 0.015** | 0.023*** | 0.027*** | 0.016** |
|                  | (3.89) | (3.97) | (2.22) | (3.03) | (6.01) | (2.30) |
| Inventory        | 0.119*** | 0.077* | 0.084** | 0.115** | 0.151*** | 0.043 |
|                  | (2.76) | (1.65) | (2.05) | (2.38) | (3.51) | (0.91) |
| RE               | −0.001 | −0.001 | −0.002** | 0.000 | 0.000 | 0.000 |
|                  | (−0.34) | (−1.33) | (−1.98) | (−0.67) | (−0.07) | (−1.16) |
| Short-term debt  | −0.001 | 0.001 | −0.001 | −0.000 | −0.000 | −0.000 |
|                  | (−0.85) | (1.22) | (−0.92) | (−0.05) | (−0.09) | (−0.42) |
| Size             | −0.101*** | −0.004 | −0.015** | −0.046*** | −0.007 | −0.049*** |
|                  | (−3.29) | (−0.35) | (−2.19) | (−3.18) | (−1.07) | (−3.23) |
| Size’2           | 0.002 | −0.001* | −0.001 | −0.004*** | −0.002*** | 0.001 |
|                  | (0.68) | (−1.76) | (−1.00) | (−5.39) | (−4.60) | (0.72) |
| Age              | 0.015*** | 0.006*** | 0.003* | 0.021*** | 0.010*** | 0.006** |
|                  | (8.81) | (4.19) | (1.77) | (4.22) | (10.14) | (2.22) |
| Constant         | 0.443*** | 0.080* | 0.139*** | 0.232** | 0.147*** | 0.172*** |
|                  | (5.09) | (1.85) | (5.46) | (2.18) | (3.68) | (3.75) |
| Firm fixed effect| Yes | Yes | Yes | Yes | Yes | Yes |
| Time fixed effect| Yes | Yes | Yes | Yes | Yes | Yes |
| N                | 5471 | 6460 | 6480 | 3189 | 7288 | 4267 |
| Estimated speed  | 0.686 | 0.542 | 0.655 | 0.544 | 0.592 | 0.671 |
| Speed difference | 0.144*** | 0.111*** | 0.079*** | 0.079*** | 0.079*** | 0.079*** |

Following T.A Vo et al.(2021), we use 2020 as the cutoff year for the COVID period. Separate estimations are performed in each subperiods to detect the change in adjustment speed. We obtain the firm-level data for US public firms from the Compustat quarterly database between 2011 and 2021. To estimate the dynamic model as described by Eq. (3), we require firms to have at least two consecutive quarters of data. Our final sample for AR (AP) regression is consisted of 68,997 (68,818) firm-quarter observation from 5961 (5987) unique firms.

Descriptive statistics are reported in Tables 1 and 2. As shown, both AR and AP are decreased after the outbreak of COVID-19. The mean (median) value of AR decreased from 14 percent (11 percent) to 11 percent (9 percent). For AP, the decrease is more significant: the mean(median) value of AP decreased from 40 percent (7 percent) to 23 percent (5 percent). The decrease in trade credit suggests that firms exposed to a pandemic cut down on credit extension to their clients and face the same squeeze from their suppliers. Compared to AR, AP is more sensitive to deteriorating economic conditions. The higher level of AP imposes higher liquidity risk during the crisis when alternative sources to finance the current liabilities are difficult to find. To reduce the liquidity risk, therefore, firms decrease AP more than AR during the pandemic. Also, the sales and cost of goods sold decreased during the pandemic.

3. Estimation method and empirical results

Our baseline results are estimated using the partial adjustment model described by Eq. (3). Previous literature suggests using the FD-GMM method (Arellano and Bond 1991) to estimate the model. However, Flannery and Rangan (2006) noted that the FD-GMM method suffers from weak instrument problems when the dependent variable exhibits high persistence. As with many financial policies, firms’ trade credit policies are sticky over time. Our sample finds that the estimated coefficient on lagged trade credit is close to 0.9 in the AR(1) model, suggesting a highly persistent dependent variable. Therefore, the FD-GMM estimator will be biased and inappropriate to use here. To overcome this problem, we estimate Eq. (3) using the Quasi-maximum likelihood (QML) method. QML method was first developed by Bhargava and Sargan (1983) and then modified by Hsiao et al. (2002) to estimate the dynamic
optimal targets exposes firms to more risks. Moreover, given the higher operating risk and tighter credit during the pandemic, the uncertainties caused by volatile cashflows, increased financing costs, and higher default risk by trading partners. Although firms may economic shocks caused by pandemics can last with no obvious end in sight. Under such circumstances, firms are exposed to significant 

This table reports the results of how cross-sectional heterogeneity of operational risk moderates the effect of COVID-19 on speeds of adjustment of AP toward the target. We use sales volatility, operating leverage, and firm size to measure a firm’s operating risk. Sales volatility is the standard deviation of a firm’s quarterly net sales over a rolling five-quarter period prior to each sample quarter. Operating leverage is measured by the inverse of the quarterly operating costs divided by assets, where operating costs are the cost of goods sold plus selling, general, and administrative expenses. For firms during the COVID period, we define high(low) risk firms as those with sales volatility (operating leverage) above(below) their cross-sectional median at time t. Firm size is calculated as the natural logarithm of the quarterly sales. Small firms are expected to have higher operational risks than large firms. For both high-risk and low-risk groups, we regress current values of trade credit on the lagged values of trade credit as well as a set of controls suggested by previous literature. The model is estimated using the Quasi-maximum likelihood (QML) method. The pre-COVID period includes nine years between 2011 and 2019. The COVID period includes 2020 and 2021. Control variable definitions are provided in Appendix Table A.1. 

| Variable                  | AP            | Cost          | Δ Cost+       | Δ Cost-       | Inventory      | RE            | Short-term debt | Size*2        | Size | Age          | Constant      | Firm fixed effect | Time fixed effect | N       | Estimated Speed | Speed difference |
|---------------------------|---------------|---------------|--------------|--------------|----------------|----------------|----------------|--------------|------|--------------|---------------|------------------|------------------|--------|----------------|-----------------|
| Pre-COVID-19              | 0.136**       | -0.306**      | 0.314*       | 0.010        | -0.094         | 0.070***       | -0.002         | -1.918**      | 0.164***      | 0.008         | 4.903***        | Yes             | Yes             | 5551   | 0.864          | 0.013***        |
| COVID-19                  | 0.149***      | -0.474*       | 0.764***     | 0.047        | -1.337*        | 0.055***       | -0.021***      | -1.819***     | 0.153***      | 0.021*        | 4.217***        | Yes             | Yes             | 6553   | 0.851          | 0.098***        |
| Pre-COVID-19              | 0.140**       | -0.276        | 0.393        | 0.222        | -0.715**       | 0.046***       | -0.002         | -1.296***     | 0.106***      | 0.009*        | 3.972***        | Yes             | Yes             | 6589   | 0.860          | 0.076           |
| COVID-19                  | 0.238***      | 0.102         | 0.201        | -0.583*      | -0.630         | 0.058**        | 0.018          | -1.949***     | 0.088***      | 0.056         | 7.182***        | Yes             | Yes             | 3245   | 0.762          | 0.076           |
| Large firms               | 0.193***      | -0.243        | 0.201        | -0.583*      | 0.467          | 0.064**        | -0.001         | -1.949***     | 0.102**       | 0.056         | 5.790***        | Yes             | Yes             | 7401   | 0.807          | 0.075**         |
| Small firms               | 0.118***      | 0.299         | 0.374        | -0.281       | 0.149          | 0.041***       | 0.001          | -1.447***     | 0.158**       | 0.012         | 2.905***        | Yes             | Yes             | 3763   | 0.882          | --              |

Columns 1 and 2 of Table 3 report the results of estimating Eq. (3) for AR. As shown, the estimated coefficient on lagged dependent variable is 0.46 in the pre-COVID19 period, suggesting the adjustment speed of 54%. However, during the COVID crisis, the implied adjustment speed increased to 64.2%, a 19% increase from pre-COVID19. To test whether the change of adjustment speed is significant in two samples, we performed the Fisher’s Permutation test and calculated the empirical p-value by bootstrapping the sample 1000 times. The result suggests that the difference in estimated adjustment speeds is significant at the 1% level. For AP(columns 4 and 5), we observe a more substantial change of convergency speed: the estimated speed of adjustment has increased by 28% from 61.4 to 78.4% after the outbreak of COVID-19. Fisher’s Permutation test confirms that the change of adjustment speeds between two subsamples is significant.

Intuitively, one possible reason to explain the increased convergence speed during the pandemic is risk avoidance. The macro-economic shocks caused by pandemics can last with no obvious end in sight. Under such circumstances, firms are exposed to significant uncertainties caused by volatile cashflows, increased financing costs, and higher default risk by trading partners. Although firms may increase or decrease the absolute level of trade credit depending on firm-specific constraints, a large deviation from firms’ respective optimal targets exposes firms to more risks. Moreover, given the higher operating risk and tighter credit during the pandemic, the higher the deviation, the more costly for the firm to converge toward the target. As a result, firms are motivated to adjust their trade credit faster to not drift too far away from the optimal level.

The results from Table 3 are consistent with the intuitive explanation above. All else equal, higher ex-ante uncertainty induced by COVID-19 implies a stronger incentive for firms to adjust faster toward the trade credit target on average. However, the “all else equal” qualifier hides an important cross-sectional prediction implied by the risk avoidance argument. Although the cost of deviation from the target is a function of uncertainties caused by the pandemic, it should be moderated by the risk level each firm faces. Intuitively, firms faced with less risk may adjust toward the target at a relatively lower speed than those faced with more risk. In other words, if our risk
The avoidance hypothesis is the valid economic mechanism through which uncertainty affects trade credit policy, we should observe firms with various ex-ante risk exposures respond to uncertainty in a slightly different way.

To test this prediction, we examine the cross-sectional variation in convergency speeds. Specifically, we consider cross-sectional heterogeneous operating risk exposure that may influence the effect of uncertainty on adjustment speeds. Following previous literature (Hill et al. 2010; Novy-Marx 2011), we use sales volatility, operating leverage, and firm size to measure a firm’s operating risk. Sales volatility is the standard deviation of a firm’s quarterly net sales over a rolling five-quarter period prior to each sample quarter. Operating leverage is measured by the inverse of the quarterly operating costs divided by assets, where operating costs are the cost of goods sold plus selling, general, and administrative expenses. For firms during the pandemic period, we define high(low) risk firms as those with sales volatility (operating leverage) above(below) their cross-sectional median at time t. Firm size is calculated as the natural logarithm of the quarterly sales. We expect smaller firms to have higher operational risk during the pandemic.

Table 4 summarizes our findings. As shown in columns 1 and 2, the estimated adjustment speed for firms with high sales volatility is 68.6%. In contrast, the adjust speed for firms with relatively low sales volatility is 54.2%, which is 20% lower than that of high sales volatility firms. Similar results are obtained when risk is proxied by operating leverage, as shown in columns 3 and 4. For firms with higher operating leverage, the speed of adjustment is 65.5%, which is higher than the adjustment speed of 54.4% for firms with relatively low operating leverage. Similarly, columns 3 and 4 show that the convergence speed for smaller firms is 13% higher than that for larger firms. All differences in estimated speeds are significant regardless of how operational risk is measured.

Table 5 presents the results for AP. Consistent with findings from Table 3, AP exhibits faster convergence speeds than AR. We also observe similar cross-sectional heterogeneities as documented in Table 4. For firms with higher operational risk, the estimated...
convergence speed is always higher. Overall, our findings are consistent with the prediction that firms with higher operational risk tend to adjust their trading credit faster than those with lower operational risk.

The observed adjustment also depends on the firm’s capability to make such an adjustment. Because trading partners work together to negotiate trade credit contracts, firms with greater market power can obtain more favorable terms to achieve their desired trade credit policy objectives. Consequently, we expect firms with more market powers to adjust trade credit faster. Following Hill et al. (2010), we calculate market power as the ratio of a firm’s quarterly sales to the total sales in a given industry. Higher ratios indicate higher market shares and suggest a higher ability to negotiate bilaterally as both client and supplier. High market power firms are those with market power higher than the cross-sectional median at time t during the pandemic. Table 6 report the results. As shown in columns 1 and 2, for AR, firms with higher market power are associated with higher adjustment speeds than firms with relatively lower market power. Similar results are obtained for AP. Firms with higher market power are able to adjust their AP faster, although the difference in adjustment speed is much smaller than that of AR.

4. Robustness check

Our previous results depend heavily on how the target trade credit is estimated. As a robustness check, we re-estimate Eq. (3) using alternative proxies for target trade credit. The first one is generated using the two-stage estimates in Fama and French (2002). In the first stage, we estimate Eq. (2) and calculate the fitted value of trade credit. We then use calculated fitted values as the target trade credit to estimate Eq. (3) in the second stage. Moreover, we use the industry median values of trade credit as the second proxy for target trade credit.

As shown in Table 7, regardless of how the target trade credit is measured, the estimated adjustment speeds are consistently faster during the pandemics for both AR and AP. The differences in convergency speed are significant across all specifications. The results are qualitatively the same as our baseline specification, and the study’s main conclusions remain unchanged.

5. Conclusion

We examine the extent to which Covid-19 health crises affect corporate trade credit policy in the US. Using a dynamic panel model framework, we find that COVID-19 significantly accelerates US firms’ convergency speed toward the target trade credit. We also find that firms subject to higher ex-ante operational risk tend to adjust trade credit toward the target faster than those with fewer risk

**Table 7**

|                    | Panel A                  | Panel B                  |
|--------------------|--------------------------|--------------------------|
|                    | Pre-COVID-19             | COVID-19                 |
|                    | (1)                      | (2)                      |
| AR                 | 0.450***                 | 0.377***                 |
|                    | (20.83)                  | (6.09)                   |
| AR_FF              | 0.116***                 | -0.148**                 |
|                    | (3.74)                   | (-2.43)                  |
| Ind_Median         |                          | 0.239***                 |
|                    |                          | (7.33)                   |
| Firm fixed effect  | Yes                      | Yes                      |
| Time fixed effect  | Yes                      | Yes                      |
| N                  | 54,795                   | 10,257                   |
| speed              | 0.55                     | 0.623                    |
|                    |                          | 0.528                    |
| Panel B            | Pre-COVID-19             | COVID-19                 |
|                    | (1)                      | (2)                      |
| AP                 | 0.429***                 | 0.227***                 |
|                    | (17.15)                  | (3.39)                   |
| AP_FF              | 1.145***                 | 1.460***                 |
|                    | (17.18)                  | (6.68)                   |
| Ind_Median         |                          | -0.429                   |
|                    |                          | (-0.89)                  |
| Firm fixed effect  | Yes                      | Yes                      |
| Time fixed effect  | Yes                      | Yes                      |
| N                  | 54,482                   | 10,410                   |
| speed              | 0.571                    | 0.773                    |
|                    |                          | 0.304                    |

**Note:** All models are estimated using the Quasi-maximum likelihood (QML) method. The pre-COVID period includes nine years between 2011 and 2019. The COVID period includes 2020 and 2021. ***, ** and * represents significance at the 1%, 5%, and 10% levels, respectively.
exposures. Overall, our evidence is consistent with the risk avoidance explanation for trade credit policy in the presence of adverse shocks.

Appendix A

Table A.1
Variable defi.

| Variable | Description                  | Definition                                                                 |
|----------|------------------------------|----------------------------------------------------------------------------|
| AR       | Account receivable           | accounts receivable standardized by total assets                           |
| AP       | Account payable              | accounts payable standardized by total assets                              |
| Sale     | Total sales                  | nominal sales standardized by assets                                       |
| ΔSale+   | indicator of positive sales  | takes the value of 1 if sales growth is positive and 0 otherwise. Sales growth is defined as the change of sales, standardized by assets. |
| ΔSale-   | indicator of negative sales  | takes the value of 1 if sales growth is negative and 0 otherwise. Sales growth is defined as the change of sales, standardized by assets. |
| Cost     | costs of goods sold          | costs of goods sold standardized by total assets                            |
| ΔCost+   | indicator of positive cost   | takes the value of 1 if cost growth is positive and 0 otherwise. Cost growth is defined as the change of the cost of goods sold, standardized by assets. |
| ΔCost-   | indicator of negative cost   | takes the value of 1 if cost growth is negative and 0 otherwise. Cost growth is defined as the change of the cost of goods sold, standardized by assets. |
| Inventory| Total inventory              | inventory divided by assets                                                 |
| RE       | Retained earnings            | the ratio of retained earnings to total asset                               |
| Short-term debt | Short-term debt | natural log of standardized (by total assets) short-term debt. |
| Size     | Firm size                    | natural log of inflation adjusted total assets                              |
| Size^2   | Squared firm size            | firm size squared                                                           |
| Age      | firm age                     | number of quarters since the firm enters the Compustat                      |

Reference

Bhargava, A., Sargan, J.D. 1983. Estimating dynamic random effects models from panel data covering short time periods. Econom. J. Econom. Soc. 1635–1659.

Choi, W.G., Kim, Y., 2005. Trade credit and the effect of macro-financial shocks: evidence from US panel data. J. Financ. Quant. Anal. 897–925.

Cook, D.O., Tang, T., 2010. Macroeconomic conditions and capital structure adjustment speed. J. Corp. Financ. 16, 73–87.

Flannery, M.J., Rangan, K.P, 2006. Partial adjustment toward target capital structures. J. Financ. Econ. 79, 469-506.

Hackbarth, D., Miao, J., Morellec, E., 2006. Capital structure, credit risk, and macroeconomic conditions. J. Financ. Econ. 82, 519–550.

Hill, M.D., Kelly, G.W., Highfield, M.J., 2010. Net operating working capital behavior: a first look. Financ. Manag 39, 783-805.

Hsiao, C., Pesaran, M.H., Tahmiscigolu, A.K., 2002. Maximum likelihood estimation of fixed effects dynamic panel data models covering short time periods. J. Econ. 109, 107–150.

Luo, H., 2021. Do firms chase trade credit target? Financ. Res. Lett., 102026

Novy-Marx, R., 2011. Operating leverage. Rev. Financ. 15, 103–134.

Petersen, M.A., Rajan, R.G, 1997. Trade credit: theories and evidence. Rev. Financ. Stud. 10, 661–691.