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Financing Constraints and Corporate Resilience: Evidence from Two Shocks in Vietnam

Thị Xuan My Duong¹

¹ Department of Finance and Banking, University of Economics and Business, Vietnam National University.
ORCID ID: 0009-0006-3929-8985.

Abstract

This study examines whether pre-shock financing constraints predict operating resilience among Vietnamese listed non-financial firms. Resilience is separated into operating resistance, measured by shock-quarter operating performance conditional on a firm-specific benchmark, and recovery, defined as the first subsequent return to that benchmark. The analysis covers Vietnam's 2021Q3 COVID-19 lockdown and the financial disruption concentrated in 2022Q4. The resistance samples contain 512 and 537 firms, respectively. Resistance is estimated using baseline-adjusted analysis-of-covariance models, while recovery is analyzed with discrete-time complementary log-log hazard models. The Whited-Wu index is the principal financing-constraint proxy, and the Hadlock-Pierce SA index provides a robustness measure. Across both shocks, the preferred models provide no statistically significant evidence that greater pre-shock constraints systematically predict weaker resistance or slower severity-adjusted recovery. Pooled interactions likewise do not establish cross-shock differences. A positive association between SA and post-2022 recovery persists under an alternative threshold set 10% of the benchmark's absolute value below the benchmark and under a binary-SA specification, but WW does not reproduce it; the result is therefore robust to these alternative specifications but remains proxy-sensitive. Initial loss severity consistently predicts a lower recovery hazard, although it also measures the distance to the recovery threshold. Conventional constraint indices consequently provide limited and unstable information about realized operating resilience in this setting.

Keywords: Corporate Resilience, Financing Constraints, Operating Performance, Recovery Hazard, Vietnam, COVID-19

1. Introduction

Major shocks reveal substantial variation in firms' ability to withstand disruption and restore operating performance. Corporate resilience is therefore viewed as a dynamic process rather than a single outcome (Linnenluecke, 2017; Williams et al., 2017). Event-based studies distinguish resistance, which refers to the ability to limit the initial performance decline, from recovery, which refers to the subsequent return to a pre-shock benchmark, because firms may perform differently across these two stages (DesJardine et al., 2019; Sajko et al., 2021). Financial flexibility may support both stages by enabling firms to fund operations when internal cash flows decline and external finance becomes costly (Gamba & Triantis, 2008; Denis, 2011). Prior studies show that financially vulnerable firms reduce investment and real activity more sharply during crises, whereas cash holdings, undrawn credit, and access to debt markets can mitigate adverse outcomes (Campello et al., 2010; Duchin et al., 2010; Ding et al., 2021; Fahlenbrach et al., 2021). Nevertheless, conventional financing-constraint indices may not capture the resources available during a particular shock. The Whited-Wu (WW) and Hadlock-Pierce SA

indices use different firm characteristics, may classify firms differently, and do not directly measure usable liquidity, refinancing needs, or credit access (Whited & Wu, 2006; Hadlock & Pierce, 2010; Farre-Mensa & Ljungqvist, 2016). Moreover, most crisis studies examine contemporaneous losses rather than the time required to regain firm-specific operating performance (Albuquerque et al., 2020; Hu & Zhang, 2021).

Vietnam offers a useful setting because listed firms experienced two distinct disruptions within a short period. The 2021 Delta-wave lockdown severely restricted production and mobility, whereas late 2022 was characterized by tightening liquidity and stress in banking, property, and corporate bond markets (World Bank, 2021; IMF, 2023). Vietnamese research has examined performance, financial distress, coping responses, and credit access during periods of disruption (Nguyen & Dinh, 2021; Nguyen et al., 2021; Bui & Do, 2022; Vu et al., 2023). However, it has not jointly modeled operating resistance and time to recovery or formally tested whether financing-constraint associations differ across shocks.

This study examines whether pre-shock WW and SA values predict operating resilience among Vietnamese listed non-financial firms. Resistance is estimated using baseline-adjusted shock-quarter operating ROA, while recovery is modeled as the first return to the firm-specific benchmark within four quarters using a discrete-time complementary log-log model. Pooled interaction tests compare the two episodes, and alternative resistance and recovery definitions assess robustness. The results provide little evidence that either index systematically predicts weaker resilience. Although SA is positively associated with recovery after the 2022 disruption, this result is not reproduced by WW and remains proxy-sensitive. By contrast, initial loss severity consistently predicts slower recovery. The study thus extends the resistance–recovery framework to operating performance and shows why resilience should be evaluated across distinct stages, shocks, and financing-constraint proxies.

2. Literature Review and Hypothesis Development

2.1 Corporate resilience as resistance and recovery

Corporate resilience refers to an organization's capacity to withstand, adapt to, and recover from adverse events (Linnenluecke, 2017; Williams et al., 2017). Because firms' responses depend on available resources and adaptive capacity, resilience is better understood as a process unfolding over time than as a fixed attribute or single outcome (Meyer, 1982; Sutcliffe & Vogus, 2003; Conz & Magnani, 2020). Event based studies therefore distinguish resistance, the ability to limit initial performance deterioration, from recovery, the subsequent return to a relevant benchmark (Ortiz-de-Mandojana & Bansal, 2016; DesJardine et al., 2019). This approach also permits analysis of recovery timing and censoring (DesJardine et al., 2019; Sajko et al., 2021).

This distinction is important because resistance and recovery describe related but separate dimensions of organizational response. A firm experiencing only a modest initial decline may nevertheless recover slowly, while a firm suffering a substantial initial loss may adjust rapidly and return to its previous performance level. Evaluating only the shock period may therefore overlook important differences in firms' subsequent trajectories. Moreover, accounting outcomes capture realized operating consequences that may differ from contemporaneous stock market reactions, which also reflect investor expectations and changes in discount rates (Albuquerque et al., 2020). Accordingly, the present study defines resistance using the change in operating performance during each shock and defines recovery as the first subsequent return to a firm specific operating benchmark.

2.2 Financial capacity and shock absorption

Financial flexibility allows firms to respond to cash-flow and investment shocks without prohibitive financing costs (Gamba & Triantis, 2008; Denis, 2011). Cash, unused debt capacity, and external market access can preserve productive assets and investment when cash generation falls. During the global financial crisis, firms reporting binding constraints planned larger cuts in investment and employment, while companies with less cash, more short-term debt, and greater external-finance dependence reduced investment more sharply (Campello et al., 2010; Duchin et al., 2010). COVID-19 evidence similarly associates cash, low leverage, profitability, and undrawn credit with milder market losses (Ding et al., 2021; Fahlenbrach et al., 2021). Liquidity survival nevertheless depends

jointly on shock severity, available cash, leverage, and operating-cost adjustment (De Vito & Gómez, 2020). Demand contraction and uncertainty may also depress activity independently of financing conditions (Kahle & Stulz, 2013).

The relationship is further complicated by precautionary behavior and state-dependent credit supply. Firms anticipating costly external finance may accumulate cash, partly offsetting the vulnerability associated with constraint status (Almeida et al., 2004; Denis, 2011). Credit-line availability and price deteriorate when aggregate risk rises, while banks' ability to honor drawdowns depends on their liquidity, capital, deposit inflows, and policy support (Acharya et al., 2013; Li et al., 2020). During the pandemic, firms initially drew committed credit, but debt markets reopened more readily for higher-quality borrowers (Acharya & Steffen, 2020). A pre-shock index may therefore predict crisis funding capacity only imperfectly.

2.3 Measuring financing constraints

Financing constraints are latent and must be inferred from observable firm characteristics, yet no single proxy captures all dimensions of restricted external finance. The Whited and Wu index combines cash flow, dividend status, leverage, size, and firm and industry sales growth (Whited & Wu, 2006), whereas the SA index relies only on size and age (Hadlock & Pierce, 2010). These different inputs may produce different firm classifications and capture non-equivalent aspects of financing constraints (Hadlock & Pierce, 2010; Farre-Mensa & Ljungqvist, 2016; Li et al., 2023). Neither index directly observes the liquidity available during a specific disruption, including unused credit facilities, refinancing requirements, borrowing costs, or new loan approvals. During COVID-19, direct measures of cash, debt capacity, funding deficits, and liquidity needs predicted corporate outcomes more consistently than broad KZ, WW, or SA classifications (Fahlenbrach et al., 2021). These limitations do not make the indices uninformative, but they require conclusions to be evaluated across alternative measurement approaches. Accordingly, this study uses WW as the principal *ex ante* proxy and SA as a robustness measure to determine whether the findings persist under a different measurement logic.

2.4 Vietnamese setting and existing evidence

Vietnam provides a relevant setting for examining financing constraints and corporate resilience because listed firms experienced two distinct disruptions within a relatively short period. During the 2021 Delta outbreak, extensive mobility restrictions interrupted production, transportation, and commercial activity, creating an operating shock for firms across multiple industries (World Bank, 2021). By contrast, the disruption concentrated in late 2022 was associated with tighter domestic liquidity and stress in property, banking, and corporate bond markets (IMF, 2023). Although the episodes had different origins, both increased the importance of firms' capacity to absorb losses and finance the restoration of operations.

Vietnamese research has examined several aspects of corporate responses to disruptive conditions. Existing studies associate pandemic period performance with risk management, managerial readiness, coping strategies, government support, and financial flexibility (Nguyen & Dinh, 2021; Nguyen et al., 2021; Nguyen & Dang, 2023). Related evidence documents the multidimensional nature of credit constraints among small and medium enterprises and uses accounting indicators to evaluate financial distress among listed nonfinancial firms (Bui & Do, 2022; Vu et al., 2023). Collectively, these studies demonstrate that financial capacity and organizational responses are relevant to firm outcomes in Vietnam.

However, the existing evidence generally evaluates performance or distress at a particular point in time. It does not show whether the factors associated with limiting an initial operating decline also predict how quickly firms subsequently regain their previous performance. Furthermore, the two recent disruptions are usually studied separately, leaving limited evidence on whether the relationship between financing constraints and resilience varies across shocks with different transmission mechanisms. These unresolved issues motivate a dynamic comparison of resistance and recovery.

2.5 Research gap and hypotheses

Despite the development of research on crisis period corporate outcomes, three gaps remain. First, the reviewed Vietnamese literature does not distinguish firms' initial operating resistance from their subsequent time to recovery. Second, it provides limited evidence on whether financing constraints predict recovery after accounting for the severity of the initial operating loss. Third, because WW and SA capture different firm characteristics, findings based on a single index may be specific to the selected proxy rather than indicative of a general financing constraint relationship (Hadlock & Pierce, 2010; Farre Mensa & Ljungqvist, 2016). The literature also lacks a formal comparison of these associations across distinct shocks in Vietnam.

Financing constraints may first influence firms' ability to withstand a disruption. When internal cash flow falls, firms with restricted access to external capital may have less capacity to finance working capital, retain productive resources, and maintain investment (Campello et al., 2010; Duchin et al., 2010). These limitations can intensify the immediate deterioration in operating performance. The first hypothesis is therefore:

H1: Firms with higher pre-shock financing constraints exhibit weaker operating resistance to major shocks.

Financing constraints may also affect the restoration of performance after the initial loss. Recovery can require additional liquidity to rebuild inventories, reorganize production, replace lost inputs, and adapt operations to changing market conditions. Firms with less financial flexibility may be unable to fund these adjustments promptly, even after the direct disruption has diminished (Gamba & Triantis, 2008; Denis, 2011). Conditional on having fallen below their benchmark, more constrained firms are therefore expected to recover more slowly. Accordingly:

H2: Among adversely affected firms, higher pre-shock financing constraints are associated with a lower subsequent recovery hazard.

Finally, the two episodes differed in their origins and transmission mechanisms. Accordingly, the association between financing constraints and resilience may vary between an operating disruption and a period of financial stress. Because existing theory does not provide a sufficiently clear basis for predicting the direction of this difference, the study examines cross shock heterogeneity through the following research question:

RQ: Does the relationship between pre-shock financing constraints and operating resilience differ across shocks with distinct economic origins?

3. Methodology

3.1 Data and sample

The study uses quarterly balance-sheet, income-statement, and cash-flow data for joint-stock companies listed on the Ho Chi Minh Stock Exchange (HOSE) and Hanoi Stock Exchange (HNX). Financial-statement data were collected from 2018Q1 to 2025Q4, although the analyses reported in this study use observations only through 2023Q4. Annual variables required for the financing-constraint measures are constructed from the quarterly financial-statement data. Industry affiliation follows the Industry Classification Benchmark (ICB). Financial firms classified under the Level 1 Financials sector (ICB code 8000) are excluded because their leverage, liquidity management, and capital requirements are not directly comparable with those of non-financial corporations (Rajan & Zingales, 1995). The resulting universe comprises 559 firms across nine broad non-financial sectors, in which 297 listed on HOSE and 262 on HNX. The panel is unbalanced, and continuous coverage throughout the study period is not required. Eligibility is determined separately for each model according to the availability of observations required to construct the benchmark, shock-period outcome, financing-constraint proxy, controls, and, where applicable, the recovery history. Missing accounting values are neither imputed nor interpolated; model-specific sample sizes are reported in Tables 1–4.

The three financial statements are merged by firm and reporting period using standardized accounting identifiers. Because cash-flow statements report cumulative year-to-date amounts, first-quarter values are retained as reported, whereas standalone flows for subsequent quarters are calculated as differences between successive cumulative values within the same fiscal year. Balance-sheet variables are treated as quarter-end stocks, while income-

statement and cash-flow variables are treated as quarterly flows. Operating ROA is calculated as operating profit divided by average total assets, using current- and preceding-quarter assets only when the observations represent consecutive quarters. For the COVID-19 episode, financing constraints are measured in 2019, the operating benchmark covers 2019Q1–2019Q4, and 2021Q3 is the shock quarter. For the 2022 financial disruption, constraints are measured in 2021, the benchmark covers 2021Q4–2022Q3, and 2022Q4 is the shock quarter. Each benchmark requires at least three valid quarterly operating-ROA observations. The two episodes are treated as aggregate settings for predictive analysis rather than as exogenous firm-level interventions.

3.2 Operating performance and benchmarks

Quarterly operating performance is measured as operating return on assets, consistent with crisis-period accounting research (Albuquerque et al., 2020; Hu & Zhang, 2021):

$$OperatingROA_{it} = \frac{Operating\ Profit_{it}}{Average\ Total\ Assets_{it}} \quad (1)$$

Average total assets use beginning- and end-of-quarter values. Operating profit limits the direct influence of financing costs, taxes, and non-operating items. Firm-specific benchmark operating ROA is defined as:

$$BenchmarkROA_i^{COVID} = \frac{1}{T_i} \sum_{t=2019Q1}^{2019Q4} OperatingROA_{it} \quad (2)$$

$$BenchmarkROA_i^{2022} = \frac{1}{T_i} \sum_{t=2021Q4}^{2022Q3} OperatingROA_{it} \quad (3)$$

In Equations (2) and (3), T_i denotes the number of non-missing quarterly operating-ROA observations available for firm i within the relevant four-quarter benchmark window. A benchmark is retained only when $T_i \geq 3$; thus, T_i equals either three or four in the analysis sample. The 2019Q1–2019Q4 window provides a pre-pandemic reference for the COVID-19 episode, whereas the 2021Q4–2022Q3 window provides a recent pre-disruption reference for the 2022 financial disruption. Consequently, the raw recovery rates are descriptive, episode-specific outcomes and should not be interpreted as directly comparable treatment effects.

3.3 Resistance and recovery

For descriptive and robustness purposes, operating resistance is the change from the benchmark to the shock quarter:

$$Resistance_{i,s} = ShockROA_{i,s} - BenchmarkROA_{i,s} \quad (4)$$

Higher values indicate stronger resistance. The preferred resistance model instead uses shock-quarter operating ROA as the dependent variable and benchmark operating ROA as a covariate. Baseline adjustment generally improves efficiency when baseline and follow-up outcomes are correlated, although ANCOVA and change-score estimates may differ in observational settings (Vickers & Altman, 2001; Van Breukelen, 2006). The resulting estimates are interpreted as conditional associations rather than causal effects.

The recovery analysis is restricted to firms whose shock-quarter operating ROA is below their firm-specific benchmark. The recovery windows are 2021Q4–2022Q3 for the COVID-19 episode and 2023Q1–2023Q4 for the 2022 financial disruption. A first-passage recovery event is defined as:

$Event_{i,t} = 1$ if $OperatingROA_{i,t} \geq BenchmarkROA_{i,s}$ and the firm has not recovered previously; 0 otherwise. (5)

A firm exits the risk set after its first recovery event. Firms that remain unrecovered at the end of the four-quarter observation window are right-censored. The person-quarter dataset contains one observation for each observed quarter during which the firm remains at risk, consistent with grouped-time event-history methods (Prentice & Gloeckler, 1978; Allison, 1982; Jenkins, 1995).

Initial loss severity is defined as:

$$LossSeverity_{i,s} = BenchmarkROA_{i,s} - ShockROA_{i,s} \quad (6)$$

Loss severity is strictly positive within the recovery risk set and measures the firm's initial distance from its recovery threshold. It is included as a prognostic state control rather than treated as an exogenous causal determinant. Accordingly, the hazard-model coefficients describe severity-adjusted recovery associations among firms whose operating performance initially fell below their respective benchmarks.

3.4 Financing constraints

The primary measure of financing constraints is the Whited–Wu (WW) index, implemented using the original coefficients reported by Whited and Wu (2006):

$$WW = -0.091 CF - 0.062 DIVPOS + 0.021 TLTD - 0.044 LNTA + 0.102 ISG - 0.035 SG. \quad (7)$$

Here, CF is operating cash flow scaled by total assets; DIVPOS indicates a cash-dividend payment, which equals one when the firm reports a cash-dividend payment and zero otherwise; TLTD is long-term borrowing scaled by total assets; LNTA is the natural logarithm of total assets expressed in millions of nominal US dollars; ISG and SG denote annual industry and firm sales growth, respectively. The continuous components are winsorized at the 1st and 99th percentiles before the index is calculated. Higher WW values indicate greater financing constraints. Total assets are converted from VND into nominal US dollars using the World Development Indicators annual-average exchange rates of VND 23,050.2 per US dollar in 2019 and VND 23,159.8 per US dollar in 2021 (World Bank, n.d.). Because this currency-and-unit conversion produces a constant shift within each construction year, it changes the reported WW levels but does not affect within-year dispersion, rankings, standardized WW values, slope coefficients, standard errors, p-values, or hazard ratios.

As an alternative proxy, the SA index is calculated using the original coefficients reported by Hadlock and Pierce (2010):

$$SA = -0.737 Size + 0.043 Size^2 - 0.040 Age. \quad (8)$$

Size is the natural logarithm of book assets measured in millions of inflation-adjusted 2004 US dollars, with assets capped at USD 4.5 billion before the logarithmic transformation; is the number of years since the firm's stock-exchange listing and is capped at 37 years (Hadlock & Pierce, 2010). Nominal VND assets are first converted into nominal US dollars using the annual-average exchange rate and then expressed in constant 2004 US dollars using the US Consumer Price Index for All Urban Consumers (U.S. Bureau of Labor Statistics, n.d.):

$$Assets_{2004USD} = \frac{Assets_{VND}}{FX_t} \times \frac{CPI_{2004}}{CPI_t}$$

where FX_t is the annual-average VND-per-US-dollar exchange rate and CPI_t is the annual-average US Consumer Price Index in year (t) (World Bank, n.d.; U.S. Bureau of Labor Statistics, n.d.). No additional winsorization is applied to the SA index beyond its built-in size and age caps. The 2019 WW and SA measures are used for the COVID-19 analysis, whereas the corresponding 2021 measures are used for the 2022 financial-disruption analysis. Firms with higher SA index values are classified as more financially constrained, regardless of whether the index values are negative or positive.

3.5 Controls and empirical models

Controls are the cash ratio, current ratio, and asset tangibility, measured at 2019Q4 and 2022Q3 for the respective episodes. The variables capture observable liquidity, short-term balance-sheet capacity, and asset structure (Ding et al., 2021; Fahlenbrach et al., 2021). Models also include broad ICB sector and exchange fixed effects; sparse Oil and Gas and Telecommunications observations are combined as Other. Size and leverage are not added separately because they enter WW directly or indirectly; the same parsimonious controls are used with SA.

The preferred resistance ANCOVA is estimated separately for each shock:

$$ShockROA_{i,s} = \alpha_s + \beta_s FC_{i,s} + \gamma_s BenchmarkROA_{i,s} + \delta'_s X_{i,s} + \lambda_{j(i)} + \mu_{e(i)} + \varepsilon_{i,s} \quad (9)$$

FC is WW or SA, X contains the controls, and $\lambda_{j(i)}$ and $\mu_{e(i)}$ represent sector and exchange fixed effects. Heteroskedasticity-robust standard errors are reported. Recovery is estimated with a complementary log-log model appropriate for grouped event times:

$$\log[-\log(1 - h_{i,t,s})] = \alpha_{t,s} + \beta_s z(FC_{i,s}) + \theta_s z(LossSeverity_{i,s}) + \delta'_s X_{i,s} + \lambda_{j(i)} + \mu_{e(i)} \quad (10)$$

The conditional recovery probability is $h_{i,t,s}$ and $\alpha_{t,s}$ denotes recovery-quarter indicators. FC and loss severity are standardized across firms before person-quarter expansion. Standard errors are clustered by firm; exponentiated coefficients are reported as hazard ratios.

3.6 Cross-shock and robustness analyses

To test formally whether financing-constraint associations differ across episodes, the shock-specific samples are pooled. WW, SA, and loss severity are standardized within each shock before pooling. For resistance, the estimated pooled ANCOVA specification is:

$$Shock ROA_{i,s} = \alpha + \beta_1 z(FC_{i,s}) + \beta_2 Shock 2022_s + \beta_3 z(FC_{i,s}) \times Shock 2022_s + \gamma Benchmark ROA_{i,s} + \delta'_s X_{i,s} + \lambda_{j(i)} + \mu_{e(i)} + \varepsilon_{i,s} \quad (11)$$

In Equation (11), $Shock2022_s$ equals one for the 2022 financial disruption and zero for the COVID-19 episode. Accordingly, COVID-19 is the reference episode. The coefficient β_1 captures the financing-constraint association for COVID-19, whereas β_3 tests whether this association differs during the 2022 financial disruption. The implied financing-constraint association for the 2022 episode is therefore $\beta_1 + \beta_3$. Thus, β_3 rather than a comparison of p-values from the separate-shock models, provides the formal test of cross-shock heterogeneity. Thus, β_3 , rather than a comparison of p values from the separate shock models, provides the formal test of cross-shock heterogeneity.

For recovery, the shock-specific risk sets are pooled within the complementary log-log framework. The model interacts the within-shock standardized financing-constraint measure with the 2022 indicator and includes standardized initial loss severity, pre-shock controls, and shock-specific recovery-quarter indicators. These indicators allow the baseline recovery hazard to vary across recovery time and episode. COVID-19 remains the reference episode. Accordingly, $\exp(\beta_1)$ is the COVID-19 financing-constraint hazard ratio, $\exp(\beta_3)$ is the ratio of hazard ratios across episodes, and $\exp(\beta_1 + \beta_3)$ is the implied 2022 hazard ratio. Financing constraints and initial loss severity are standardized within each shock before expansion into person-quarter observations, and standard errors are clustered by firm because the same firm may enter both risk sets.

Three prespecified robustness checks are then conducted. First, recovery is redefined using an alternative threshold set 10% of the firm-specific benchmark's absolute value below that benchmark:

$$Alternative\ threshold_{i,s} = Benchmark\ ROA_{i,s} - 0.10 \times |Benchmark\ ROA_{i,s}| \quad (12)$$

The absolute-value term ensures that the alternative threshold remains below the original benchmark even when benchmark operating ROA is negative, and the risk set is reconstructed. Second, Equation (4) is used directly as the resistance outcome without separately controlling for benchmark ROA. Third, post-2022 recovery is re-estimated with an indicator for SA above its yearly median. The proxy comparison and robustness analyses are interpreted jointly rather than selected by significance.

4. Results

4.1 Sample characteristics

Table 1 summarizes the samples and descriptive statistics for both shock episodes. The resistance analyses include 512 firms for COVID-19 and 537 firms for the 2022 disruption. Among firms whose shock-period performance

fell below their benchmarks, 239 of 323 firms recovered within four quarters after COVID-19, representing a recovery rate of 74.0%. By comparison, 161 of 330 firms recovered after the 2022 disruption, corresponding to a rate of 48.8%. This difference of 25.2 percentage points is descriptive and should not be interpreted as a causal cross-shock effect. Mean resistance was -0.53 percentage points for COVID-19 and -0.60 percentage points for 2022, while affected firms entered recovery an average of 1.75 and 1.86 percentage points below their respective benchmarks. These differences are descriptive, episode-specific patterns and should not be interpreted as causal estimates of differences between the two shocks.

Table 1: Sample Composition and Descriptive Statistics

Panel A. Sample composition

Sample characteristic	COVID-19	2022 financial disruption
Firms in resistance sample	512	537
Firms with valid WW	478	512
Firms with valid SA	506	533
Firms requiring recovery	323	330
Recovered within four quarters	239	161
Right-censored	84	169
Recovery rate (%)	74.0	48.8
Person-quarter observations	717	1,019

Panel B. COVID-19 resistance sample

Variable	N	Mean	SD	P25	Median	P75
WW index	478	-0.2066	0.0739	-0.2526	-0.2021	-0.1579
SA index	506	-2.2180	0.6968	-2.7372	-2.2637	-1.7757
Benchmark operating ROA	512	0.0190	0.0216	0.0062	0.0139	0.0259
Shock-period operating ROA	512	0.0137	0.0259	0.0011	0.0082	0.0213
Operating resistance	512	-0.0053	0.0267	-0.0149	-0.0032	0.0040
Cash ratio	512	0.0827	0.0896	0.0218	0.0546	0.1101
Current ratio	512	2.5265	3.5663	1.1070	1.4966	2.4100
Tangibility	512	0.2323	0.2207	0.0626	0.1643	0.3370

Panel C. 2022 financial-disruption resistance sample

Variable	N	Mean	SD	P25	Median	P75
WW index	512	-0.2037	0.0825	-0.2576	-0.1973	-0.1455
SA index	533	-2.2975	0.7020	-2.8168	-2.3581	-1.8557
Benchmark operating ROA	537	0.0218	0.0260	0.0068	0.0150	0.0297
Shock-period operating ROA	537	0.0158	0.0302	0.0012	0.0109	0.0289
Operating resistance	537	-0.0060	0.0275	-0.0147	-0.0032	0.0032
Cash ratio	537	0.0794	0.0879	0.0201	0.0487	0.1107
Current ratio	537	2.9911	5.4847	1.2030	1.5668	2.6441
Tangibility	537	0.1970	0.1982	0.0475	0.1292	0.2867

Panel D. COVID-19 recovery sample

Variable	N	Mean	SD	P25	Median	P75
WW index	303	-0.2068	0.0747	-0.2531	-0.1995	-0.1603

Variable	N	Mean	SD	P25	Median	P75
SA index	317	-2.1900	0.7105	-2.7256	-2.2325	-1.7623
Initial loss severity	323	0.0175	0.0207	0.0045	0.0108	0.0223
Cash ratio	323	0.0843	0.0923	0.0213	0.0555	0.1107
Current ratio	323	2.6635	3.5086	1.1180	1.5403	2.6597
Tangibility	323	0.2138	0.2143	0.0542	0.1494	0.2963

Panel E. 2022 financial-disruption recovery sample

Variable	N	Mean	SD	P25	Median	P75
WW index	312	-0.2082	0.0840	-0.2670	-0.2050	-0.1506
SA index	327	-2.3390	0.7057	-2.8549	-2.4221	-1.9122
Initial loss severity	330	0.0186	0.0221	0.0047	0.0116	0.0223
Cash ratio	330	0.0818	0.0875	0.0202	0.0542	0.1199
Current ratio	330	3.1226	5.5852	1.2249	1.5790	2.6758
Tangibility	330	0.1833	0.1877	0.0430	0.1237	0.2576

Note. Operating resistance is shock-period operating ROA minus benchmark operating ROA. Initial loss severity is benchmark operating ROA minus shock-period operating ROA. Recovery occurs in the first quarter in which operating ROA returns to or exceeds the firm-specific benchmark; otherwise, the episode is right-censored after four quarters. The person-quarter observations reported in Panel A refer to the full recovery risk sets, whereas Tables 2 and 3 report model-specific counts after applying proxy availability and complete-case requirements. Higher WW and SA values indicate greater financing constraints.

4.2 COVID-19 results

Table 2 reports the COVID-19 results. Neither financing-constraint proxy is significantly associated with shock-period operating performance. The WW coefficient is 0.0156 ($p = .343$), and the SA coefficient is 0.0013 ($p = .426$), while benchmark operating ROA remains positively associated with shock-period performance in both models (both $p < .001$). The recovery estimates likewise do not support H2, with hazard ratios of 1.073 for WW ($p = .385$) and 0.961 for SA ($p = .636$). In contrast, a one standard deviation increase in initial loss severity is associated with approximately 22% to 25% lower recovery hazards across the two specifications (HR = 0.777, $p = .008$; HR = 0.749, $p = .003$). Overall, neither H1 nor H2 is supported for the COVID-19 episode.

Table 2: COVID-19 Resistance and Recovery

Variable/statistic	Resistance: WW	Resistance: SA	Recovery: WW	Recovery: SA
Financing constraints	0.0156 [-0.0166, 0.0477] ($p=.343$)	0.0013 [-0.0018, 0.0044] ($p=.426$)	HR 1.073 [0.915, 1.257] ($p=.385$)	HR 0.961 [0.815, 1.133] ($p=.636$)
Benchmark operating ROA	0.4644 [0.2781, 0.6507] ($p<.001$)	0.4520 [0.2765, 0.6275] ($p<.001$)	—	—
Initial loss severity	—	—	HR 0.777 [0.644, 0.936] ($p=.008$)	HR 0.749 [0.618, 0.906] ($p=.003$)
Pre-shock controls	Yes	Yes	Yes	Yes
Sector fixed effects	Yes	Yes	Yes	Yes
Exchange fixed effects	Yes	Yes	Yes	Yes
Recovery-quarter effects	—	—	Yes	Yes
Observations	478	506	678 person-quarters	704 person-quarters
Firm clusters	—	—	303	317
Recovery events	—	—	224	234

Variable/statistic	Resistance: WW	Resistance: SA	Recovery: WW	Recovery: SA
R ²	0.2298	0.2273	—	—

Note. Resistance columns report OLS coefficients with heteroskedasticity-robust 95% confidence intervals; WW and SA enter in their original units. Recovery columns report hazard ratios with firm-clustered 95% confidence intervals for one-standard-deviation increases in financing constraints and initial loss severity. All models include pre-shock controls and sector and exchange fixed effects; recovery models additionally include recovery-quarter effects. Two-sided p values are reported.

4.3 Results for the 2022 disruption

Table 3 reports the results for the 2022 financial disruption. Neither WW ($\beta = 0.0230$, $p = .109$) nor SA ($\beta = 0.0029$, $p = .128$) is significantly associated with resistance, whereas benchmark operating ROA remains strongly predictive in both models (both $p < .001$). For recovery, WW remains statistically insignificant (HR = 1.122, $p = .264$). The SA estimate is positive but imprecisely estimated and does not meet the conventional 5% significance threshold (HR = 1.201, $p = .059$). Because WW does not reproduce this pattern, it is treated as proxy-sensitive. Initial loss severity again predicts slower recovery, with hazard ratios of 0.680 ($p = .008$) and 0.637 ($p = .002$), corresponding to approximately 32% and 36% lower recovery hazards. Overall, H1 is not supported, while the evidence does not support the negative association proposed in H2.

Table 3: Resistance and Recovery after the 2022 Financial Disruption

Variable/statistic	Resistance: WW	Resistance: SA	Recovery: WW	Recovery: SA
Financing constraints	0.0230 [-0.0051, 0.0511] ($p=.109$)	0.0029 [-0.0008, 0.0066] ($p=.128$)	HR 1.122 [0.917, 1.374] ($p=.264$)	HR 1.201 [0.993, 1.452] ($p=.059$)
Benchmark operating ROA	0.6458 [0.4885, 0.8030] ($p<.001$)	0.6249 [0.4742, 0.7755] ($p<.001$)	—	—
Initial loss severity	—	—	HR 0.680 [0.511, 0.904] ($p=.008$)	HR 0.637 [0.479, 0.848] ($p=.002$)
Pre-shock controls	Yes	Yes	Yes	Yes
Sector fixed effects	Yes	Yes	Yes	Yes
Exchange fixed effects	Yes	Yes	Yes	Yes
Recovery-quarter effects	—	—	Yes	Yes
Observations	512	533	955 person-quarters	1,008 person-quarters
Firm clusters	—	—	312	327
Recovery events	—	—	154	159
R ²	0.3523	0.3368	—	—

Note. Resistance columns report OLS coefficients with heteroskedasticity-robust 95% confidence intervals; WW and SA enter in their original units. Recovery columns report hazard ratios with firm-clustered 95% confidence intervals for one-standard-deviation increases in financing constraints and initial loss severity. All models include pre-shock controls and sector and exchange fixed effects; recovery models additionally include recovery-quarter effects. Two-sided p values are reported.

4.4 Cross-shock and robustness results

Panel A of Table 4 reports the pooled cross-shock tests. The financing-constraint interactions are statistically insignificant for both resistance and recovery under the WW and SA measures. Thus, despite the different descriptive recovery rates, the formal tests provide no evidence that financing-constraint associations differ systematically between COVID-19 and the 2022 financial disruption. Initial loss severity remains strongly

associated with slower recovery in the pooled models, with hazard ratios of 0.753 for WW and 0.726 for SA (both $p < .001$).

Panel B applies the alternative recovery threshold set 10% of the firm-specific benchmark's absolute value below that benchmark. Financing constraints remain statistically insignificant for COVID-19 under both proxies and for the 2022 disruption under WW. However, the positive post-2022 SA association persists and becomes statistically significant ($HR = 1.221$, $p=.038$). Loss severity remains negative and significant in all specifications.

The change-score models in Panel C yield positive WW coefficients, including a significant estimate for the 2022 disruption ($\beta = 0.0335$, $p=.019$). However, this counter-hypothesis result is absent from the preferred ANCOVA and SA specifications. Finally, the binary SA model indicates a higher post-2022 recovery hazard among firms above the median ($HR = 1.441$, $p=.043$). Overall, the positive SA recovery pattern is robust to the alternative threshold and binary specification but remains proxy-sensitive.

Table 4: Cross-Shock Tests and Robustness Analyses

Panel A. Pooled cross-shock interaction tests

Outcome	Proxy	COVID effect	Implied 2022 effect	FC × 2022 interaction
Resistance	WW	0.0019 [−0.0006, 0.0044] ($p=.134$)	0.0011 [−0.0012, 0.0033] ($p=.361$)	−0.0008 [−0.0040, 0.0024] ($p=.604$)
Resistance	SA	0.0012 [−0.0011, 0.0034] ($p=.317$)	0.0023 [−0.0003, 0.0049] ($p=.086$)	0.0011 [−0.0020, 0.0043] ($p=.476$)
Recovery	WW	HR 1.067 [0.928, 1.227] ($p=.361$)	HR 1.103 [0.916, 1.328] ($p=.300$)	HR 1.034 [0.823, 1.298] ($p=.776$)
Recovery	SA	HR 0.978 [0.843, 1.133] ($p=.763$)	HR 1.150 [0.976, 1.355] ($p=.094$)	HR 1.176 [0.949, 1.459] ($p=.139$)

Panel B. Alternative recovery threshold within 10% of benchmark

Shock	Proxy	FC hazard ratio	Loss-severity hazard ratio
COVID-19	WW	1.098 [0.936, 1.288] ($p=.252$)	0.761 [0.647, 0.895] ($p=.001$)
COVID-19	SA	0.987 [0.834, 1.169] ($p=.883$)	0.741 [0.638, 0.862] ($p<.001$)
2022 disruption	WW	1.082 [0.890, 1.315] ($p=.431$)	0.668 [0.504, 0.885] ($p=.005$)
2022 disruption	SA	1.221 [1.011, 1.475] ($p=.038$)	0.622 [0.469, 0.826] ($p=.001$)

Panel C. Change-score resistance

Shock	Proxy	FC coefficient	95% CI	p-value
COVID-19	WW	0.0330	[−0.0013, 0.0672]	.059
COVID-19	SA	0.00076	[−0.0025, 0.0040]	.651
2022 disruption	WW	0.0335	[0.0055, 0.0615]	.019
2022 disruption	SA	0.00195	[−0.0026, 0.0065]	.404

Panel D. Binary-SA recovery robustness

Shock/outcome	Alternative measure	FC Hazard ratio	Loss-severity HR	Interpretation
2022 disruption/recovery	SA above median	yearly 1.441 [1.012, 2.053] ($p=.043$)	0.637 [0.478, 0.848] ($p=.002$)	Positive but proxy-sensitive

Note. Square brackets contain 95% confidence intervals. In Panel A, financing constraints are standardized within shock; resistance estimates are coefficients and recovery estimates are hazard ratios for a one-standard-deviation increase. Panel B hazard ratios also correspond to one-standard-deviation increases in continuous financing constraints and loss severity. Panel C uses financing-constraint measures in their original units, while Panel D compares firms above the yearly SA median with the remaining firms. The $FC \times 2022$ interaction provides the formal cross-shock test. The implied 2022 resistance effect equals the COVID-19 coefficient plus the interaction coefficient, whereas the implied 2022 recovery hazard ratio equals the COVID-19 hazard ratio multiplied by the interaction hazard ratio. Pooled standard errors are clustered by firm.

5. Discussion

5.1 Interpreting the financing-constraint results

The preferred estimates do not support H1 or H2: neither WW nor SA systematically predicts weaker shock-period performance, and most recovery associations are statistically imprecise. This finding concerns the predictive limitations of these indices rather than the importance of finance during crises. Direct measures of liquidity, debt capacity, profitability, and committed credit have predicted crisis outcomes more consistently (Ding et al., 2021; Fahlenbrach et al., 2021), while operating performance also reflects demand losses, operational restrictions, sector exposure, and managerial responses (Kahle & Stulz, 2013; Nguyen et al., 2021). WW and SA may therefore omit important dimensions of firms' realized financing capacity and shock exposure.

Precautionary behavior may further weaken the expected relationship. Firms anticipating costly external finance can accumulate cash or adopt conservative financial policies before a downturn (Almeida et al., 2004). They may also substitute among internal funds, bank loans, debt markets, equity, asset sales, and trade credit when one financing channel becomes restricted (Kahle & Stulz, 2013; Wang & Yu, 2023). Because access to these alternatives depends on borrower quality, intermediary conditions, and policy support (Acharya et al., 2013; Acharya & Steffen, 2020; Li et al., 2020), similar WW or SA values need not imply similar financing capacity during recovery. The null results therefore indicate that these indices do not consistently distinguish firms with stronger operating resilience in this setting.

5.2 SA after 2022 and the role of severity

The positive post-2022 SA association is the principal exception. Its persistence under the alternative recovery threshold and the median-split specification indicates that it is not solely produced by one recovery definition or by the continuous functional form. Nevertheless, WW does not reproduce the result, and the pooled interaction does not establish that the SA association differs significantly across shocks. The finding is therefore robust to these alternative specifications but remains proxy-sensitive. Since SA is constructed exclusively from firm size and age, higher SA values primarily identify smaller or younger listed firms (Hadlock & Pierce, 2010). The positive association may consequently reflect greater operational flexibility, shorter decision-making structures, sector composition, or differences in firms' adjustment scales rather than a beneficial effect of financing constraints. The present models do not directly test these mechanisms. Accordingly, the result should not be interpreted as evidence that constrained access to finance accelerates recovery.

Initial loss severity produces a more consistent pattern. Firms beginning farther below their benchmarks have a lower quarterly probability of crossing the recovery threshold. Part of this relationship is mechanical because severity measures the initial distance that must be recovered. However, it may also summarize realized differences in demand, supply disruption, operating costs, and organizational exposure that pre-shock indices do not capture (De Vito & Gómez, 2020). Severity is therefore best understood as a prognostic state variable indicating the difficulty of the subsequent recovery path, rather than as an independently identified causal determinant.

5.3 Contributions and implications

The study makes three contributions. First, it applies the distinction between resistance and recovery to firm-level operating ROA and demonstrates why the two stages should be modeled separately (DesJardine et al., 2019; Sajko et al., 2021). Second, the findings illustrate the importance of evaluating financing constraints using non-equivalent proxies. Although WW and SA generally produce similar null conclusions, they diverge for recovery following the 2022 disruption. The pooled analysis also shows that cross-shock differences should be assessed through formal interaction tests rather than comparisons of separate-regression p-values. Third, the study distinguishes pre-existing financial vulnerability from realized shock damage. WW and SA provide limited and inconsistent information about resilience, whereas initial loss severity consistently predicts recovery. Realized operating damage may therefore be more informative about the subsequent recovery path than broad pre-shock constraint classifications.

The insignificant interactions do not imply that the shocks were economically equivalent. COVID-19 was dominated by mobility, production, and demand disruptions, whereas 2022Q4 involved banking, liquidity, exchange-rate, and corporate-bond-market stress (IMF, 2023; World Bank, 2021). The results indicate only that the WW and SA associations do not differ significantly across episodes. For managers and investors, resilience assessments should consider operating losses, liquidity, refinancing exposure, and alternative funding access alongside WW or SA. Policymakers similarly require direct measures of financing access and shock exposure. These implications should not be generalized to private firms and SMEs, whose financing conditions may be more restricted (Bui & Do, 2022).

5.4 Limitations

Several limitations qualify the findings. First, the observational design identifies conditional associations rather than causal effects, as unobserved firm characteristics may influence both financing conditions and resilience. Second, WW and SA were developed outside Vietnam and do not directly measure credit approvals, unused commitments, refinancing needs, borrowing costs, or access to bank and bond financing. Because SA relies only on size and age, its positive post-2022 association may also reflect the adaptability of smaller or younger firms rather than financing constraints themselves. Third, sector fixed effects cannot fully capture differences in firms' exposure to demand, supply chain disruption, bank dependence, and refinancing pressure. Moreover, because the shocks occurred sequentially, adaptations made during COVID-19 may have influenced responses in 2022. Fourth, recovery is defined as the first return to the operating benchmark within four quarters and therefore does not require persistent recovery or capture changes in sales, cash flow, investment, or market value. Finally, the recovery analysis is conditional on an initial loss and limited to listed nonfinancial firms, restricting its generalizability to private firms and SMEs. Future research could use direct financing and shock exposure measures, loan and debt maturity data, and longer windows requiring sustained recovery.

6. Conclusion

This study examines whether pre-shock financing constraints predict two dimensions of corporate resilience: operating resistance and recovery among Vietnamese listed non-financial firms. The analysis compares the 2021Q3 COVID-19 lockdown with the 2022Q4 financial disruption and employs ANCOVA models for resistance and discrete-time complementary log-log models for recovery. Financing constraints are measured using the WW index, with SA serving as an alternative proxy. The preferred estimates provide no evidence that either WW or SA systematically predicts weaker operating resistance. Most severity-adjusted recovery estimates are also statistically insignificant, while the pooled interaction tests do not establish that financing-constraint associations differ across the two shocks. Accordingly, neither H1 nor H2 is supported. The principal exception is the positive post-2022 SA association, which persists under the alternative recovery threshold and binary specification. However, because WW does not reproduce this result, it is best interpreted as robust to the alternative threshold and binary specification but proxy-sensitive.

Initial loss severity provides the most consistent prognostic information: firms beginning farther below their benchmarks exhibit lower subsequent recovery hazards. Overall, the findings distinguish pre-existing financing constraints from realized shock damage and demonstrate the value of modeling resistance and recovery separately.

For managers and policymakers, resilience assessments should combine conventional financial characteristics with direct measures of funding access and firm-specific shock exposure. Given the observational design and listed-firm sample, the results represent conditional associations and should not be interpreted causally or generalized automatically to private firms and SMEs.

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References

- Acharya, V. V., Almeida, H., & Campello, M. (2013). Aggregate risk and the choice between cash and lines of credit. *The Journal of Finance*, 68(5), 2059–2116. <https://doi.org/10.1111/jofi.12056>
- Acharya, V. V., & Steffen, S. (2020). The risk of being a fallen angel and the corporate dash for cash in the midst of COVID. *The Review of Corporate Finance Studies*, 9(3), 430–471. <https://doi.org/10.1093/rcfs/cfaa013>
- Albuquerque, R., Koskinen, Y., Yang, S., & Zhang, C. (2020). Resiliency of environmental and social stocks: An analysis of the exogenous COVID-19 market crash. *The Review of Corporate Finance Studies*, 9(3), 593–621. <https://doi.org/10.1093/rcfs/cfaa011>
- Allison, P. D. (1982). Discrete-time methods for the analysis of event histories. *Sociological Methodology*, 13, 61–98. <https://doi.org/10.2307/270718>
- Almeida, H., Campello, M., & Weisbach, M. S. (2004). The cash flow sensitivity of cash. *The Journal of Finance*, 59(4), 1777–1804. <https://doi.org/10.1111/j.1540-6261.2004.00679.x>
- Bui, T. Q., & Do, A. V. P. (2022). Does technological inclusion reduce financial constraints on small and medium sized enterprises? The case of Vietnam. *Finance Research Letters*, 47, 102534. <https://doi.org/10.1016/j.frl.2021.102534>
- Campello, M., Graham, J. R., & Harvey, C. R. (2010). The real effects of financial constraints: Evidence from a financial crisis. *Journal of Financial Economics*, 97(3), 470–487. <https://doi.org/10.1016/j.jfineco.2010.02.009>
- Conz, E., & Magnani, G. (2020). A dynamic perspective on the resilience of firms: A systematic literature review and a framework for future research. *European Management Journal*, 38(3), 400–412. <https://doi.org/10.1016/j.emj.2019.12.004>
- De Vito, A., & Gómez, J.-P. (2020). Estimating the COVID-19 cash crunch: Global evidence and policy. *Journal of Accounting and Public Policy*, 39(2), 106741. <https://doi.org/10.1016/j.jaccpubpol.2020.106741>
- Denis, D. J. (2011). Financial flexibility and corporate liquidity. *Journal of Corporate Finance*, 17(3), 667–674. <https://doi.org/10.1016/j.jcorpfin.2011.03.006>
- 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. *Journal of Management*, 45(4), 1434–1460. <https://doi.org/10.1177/0149206317708854>
- Ding, W., Levine, R., Lin, C., & Xie, W. (2021). Corporate immunity to the COVID-19 pandemic. *Journal of Financial Economics*, 141(2), 802–830. <https://doi.org/10.1016/j.jfineco.2021.03.005>

- Duchin, R., Ozbas, O., & Sensoy, B. A. (2010). Costly external finance, corporate investment, and the subprime mortgage credit crisis. *Journal of Financial Economics*, 97(3), 418–435. <https://doi.org/10.1016/j.jfineco.2009.12.008>
- Fahlenbrach, R., Ragheth, K., & Stulz, R. M. (2021). How valuable is financial flexibility when revenue stops? Evidence from the COVID-19 crisis. *The Review of Financial Studies*, 34(11), 5474–5521. <https://doi.org/10.1093/rfs/hhaa134>
- Farre-Mensa, J., & Ljungqvist, A. (2016). Do measures of financial constraints measure financial constraints? *The Review of Financial Studies*, 29(2), 271–308. <https://doi.org/10.1093/rfs/hhv052>
- Gamba, A., & Triantis, A. (2008). The value of financial flexibility. *The Journal of Finance*, 63(5), 2263–2296. <https://doi.org/10.1111/j.1540-6261.2008.01397.x>
- Hadlock, C. J., & Pierce, J. R. (2010). New evidence on measuring financial constraints: Moving beyond the KZ index. *The Review of Financial Studies*, 23(5), 1909–1940. <https://doi.org/10.1093/rfs/hhq009>
- Hu, S., & Zhang, Y. (2021). COVID-19 pandemic and firm performance: Cross-country evidence. *International Review of Economics & Finance*, 74, 365–372. <https://doi.org/10.1016/j.iref.2021.03.016>
- International Monetary Fund. (2023). *Vietnam: 2023 Article IV consultation - Press release; staff report; and statement by the Executive Director for Vietnam* (IMF Country Report No. 23/338). <https://doi.org/10.5089/9798400256899.002>
- Jenkins, S. P. (1995). Easy estimation methods for discrete-time duration models. *Oxford Bulletin of Economics and Statistics*, 57(1), 129–136. <https://doi.org/10.1111/j.1468-0084.1995.tb00031.x>
- Kahle, K. M., & Stulz, R. M. (2013). Access to capital, investment, and the financial crisis. *Journal of Financial Economics*, 110(2), 280–299. <https://doi.org/10.1016/j.jfineco.2013.02.014>
- Li, C., Wang, Y., Zhou, Z., Wang, Z., & Mardani, A. (2023). Digital finance and enterprise financing constraints: Structural characteristics and mechanism identification. *Journal of Business Research*, 165, 114074. <https://doi.org/10.1016/j.jbusres.2023.114074>
- Li, L., Strahan, P. E., & Zhang, S. (2020). Banks as lenders of first resort: Evidence from the COVID-19 crisis. *The Review of Corporate Finance Studies*, 9(3), 472–500. <https://doi.org/10.1093/rcfs/cfaa009>
- Linnenluecke, M. K. (2017). Resilience in business and management research: A review of influential publications and a research agenda. *International Journal of Management Reviews*, 19(1), 4–30. <https://doi.org/10.1111/ijmr.12076>
- Meyer, A. D. (1982). Adapting to environmental jolts. *Administrative Science Quarterly*, 27(4), 515–537. <https://doi.org/10.2307/2392528>
- Nguyen, H. H., Ngo, V. M., & Tran, A. N. T. (2021). Financial performances, entrepreneurial factors and coping strategy to survive in the COVID-19 pandemic: Case of Vietnam. *Research in International Business and Finance*, 56, 101380. <https://doi.org/10.1016/j.ribaf.2021.101380>
- Nguyen, L. T. M., & Dinh, P. H. (2021). Ex-ante risk management and financial stability during the COVID-19 pandemic: A study of Vietnamese firms. *China Finance Review International*, 11(3), 349–371. <https://doi.org/10.1108/CFRI-12-2020-0177>
- Nguyen, Q. K., & Dang, V. C. (2023). Does the financial flexibility prevent stock price crash risk during COVID-19 crisis? Evidence from the Vietnamese stock market. *Heliyon*, 9(11), e22287. <https://doi.org/10.1016/j.heliyon.2023.e22287>
- Ortiz-de-Mandojana, N., & Bansal, P. (2016). The long-term benefits of organizational resilience through sustainable business practices. *Strategic Management Journal*, 37(8), 1615–1631. <https://doi.org/10.1002/smj.2410>
- Prentice, R. L., & Gloeckler, L. A. (1978). Regression analysis of grouped survival data with application to breast cancer data. *Biometrics*, 34(1), 57–67. <https://doi.org/10.2307/2529588>
- Ramelli, S., & Wagner, A. F. (2020). Feverish stock price reactions to COVID-19. *The Review of Corporate Finance Studies*, 9(3), 622–655. <https://doi.org/10.1093/rcfs/cfaa012>
- Rajan, R. G., & Zingales, L. (1995). What do we know about capital structure? Some evidence from international data. *The Journal of Finance*, 50(5), 1421–1460. <https://doi.org/10.1111/j.1540-6261.1995.tb05184.x>
- Sajko, M., Boone, C., & Buyl, T. (2021). CEO greed, corporate social responsibility, and organizational resilience to systemic shocks. *Journal of Management*, 47(4), 957–992. <https://doi.org/10.1177/0149206320902528>
- Sutcliffe, K. M., & Vogus, T. J. (2003). Organizing for resilience. In K. S. Cameron, J. E. Dutton, & R. E. Quinn (Eds.), *Positive organizational scholarship: Foundations of a new discipline* (pp. 94–110). Berrett-Koehler.
- U.S. Bureau of Labor Statistics. (n.d.). *Consumer Price Index for All Urban Consumers: All items in U.S. city average (CUUR0000SA0)*. <https://data.bls.gov/timeseries/CUUR0000SA0>
- van Breukelen, G. J. P. (2006). ANCOVA versus change from baseline had more power in randomized studies and more bias in nonrandomized studies. *Journal of Clinical Epidemiology*, 59(9), 920–925. <https://doi.org/10.1016/j.jclinepi.2006.02.007>
- Vickers, A. J., & Altman, D. G. (2001). Analysing controlled trials with baseline and follow up measurements. *BMJ*, 323(7321), 1123–1124. <https://doi.org/10.1136/bmj.323.7321.1123>

- Vu, N. T., Nguyen, N. H., Tran, T., Le, B. T., & Vo, D. H. (2023). A LASSO-based model for financial distress of the Vietnamese listed firms: Does the COVID-19 pandemic matter? *Cogent Economics & Finance*, 11(1), 2210361. <https://doi.org/10.1080/23322039.2023.2210361>
- Wang, X., & Yu, J. (2023). COVID-19 pandemic and corporate liquidity: The role of SOEs' trade credit response. *Journal of International Money and Finance*, 137, 102901. <https://doi.org/10.1016/j.jimonfin.2023.102901>
- Whited, T. M., & Wu, G. (2006). Financial constraints risk. *The Review of Financial Studies*, 19(2), 531–559. <https://doi.org/10.1093/rfs/hhj012>
- Williams, T. A., Gruber, D. A., Sutcliffe, K. M., Shepherd, D. A., & Zhao, E. Y. (2017). Organizational response to adversity: Fusing crisis management and resilience research streams. *Academy of Management Annals*, 11(2), 733–769. <https://doi.org/10.5465/annals.2015.0134>
- World Bank. (2021). *Vietnam macro monitoring*. <https://documents.worldbank.org/curated/en/207241631634908840/pdf/Vietnam-Macro-Monitoring.pdf>
- World Bank. (n.d.). *Official exchange rate (LCU per US\$, period average)—Viet Nam*. World Development Indicators. <https://data.worldbank.org/indicator/PA.NUS.FCRF?locations=VN>