

Liquidity Management and Financial Performance Across Pandemic Phases: Evidence from Listed Manufacturing Firms in Tanzania

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Article History

Received 2026-07-18

Reviewed 2026-09-12

Reviewed 2026-09-25

Accepted 2026-10-01

Published 2026-10-04

Keywords

Financial performance

Liquidity management

Manufacturing firms

Pandemic phases

Trade-Off Theory

Abstract

Purpose: This study examines whether the association between liquidity management and financial performance differs across pre-pandemic, pandemic, and post-pandemic periods.

Design/Methodology: Quarterly data from seven manufacturing firms listed on the Dar es Salaam Stock Exchange (2018–2023) were analyzed using fixed-effects interaction models with firm-clustered and Webb-bootstrap inference.

Findings: The Quick Ratio (QR)–financial performance association varied across pandemic phases, while no comparable evidence emerged for the Current Ratio (CR). The QR pattern remained under calendar-time controls but weakened after winsorization and was not reproduced by alternative liquidity measures or first-difference analysis. Thus, the evidence is specification-sensitive rather than conclusive.

Practical Implications: Liquidity indicators should be interpreted alongside asset composition, operating requirements, and economic conditions rather than as uniform targets.

Originality: The study provides a phase-sensitive application of Trade-Off Theory by showing that liquidity–performance relationships may vary across economic conditions and liquidity measures.

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Introduction

Corporate resilience is one of the main issues addressed in accounting and finance studies in view of economic upheavals such as the global financial crisis of 2008 and the COVID-19 pandemic. In times of uncertainty, it is important for companies to have adequate liquidity in order to ensure that all their short-term commitments are met and that financial resources are managed optimally in order to ensure profitability. Effective liquidity management enables firms to withstand cash flow disruptions, finance working capital requirements, and pursue investment opportunities. This can however lead to reduced profitability due to tying up financial resources on less profitable investments (Nguyen & Dao, 2022).

The critical role played by liquidity was most noticeable during the pandemic that led to interruptions in the production process, supply chain management, labor markets, consumer demand, and sources of external financing. Manufacturers were especially at risk since any shortages in materials, late payments from customers, as well as high operational costs, contributed significantly to working capital problems. With the growth of uncertainty, numerous firms built cash reserves to increase financial stability (Bates et al., 2009; Opler et al., 1999). However, improved liquidity was not reflected in profitability due to production bottlenecks and low demand from consumers (Kumar & Zbib, 2022).

The growing importance of liquidity has attracted considerable scholarly interest in exploring its connection with financial performance. Nevertheless, this empirical literature is ambiguous. Many studies find a positive effect of sound liquidity management on the financial performance of organizations through reduction in default risks, greater financial flexibility, and creation of investment opportunities (Deloof, 2003; Lazaridis & Tryfonidis, 2006). However, some researchers claim that excess liquidity is not good for the bottom line, as holding large cash, inventory and receivables incur opportunity costs and lower asset utilization efficiency (Akinleye & Ogunleye, 2019; Almakura et al., 2024). A meta-analysis of 55 studies (632,196 firm-year observations) has recently found that the effect of liquidity on financial performance is industry-specific, institutional environment-specific and type of liquidity measure-specific (Nguyen & Dao, 2022). Such heterogeneity is also observed in times of crisis. For example, Sumawe & Magoti (2025) found positive effect of liquidity on profitability of listed manufacturing companies in Tanzania while Nguyen et al., (2024) found negative effect of liquidity on financial performance of firms during the COVID-19 crisis in Vietnam.

A major limitation of the current literature is that many empirical investigations evaluate the liquidity impact by focusing on its average value over the whole period of observation, thus implicitly assuming its contribution to financial performance to be fixed over time. Other empirical papers simply focus on comparing the pre-crisis and pandemic periods without paying attention to the recovery period. However, the importance of liquidity should vary over different phases of a systemic shock. Thus, prior to the crisis, liquidity can help increase operational efficiency; during the crisis avoid financial distress; after the crisis – restore production capacity and invest in new projects (Stanić et al., 2022).

Beyond the level of liquidity, its composition may determine how effectively firms respond to changing economic conditions. Convertibility and availability of assets is also related to the more general measures of liquidity. Current Ratio (CR) includes inventories and other current assets which may take time to be converted into cash whereas Quick Ratio (QR) focuses on more readily available assets to meet short term obligations (Lalithchandra & Rajendhiran, 2021). This distinction may be particularly important during systemic disruptions when firms have limited cash flows and uncertain demand and during recovery when easy resources may help in resumption of operations. Hence the analysis of liquidity at the aggregate level may mask differences in the economic utility of its underlying components during different phases of a crisis.

This issue is especially significant when it comes to developing nations, since such countries experience difficulties with accessing external finance and depend heavily on internal funding. Tanzania provides an important context because manufacturing is central to industrial development while remaining highly exposed to supply-chain disruptions and working capital constraints. Although liquidity management has received increasing scholarly attention, evidence from listed manufacturing firms operating in frontier African capital markets remains limited. By contrast, existing research mainly concentrates on banks, SMEs, and individual sectors (Agbana et al., 2023), while limited evidence examines the liquidity–performance relationship across the complete pre-pandemic, pandemic, and post-pandemic periods.

Accordingly, this study addresses three gaps in the literature. First, it provides new evidence on the phase-specific relationship between liquidity management and financial performance among listed manufacturing firms in a frontier African capital market. Second, it extends the application of the Trade-Off Theory by examining whether the financial value of liquidity varies before, during and after a systemic crisis and whether this pattern differs according to liquidity composition. Third, unlike studies that estimate a single average liquidity–performance relationship or focus mainly on crisis and pre-crisis comparisons, this study distinguishes between the Quick Ratio and Current Ratio within an interaction-based panel framework covering the pre-pandemic, pandemic and post-pandemic periods. Its point of departure is therefore the joint consideration of liquidity composition and economic phase rather than treating liquidity as a uniform financial resource across time.

Using an unbalanced quarterly panel of manufacturing firms listed on the Dar es Salaam Stock Exchange from 2018 to 2023, this study examines whether the associations of the Current Ratio and Quick Ratio with return on assets differ across the pre-pandemic, pandemic and post-pandemic periods. The study contributes to the liquidity management literature by testing whether the financial value of different forms of liquidity is state-dependent and by providing evidence from an underexplored frontier capital market. The results also offer practical insights for managers seeking to optimize liquidity strategies and for policymakers aiming to strengthen the resilience of manufacturing firms during future systemic shocks.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature and develops the study hypotheses. Section 3 describes the research methodology. Section 4 and 5 present the results and discuss the empirical findings. Section 6 concludes the paper and outlines its theoretical, managerial and policy implications.

Literature Review

Theoretical review

Liquidity Management, Trade-Off Theory and Financial Performance

Liquidity management is the capability of an organization to ensure that they have enough liquidity to settle any short-term liabilities but also at a minimum cost of having idle resources (Deloof, 2003; Myers, 1984; Opler et al., 1999). As part of working capital management, it facilitates organizations be able to fund their day-to-day activities without necessarily having too much reliance on external funding. However, too much liquidity reduces the profit potential of a business since liquidity resources tend to earn less compared to long-term investments (Kim et al., 1998; Nguyen & Dao, 2022).

The Trade-off Theory forms the main theoretical basis for this research. The theory was originally developed to explain firms' financing choices (Kraus & Litzenberger, 1973; Modigliani & Miller, 1963). The theory suggests that the firm maximizes value by balancing the benefits of having liquidity (e.g., lower likelihood of financial

distress and greater financial flexibility) with the costs of holding large amounts of liquidity as capital used to finance liquid assets is capital not used to take profitable business opportunities (Almeida et al., 2004; Campello et al., 2010; Nguyen & Dao, 2022).

The Trade-Off Theory states that firms trade off the marginal benefits of holding cash (i.e., savings in financial distress and investment opportunities) with the marginal costs (inefficient usage of cash and other assets). This equilibrium, though, is a shifting one. During times of macroeconomic stability, the opportunity cost of holding cash will be greater than its precautionary benefit and companies will try to reduce unproductive cash. On the contrary, during crises, the precautionary benefit will be much higher than the opportunity cost due to difficulties in raising funds and problems with the continuity of operations. This dynamic Trade-Off Theory, developed from the precautionary motive by Keynes (1936), indicates that the optimal level of cash holdings will depend on the economic condition.

The present study adopts the Trade-Off Theory as a theoretical framework to understand the competing benefits and costs of holding liquidity, rather than testing for an optimal level of liquidity. Holding liquid resources may help firms meet short-term obligations and respond to financial uncertainty, but holding excess resources may involve opportunity costs when funds could be used in productive activities. The relative importance of these considerations may depend on economic conditions. Therefore, the study applies the theory in a phase-sensitive manner by examining whether the association between liquidity and financial performance differs across the pre-pandemic, pandemic, and post-pandemic periods. Since the empirical model is linear, the study does not estimate a nonlinear relationship, optimal liquidity threshold, or turning point.

Liquidity is commonly calculated using the Current Ratio and Quick Ratio, each of which is able to reflect different aspects of financial flexibility. The Current Ratio gives a general picture of the company's liquidity position through the comparison of current assets to current liabilities, while the Quick Ratio ignores the inventory balance and considers only assets that are easily converted to cash. This aspect becomes especially relevant for manufacturing companies, whose balance sheet includes a significant share of inventory in the current assets category.

The pandemic challenges the notion that an ideal level of liquidity does not change through time. Under normal macroeconomic circumstances, businesses usually try to avoid idle liquidity in order to achieve maximum profit. Accordingly, in times of a crisis, liquidity is important in maintaining business activities and in preventing any financial hardship; on the other hand, in times of recovery, liquidity is essential in enabling production, inventories, and investments. This is the idea behind the Trade-Off Theory, which states that the profitability value of liquidity is time-varying.

This phase-sensitive application of Trade-Off Theory does not require the liquidity–performance relationship to have the same direction or magnitude across different economic conditions. Moreover, the composition of liquidity may matter because the Quick Ratio excludes inventories, while the Current Ratio includes them. The study therefore examines the two liquidity measures separately and tests whether their associations with financial performance vary across the three pandemic phases.

Empirical review

Liquidity Management and Financial Performance

In regard to empirical findings concerning the relationship between liquidity management and financial performance, the evidence is rather ambiguous. Many studies have found that the right kind of liquidity management has a positive impact on financial performance through the enhancement of financial flexibility, the overcoming of financing constraints and the efficient management of working capital (Benjamin et al., 2023;

Deloof, 2003; Lazaridis & Tryfonidis, 2006; Saiyya et al., 2023). In addition to that, Nguyen & Dao (2022) have performed a meta-analysis that involved 55 papers and more than 632,000 firm-year data. The results suggest that liquidity impacts positively financial performance.

In contrast, there is an alternative stream which argues that liquidity leads to lower profits because idle money, inventory, and accounts receivable increase opportunity cost and lead to inefficiencies in asset management (Akinleye & Ogunleye, 2019; Almakura et al., 2024; Eldi et al., 2023). Overall, these studies argue that higher than necessary liquidity can harm shareholder value even if it increases solvency of the firm.

Recent literature also shows that the link between liquidity and performance depends on the economic condition. Under stable market conditions, companies experience benefits from reduction in idle liquidity and investment of additional capital in productive assets. In the systemic crisis, liquidity is mainly needed as a safeguard to keep the operations going (Campello et al., 2010; Ding et al., 2021; Paminto et al., 2023). Recent times of COVID-19 show conflicting findings. For example, Paminto et al., (2023) indicate insignificant link between liquidity and performance, while Oskouei & Borhanib (2025) demonstrate the role of higher liquidity in faster recovery after the crisis.

Despite these advances, three important gaps remain. First, most studies estimate a single average liquidity effect, implicitly assuming that the relationship remains constant over time. Second, relatively few studies examine the complete sequence of pre-pandemic, pandemic and post-pandemic periods. Third, empirical evidence from listed manufacturing firms in frontier African capital markets remains limited. These limitations suggest that the financial value of liquidity may be better understood by explicitly modelling how its effects vary across different phases of a systemic crisis.

Hypothesis Development

According to the trade-off theory, firms maximize their values by balancing the benefits of liquidity protection and the opportunity cost of holding excess liquidity (Kraus & Litzenberger, 1973; Myers, 1984). Adequate liquidity levels provide firms with financial flexibility and operational continuity, while excess liquidity may decrease firms' profitability because of its effect on decreasing investments in high-return assets (Almeida et al., 2004; Deloof, 2003). Evidence shows that the association between liquidity and corporate performance depends on institutional and macroeconomic circumstances (Nguyen & Dao, 2022).

These aspects become especially relevant for manufacturers quoted on the Dar es Salaam Stock Exchange. In the course of the pandemic, companies faced the disruption of the supply chain, the increase of production costs, as well as difficult financing conditions. These conditions may have increased firms' reliance on internally available liquidity. In turn, when the economy stabilized, companies with better liquidity should have recovered faster due to production recovery and financing of working capital. Consequently, the association between liquidity management and financial performance is expected to vary across pandemic phases.

The Quick Ratio measures relatively liquid current assets by excluding inventories, which may not be readily convertible into cash. Its relationship with financial performance may thus differ when firms operate in different operating and financial conditions. In times of uncertainty, high availability of liquid assets may support short-term obligations and continuity of operations; while holding too much liquid resources may also incur opportunity costs. As economic conditions vary, the trade-off between these considerations may also vary. Thus, the study proposes that:

H_{1a}: The association between the Quick Ratio and financial performance differs across the pre-pandemic, pandemic, and post-pandemic phases.

The Current Ratio is a more general indication of short-term financial ability, as it includes inventories along with other current assets. This difference is important for manufacturing firms as inventories can be a substantial part of current assets and may not be as quickly convertible to cash as cash, receivables and other more liquid assets. Therefore, the relationship between the Current Ratio and financial performance may be affected by changes in operating conditions during the pandemic phases. Based on this reasoning, the study proposes:

H_{1b} : The association between the Current Ratio and financial performance differs across the pre-pandemic, pandemic, and post-pandemic phases.

Conceptual Framework

Figure 1 presents the conceptual framework, which proposes that liquidity management, measured by the Current Ratio and Quick Ratio, is associated with the financial performance of manufacturing firms listed on the Dar es Salaam Stock Exchange. The relationship is examined across the pre-pandemic, pandemic and post-pandemic periods to determine whether the profitability value of liquidity changes under different economic conditions.

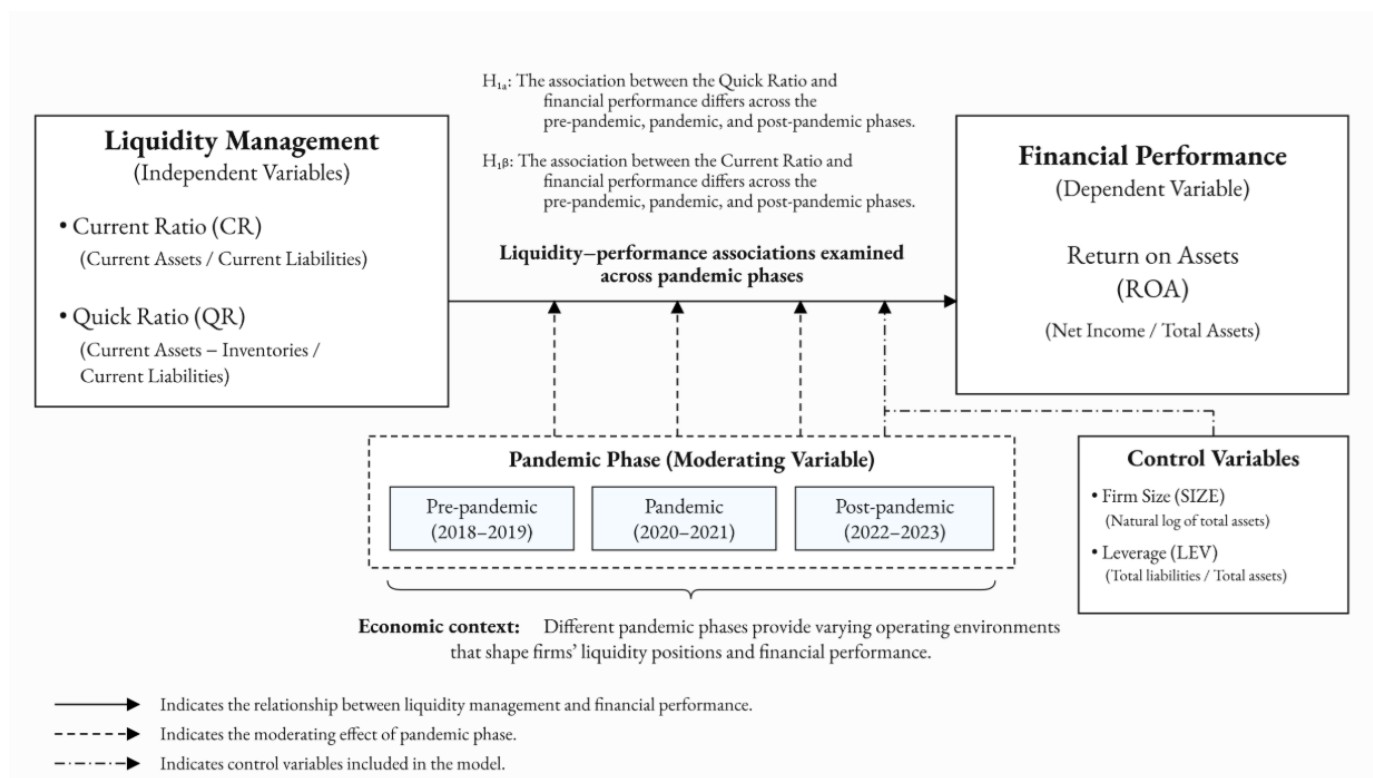


Figure 1. Conceptual Framework of Liquidity Management and Financial Performance Across Three Pandemic Phases

Source: Authors (2026)

Based on the Trade-Off Theory, the framework shows that liquidity management (Current Ratio and Quick Ratio) has a relationship with the financial performance of the manufacturing firms listed in the Dar es Salaam Stock Exchange measured by Return on Assets (ROA). The relationship is examined across the pre-pandemic, pandemic, and post-pandemic periods, with pandemic phase serving as the moderating variable. Firm Size and Leverage are included as control variables to account for observable firm characteristics that may also be associated with financial performance.

Research Methodology

Research Design

This study employed a quantitative explanatory research design using longitudinal panel data to examine the association between liquidity management and financial performance of manufacturing firms listed on the Dar es Salaam Stock Exchange (DSE) across the pre-pandemic, pandemic and post-pandemic periods. An explanatory design was appropriate because the study tested theoretically derived relationships between liquidity management and financial performance. The use of panel data was deemed relevant since they use both cross-sectional and time-series data, hence improving estimation efficiency while accounting for firm-specific heterogeneity that may not be observed (Baltagi, 2021; Hsiao, 2007; Wooldridge, 2020). This design is particularly useful in determining whether the association between liquidity management and financial performance differs across the stages of a macroeconomic shock.

Study Context, Sample and Data

The current research focused on the analysis of the manufacturing companies listed on the Dar es Salaam Stock Exchange during the period of the first quarter of 2018 through the fourth quarter of 2023. Manufacturing firms provide an appropriate setting because their operations depend heavily on working capital management and are therefore particularly sensitive to changes in liquidity conditions. The analyzed time interval consists of three periods: pre-COVID-19 (2018-2019), during COVID-19 (2020-2021), and post-COVID-19 (2022-2023).

The final sample comprised seven manufacturing firms listed on the Dar es Salaam Stock Exchange. The number of firms was determined by the population of listed manufacturing companies for which the required financial information was available over the study period. Although the cross-sectional dimension is relatively small, the study focuses specifically on listed manufacturing firms in order to remain consistent with its research objective and empirical context. The resulting dataset is an unbalanced quarterly panel because the availability of financial information differs across firms and reporting periods.

Quarterly observations were used because liquidity and financial performance can adjust within relatively short periods, particularly during periods of economic disruption. Compared with annual observations, quarterly data provide greater temporal resolution for examining changes before, during and after the pandemic. However, the use of quarterly observations does not substitute for a larger cross-sectional sample. Accordingly, the limited number of listed manufacturing firms is acknowledged as an important constraint on statistical inference and generalizability. To address this limitation, the empirical analysis applies panel estimators and inference procedures appropriate for the observed panel structure, including firm-clustered standard errors and small-cluster bootstrap inference.

Although the underlying panel framework covers seven firms over 24 quarters, giving 168 possible firm-quarter positions, the final regression sample is unbalanced because complete information required for all variables was not available for every firm-quarter. The main fixed-effects estimation therefore uses 101 complete firm-quarter observations. Table 1 presents the distribution of these observations across firms and pandemic phases.

As shown in Table 1, all seven firms are represented in each of the three phases, although the number of available quarterly observations differs across firms and periods. Observations were excluded from the main estimation sample when information required to calculate one or more model variables was unavailable for the corresponding quarter. No observations were intentionally excluded based on the level of financial performance. Nevertheless, the possibility that missing financial information is related to firms' reporting conditions or financial circumstances cannot be completely excluded. Therefore, the study does not assume

that the missing observations are completely random, and this issue is considered when interpreting the findings.

Table 1. Distribution of Main-Sample Observations by Firm and Pandemic Phase

Firm	Pre-pandemic	Pandemic	Post-pandemic	Total
Firm 1	4	4	4	12
Firm 2	5	5	7	17
Firm 3	3	5	6	14
Firm 4	5	4	7	16
Firm 5	4	4	7	15
Firm 6	4	5	5	14
Firm 7	4	4	5	13
Total	29	31	41	101

Note: Pre-pandemic = 2018–2019; pandemic = 2020–2021; post-pandemic = 2022–2023. Counts represent firm-quarter observations included in the main fixed-effects estimation sample

Variable Measurement

The financial performance was measured through the Return on Assets (ROA), where ROA was calculated through the net income divided by total assets. ROA was selected because it reflects how efficiently companies utilize their resources in order to generate profit.

Liquidity management was measured using the Current Ratio (CR) and the Quick Ratio (QR). The Current Ratio evaluates a firm's overall ability to meet short-term obligations using total current assets, whereas the Quick Ratio excludes inventories and therefore captures immediately available liquidity. Using both measures enables the study to distinguish between general working-capital adequacy and highly liquid asset availability, an important distinction for manufacturing firms where inventories constitute a substantial proportion of current assets. Table 2 summarises the operational definitions and measurement of the study variables.

Table 2. Measurement of Study Variables

Variable	Type	Indicator(s)	Measurement Scale	Coding	Source
Financial Performance (FP)	Dependent	Return on Assets (ROA)	Ratio	(Net income/Total assets)	(Lontchi et al., 2023)
Liquidity Management (LIQ)	Independent	Quick Ratio (QR)	Ratio	(Current Assets – Inventory) ÷ Current Liabilities	(Almeida et al., 2004; Gull et al., 2023)
		Current ratio (CR)		Current Assets/Current Liabilities	

Authors, (2026)

Econometric Model Specification

To examine whether the association between liquidity management and financial performance varied across pandemic phases, the study estimated an interaction-based panel regression model. This specification allows the associations of the Current Ratio (CR) and Quick Ratio (QR) with financial performance to differ across the pre-pandemic, pandemic, and post-pandemic periods.

The empirical model is specified as:

$$ROA_{it} = \beta_0 + \beta_1 QR_{it} + \beta_2 CR_{it} + \beta_3 Pandemic_t + \beta_4 (QR \times Pandemic) + \beta_5 (CR \times Pandemic) + \mu_i + \varepsilon_{it} \dots \dots \dots \text{Model 1}$$

where ROA_{it} denotes the financial performance of firm i in period t , QR and CR represent the Quick Ratio and Current Ratio respectively; the pandemic variable distinguishes the three economic phases; μ_i captures unobserved firm-specific effects; and ε_{it} denotes the idiosyncratic error term.

Estimation Strategy

Panel regression models were estimated using fixed-effects and random-effects specifications, with the Hausman specification test used to guide estimator selection. The Hausman test supported the fixed-effects estimator, indicating that unobserved firm-specific effects were correlated with the explanatory variables. Consequently, the fixed-effects interaction model was used as the main specification.

The model included Firm Size and Leverage as control variables to account for observable firm characteristics that may influence financial performance. Because diagnostic testing indicated heteroskedasticity, standard errors were clustered at the firm level. Since the study contains only seven firms, conventional cluster-robust inference may be sensitive to the small number of clusters. Therefore, Webb-weighted wild-cluster bootstrap inference with 9,999 replications was additionally employed for the formal tests of the pandemic-phase interaction terms.

Average marginal effects were estimated to facilitate interpretation of the interaction model because the coefficients of interacted variables do not directly represent the liquidity associations within each pandemic phase. Additional robustness analyses included winsorization, first-difference specifications, alternative liquidity measures, and calendar-time controls.

Estimation settings

All analyses were conducted using Stata 18. Average marginal effects were obtained after the interaction models using Stata's margins procedure, with standard errors calculated using the delta method. Given the small number of firm clusters, joint interaction hypotheses were additionally evaluated using Webb-weighted wild-cluster bootstrap inference with 9,999 replications, clustering at the firm level and using a fixed random-number seed of 12345. For the winsorization sensitivity analysis, ROA, Quick Ratio, and Current Ratio were winsorized at the 1st and 99th percentiles before re-estimating the same fixed-effects interaction specification. Panel stationarity was assessed using Fisher-type unit-root tests based on firm-specific Phillips–Perron tests, with one Newey–West lag and panel means included. First-difference tests were used where reliable level tests could not be obtained or where level non-stationarity was indicated.

Diagnostic Tests

Several diagnostic and specification tests were conducted prior to the final estimation. Multicollinearity was assessed using the Variance Inflation Factor (VIF). Groupwise heteroskedasticity was examined using the Modified Wald test, while first-order serial correlation was assessed using the Wooldridge test. Cross-sectional dependence was evaluated using the Pesaran CD test. The Hausman specification test was used to determine whether the fixed-effects or random-effects estimator was more appropriate.

In response to the use of quarterly panel data, panel stationarity was also examined using Fisher-type panel unit-root tests based on Phillips–Perron procedures. Because the panel is short and unbalanced, these tests were

interpreted cautiously and used as diagnostic evidence rather than as definitive time-series classification tests. Where variables showed evidence of non-stationarity at levels, first-difference tests were additionally examined.

Robustness was further assessed through winsorization, firm-clustered standard errors, Webb-weighted wild-cluster bootstrap inference, first-difference specifications, alternative liquidity measures, and calendar-time controls.

As an additional preliminary analysis, a baseline pooled OLS model and classical regression diagnostic tests were estimated before the panel-data analysis. The baseline OLS estimates and diagnostic results, reported in Appendix Tables 1–3, revealed significant heteroskedasticity and departures from the classical OLS assumptions, supporting the use of panel-data estimation with robust inference.

Results

Descriptive Statistics

Table 3 presents descriptive statistics for financial performance, liquidity management, firm size and leverage for the pre-pandemic, pandemic and post-pandemic periods. The statistics indicate important variation in the mean values and dispersion of the variables across the three phases, providing an initial description of the evolution of financial performance and liquidity conditions over the study period. Formal econometric analysis is subsequently used to determine whether the observed differences are statistically supported.

Table 3. Descriptive Statistics by Pandemic Phase

Variable	Phase	N	Mean	SD	Min	Max
ROA	Pre-pandemic	29	0.0835	0.0075	0.0709	0.0980
	Pandemic	31	0.0346	0.0125	0.0056	0.0529
	Post-pandemic	41	0.0801	0.0427	0.0506	0.2324
Quick Ratio	Pre-pandemic	29	1.3118	0.3569	0.7600	2.5200
	Pandemic	31	1.0728	0.5973	0.1230	2.2670
	Post-pandemic	41	0.6843	0.6512	0.0600	2.2300
Current Ratio	Pre-pandemic	29	1.8384	0.3251	1.2270	2.5200
	Pandemic	31	1.6203	0.6777	0.3680	2.7800
	Post-pandemic	41	1.5882	0.6754	0.2000	3.1800
Cash Ratio	Pre-pandemic	29	0.4260	0.3267	0.0360	1.0090
	Pandemic	31	0.5210	0.4216	0.0380	1.1920
	Post-pandemic	41	0.4873	0.4225	0.0390	1.3360
Net Working Capital Ratio	Pre-pandemic	29	-0.0028	0.2015	-0.5180	0.2720
	Pandemic	31	-0.0115	0.3013	-0.6850	0.3070
	Post-pandemic	41	0.0185	0.3542	-0.7500	0.4840
Firm Size	Pre-pandemic	29	16.7645	2.6555	12.2080	19.8960
	Pandemic	31	16.8976	2.5192	12.1350	19.8300
	Post-pandemic	41	17.0046	2.5100	12.4720	19.8290
Leverage	Pre-pandemic	29	0.5217	0.3115	0.0710	1.2083
	Pandemic	31	0.6063	0.3878	0.0767	1.7209
	Post-pandemic	41	0.5745	0.2560	0.2628	1.0943

Note: Pre-pandemic = 0, Pandemic = 1, Post-pandemic = 2. Total observations = 101.

Source: Stata Version 18 (2026)

Table 3 presents the descriptive statistics across the three pandemic phases. Mean ROA declined substantially from 0.0835 in the pre-pandemic period to 0.0346 during the pandemic before recovering to 0.0801 post-pandemic. The mean Quick Ratio also declined progressively from 1.3118 before the pandemic to 1.0728 during the pandemic and 0.6843 afterward. Similarly, the Current Ratio declined from 1.8384 to 1.6203 and 1.5882 across the three phases. In contrast, the Cash Ratio increased during the pandemic from 0.4260 to 0.5210 before declining slightly to 0.4873 post-pandemic, while the Net Working Capital Ratio improved from negative values before and during the pandemic to 0.0185 afterward. These descriptive patterns indicate changes in both financial performance and liquidity composition across the pandemic phases, although statistical tests are required to determine whether such differences represent significant relationships.

Differences in Financial Performance Across Pandemic Phases

As a preliminary analysis, differences in financial performance across the pre-pandemic, pandemic, and post-pandemic periods were examined using a regression-based phase comparison with standard errors clustered at the firm level. This approach accounts for within-firm dependence in the quarterly observations and provides a more robust preliminary assessment of differences in ROA across the three pandemic phases before estimating the interaction-based panel regression model.

Table 4. Cluster-Robust Comparison of ROA Across Pandemic Phases

Comparison/Statistic	Estimate	Robust SE	p-value
Pre-pandemic mean ROA	0.0835	0.0026	<0.001
During-pandemic mean ROA	0.0346	0.0032	<0.001
Post-pandemic mean ROA	0.0801	0.0147	0.002
During vs. Pre	-0.0489	0.0042	<0.001
Post vs. Pre	-0.0034	0.0134	1.000
Post vs. During	0.0455	0.0170	0.110
Joint phase test	$F(2,6) = 181.11$	—	<0.001
Webb wild-cluster joint test	$F(2,6) = 181.1129$	—	0.0018

Note: Standard errors are clustered at the firm level (7 clusters). Pairwise p-values are Bonferroni-adjusted. The Webb-weighted wild-cluster bootstrap joint test is based on 9,999 replications.

Source: Stata Version 18 (2026).

Table 4 shows significant differences in financial performance across the pandemic phases. The cluster-robust joint test rejected equality of ROA across the three periods, $F(2,6) = 181.11$, $p < 0.001$. Given the small number of firm clusters, Webb-weighted wild-cluster bootstrap inference was also applied, and the overall phase difference remained statistically significant ($F(2,6) = 181.1129$, $p = 0.0018$). Mean ROA declined from 0.0835 before the pandemic to 0.0346 during the pandemic before recovering to 0.0801 post-pandemic.

The Bonferroni-adjusted comparisons show that ROA was significantly lower during the pandemic than before the pandemic (mean difference = -0.0489 , $p < 0.001$). However, post-pandemic ROA did not differ significantly from pre-pandemic ROA (mean difference = -0.0034 , $p = 1.000$). Although ROA increased by 0.0455 between the pandemic and post-pandemic periods, the difference was not statistically significant after Bonferroni adjustment ($p = 0.110$). Thus, profitability declined substantially during the pandemic and subsequently returned close to its pre-pandemic level.

These comparisons concern differences in the level of financial performance and do not establish moderation. The subsequent interaction analysis separately examines whether the relationship between liquidity and ROA changed across pandemic phases.

Table 5. Distribution of Observations Across Pandemic Phases

Pandemic Phase	Frequency	Percent
Pre-pandemic (2018–2019)	29	28.71
During-pandemic (2020–2021)	31	30.69
Post-pandemic (2022–2023)	41	40.59
Total	101	100.00

Source: Stata Version 18 (2026)

Table 5 presents the distribution of firm-quarter observations across the three pandemic phases. The final estimation sample comprises 101 observations from seven firms. Because the panel is unbalanced, the number of observations varies across firms and pandemic phases. Of the 101 observations, 29 (28.71%) relate to the pre-pandemic period, 31 (30.69%) to the pandemic period, and 41 (40.59%) to the post-pandemic period. The post-pandemic phase therefore accounts for the largest proportion of observations in the estimation sample.

Model Diagnostics and Specification Tests

Before estimating the main regression model, diagnostic and specification tests were conducted to assess the suitability of the panel estimation procedure. The Variance Inflation Factor (VIF) produced a mean value of 1.54, indicating no serious multicollinearity among the explanatory variables. The Modified Wald test revealed significant groupwise heteroskedasticity ($\chi^2(7) = 61.09$, $p < 0.001$), while subsequent tests examined serial correlation and cross-sectional dependence. The Hausman specification test was also conducted to determine the appropriate panel estimator. Based on these diagnostic results, the fixed effects model with standard errors clustered at the firm level was adopted as the main estimation approach. Given the small number of firm clusters, Webb-weighted wild-cluster bootstrap inference was additionally employed to strengthen the reliability of the statistical tests. Table 6 presents the diagnostic and specification test results.

Table 6. Diagnostic and Specification Test Results

Diagnostic / robustness test	Result	Decision
Variance Inflation Factor	Mean VIF = 1.54	No serious multicollinearity among core regressors
Hausman specification test	$\chi^2(6) = 30.36$, $p = 0.000$	Fixed effects model preferred
Modified Wald test	$\chi^2(7) = 61.09$, $p < 0.001$	Groupwise heteroskedasticity present
Wooldridge serial-correlation test	$F(1,5) = 3.600$, $p = 0.1163$	No first-order serial correlation
Pesaran CD test	$CD = 0.853$, $p = 0.3936$	No evidence of cross-sectional dependence
Firm-clustered standard errors	Applied at firm level	Accounts for heteroskedasticity and within-firm dependence
Webb wild-cluster bootstrap	9,999 replications; $QR \times Phase: F(2,6) = 5.8208$, $p = 0.0332$; $CR \times Phase: F(2,6) = 1.7444$, $p = 0.2844$	QR phase differences supported; CR phase differences not supported
Winsorization robustness	1st and 99th percentiles; $QR \times Phase: F(2,6) = 4.4030$, $p = 0.0641$; $CR \times Phase: F(2,6) = 1.7409$, $p = 0.2869$	QR phase pattern persists but becomes marginal at 10%; CR remains insignificant

Source: Author's computations using Stata 18.

The Wooldridge test did not indicate first-order serial correlation ($F(1,5) = 3.600$, $p = 0.1163$). Similarly, the Pesaran CD test provided no evidence of cross-sectional dependence ($CD = 0.853$, $p = 0.3936$). However, the Modified Wald test indicated that groupwise heteroskedasticity was present ($\chi^2(7) = 61.09$, $p < 0.001$). The Hausman specification test was statistically significant ($\chi^2(6) = 30.36$, $p = 0.000$) indicating that the fixed effects estimator should be used rather than Random Effects. Therefore, the fixed effects model was estimated with standard errors clustered at the firm level to account for heteroskedasticity and within-firm dependence.

Given the small number of firm clusters, the joint interaction hypotheses were additionally evaluated using the Webb bootstrap procedure described in the Estimation Strategy. The test provided evidence of phase variation for the Quick Ratio ($F(2,6) = 5.8208$, $p = 0.0332$), whereas the corresponding test for the Current Ratio was not statistically significant ($F(2,6) = 1.7444$, $p = 0.2844$).

Panel Stationarity Tests

To assess the time-series properties of the variables and address the possibility of non-stationarity in the panel data, Fisher-type panel unit-root tests based on the Phillips–Perron procedure were conducted. The Fisher-type approach was considered appropriate because it permits unbalanced panels and allows the autoregressive parameter to vary across firms. The null hypothesis is that all panels contain a unit root, while rejection of the null provides evidence of stationarity. Given the relatively small and unbalanced panel with gaps in some quarterly observations, the results are interpreted cautiously.

Table 7. Fisher-Type Panel Unit-Root Test Results

Variable	Test form	No. of panels	Fisher PP statistic (P)	p-value	Decision
ROA	Level	7	0.9024	1.0000	Non-stationary
ROA	First difference	7	212.0523	<0.001	Stationary
Quick Ratio	Level	—	—	—	Not estimable due to panel gaps
Quick Ratio	First difference	6	202.7725	<0.001	Stationary
Current Ratio	Level	—	—	—	Not estimable due to panel gaps
Current Ratio	First difference	6	153.7897	<0.001	Stationary
Firm Size	Level	7	30.1612	0.0073	Evidence of stationarity*
Firm Size	First difference	7	213.3293	<0.001	Stationary
Leverage	Level	7	66.1821	<0.001	Stationary
Leverage	First difference	7	153.0734	<0.001	Stationary

Note: The table reports the Fisher inverse chi-squared (P) statistic from Phillips–Perron tests with one Newey–West lag and panel means included. H_0 : all panels contain unit roots. *Firm Size produced mixed evidence across the alternative Fisher statistics at level; therefore, its level-stationarity result is interpreted cautiously. The level tests for the Quick Ratio and Current Ratio could not be reliably estimated because of gaps in the unbalanced quarterly panel.

Source: Author's computations using Stata 18

Table 7 presents the Fisher-type Phillips–Perron panel unit-root results. The study comprises seven firms. However, the Fisher-type tests for the first-differenced Quick Ratio and Current Ratio were based on six panels because differencing, combined with gaps in the unbalanced quarterly data, left one firm with insufficient usable consecutive observations for the firm-specific Phillips–Perron test.

ROA was non-stationary at level ($P = 0.9024$, $p = 1.0000$) but became stationary after first differencing ($P = 212.0523$, $p < 0.001$). Reliable level tests could not be obtained for the Quick Ratio and Current Ratio because of gaps in the unbalanced quarterly observations; however, both variables were stationary at first difference, with Fisher statistics of 202.7725 ($p < 0.001$) and 153.7897 ($p < 0.001$), respectively. Leverage was stationary at level ($P = 66.1821$, $p < 0.001$), while the inverse chi-squared statistic also indicated level stationarity for Firm Size ($P = 30.1612$, $p = 0.0073$), although the alternative Fisher statistics for Firm Size provided mixed evidence. Both control variables were clearly stationary after first differencing.

The first-difference results establish stationarity of the transformed series but do not, by themselves, validate the level fixed-effects specification. Accordingly, a first-difference regression sensitivity analysis was conducted to assess whether the substantive pattern observed in the level model persisted after removing level persistence. Given the small and unbalanced panel, the unit-root results are treated as supplementary diagnostic evidence and interpreted cautiously.

First-Difference Sensitivity Analysis. Given the evidence of non-stationarity in ROA and the inability to estimate reliable level unit-root tests for the liquidity measures, an additional first-difference specification was estimated as a sensitivity analysis. The model related quarterly changes in ROA to changes in the Quick Ratio and Current Ratio and their interactions with the pandemic phases. The usable sample declined to 37 observations from six firms because first differencing requires consecutive non-missing observations for the variables included in the model. The marginal association of the change in Quick Ratio was negative and significant in the pre-pandemic phase (-0.0667 , $p = 0.002$), but was insignificant during the pandemic (0.0013 , $p = 0.594$) and post-pandemic (-0.0010 , $p = 0.958$). A similar pattern was observed for the change in Current Ratio, which was negative and significant before the pandemic (-0.0209 , $p = 0.005$), but insignificant during and after the pandemic. Conventional joint tests indicated phase differences for both liquidity measures. However, these differences were not supported by Webb-weighted wild-cluster bootstrap inference for the Quick Ratio ($p = 0.3603$) or Current Ratio ($p = 0.2437$). Therefore, the first-difference results do not fully reproduce the phase pattern observed in the level fixed-effects model. Given the substantially smaller differenced sample, these results are treated as a sensitivity check rather than a replacement for the main specification. Overall, they reinforce the need for cautious interpretation of the level-model findings as associations rather than causal effects.

Robustness Checks

Robustness analyses were conducted to assess whether the main findings were sensitive to extreme observations and the choice of liquidity measure. First, ROA, the Quick Ratio, and the Current Ratio were winsorized at the 1st and 99th percentiles, and the fixed effects model was re-estimated using firm-clustered standard errors. Following winsorization, the phase-specific marginal associations of the Quick Ratio were negative and statistically significant in the pre-pandemic ($AME = -0.0257$, $p = 0.006$) and pandemic periods ($AME = -0.0441$, $p = 0.020$), but positive and statistically insignificant at the 5% level in the post-pandemic period ($AME = 0.0241$, $p = 0.095$). For the Current Ratio, the marginal associations were not statistically significant at the 5% level in any phase. Importantly, the Webb-weighted wild-cluster bootstrap joint tests did not establish statistically significant phase variation at the 5% level for either the Quick Ratio ($F(2,6) = 4.4030$, $p = 0.0641$) or the Current Ratio ($F(2,6) = 1.7409$, $p = 0.2869$). Thus, the direction of the phase-varying Quick Ratio pattern remains after winsorization, but the statistical evidence becomes weaker, with the Webb bootstrap test

significant only at the 10% level. This indicates that the main finding of Quick Ratio phase variation is somewhat sensitive to extreme observations and should therefore be interpreted cautiously.

Second, the analysis was repeated using the Cash Ratio and Net Working Capital Ratio (NWCAR) as alternative measures of liquidity. Each alternative measure was estimated separately using the fixed effects specification with firm-clustered standard errors and the same 101-observation sample used in the main analysis. Given the small number of firm clusters, the phase interactions were additionally evaluated using Webb-weighted wild-cluster bootstrap inference with 9,999 replications. Table 8 presents robustness checks using alternative liquidity measures.

Table 8. Robustness Checks Using Alternative Liquidity Measures

Liquidity measure	Pre AME	p	During AME	p	Post AME	p	Conventional F	Conventional p	Webb F	Webb p
Cash Ratio	-0.0085	.708	-0.0318	.086	0.0612	.076	5.58	.0427	5.6440	.1676
Net Working Capital Ratio	-0.1385	.194	-0.1371	.149	-0.0379	.384	1.12	.3859	1.1325	.6301

Note: AME = average marginal effect; p = p-value. All models use firm fixed effects with firm-clustered standard errors based on 101 observations from seven firms. Webb-weighted wild-cluster bootstrap tests use 9,999 replications and assess the joint significance of the phase-interaction coefficients.

Source: Author's computations using Stata 18

The alternative liquidity measures provide partial rather than complete support for the phase-sensitive pattern observed for the Quick Ratio. The Cash Ratio changed from a negative association in the pre-pandemic period (AME = -0.0085, $p = 0.708$) and pandemic period (AME = -0.0318, $p = 0.086$) to a positive association in the post-pandemic period (AME = 0.0612, $p = 0.076$). Although the conventional joint interaction test indicated statistically significant phase differences ($F(2,6) = 5.58$, $p = 0.0427$), this result was not supported by Webb-weighted wild-cluster bootstrap inference ($F(2,6) = 5.6440$, $p = 0.1676$). Similarly, the Net Working Capital Ratio was not statistically significant in any phase, and neither the conventional joint test ($F(2,6) = 1.12$, $p = 0.3859$) nor the Webb bootstrap test ($F(2,6) = 1.1325$, $p = 0.6301$) indicated significant phase moderation. These findings suggest that the statistically supported phase dependence identified for the Quick Ratio in the main analysis is not consistently reproduced by alternative liquidity measures and should therefore not be generalized to liquidity management as a whole.

Calendar-Time Controls

To examine whether the phase-specific associations were capturing broader calendar-time shocks, an additional specification included calendar-year indicators alongside firm fixed effects. This robustness test was intended to absorb common annual conditions, such as macroeconomic, regulatory, exchange-rate, inflationary, and sector-wide changes that could coincide with the pandemic phases. Because the pandemic phases are themselves defined by calendar years, some year indicators were collinear with the phase indicators and were automatically omitted by Stata. The specification should therefore be interpreted as a robustness check rather than as a complete separation of pandemic-related conditions from other common time shocks. After including calendar-year controls, the Quick Ratio phase interactions remained jointly significant under conventional cluster-robust inference ($F(2,6)=5.81$, $p=.0395$) and Webb-weighted wild-cluster bootstrap inference ($F(2,6)=5.8780$, $p=.0339$). In contrast, the Current Ratio interactions remained insignificant (conventional $p=.2486$; Webb $p=.3587$). These results suggest that the phase variation identified for the Quick Ratio is not entirely explained by common annual conditions, although the observational design does not permit these differences to be attributed specifically to the pandemic. The calendar-time-control results are presented in Appendix 4.

Regression Results

Table 9 presents the results of the fixed effects model examining whether the relationship between liquidity management and financial performance differs across the pre-pandemic, pandemic and post-pandemic periods. Standard errors are clustered at the firm level to account for within-firm dependence and heteroskedasticity. The interaction terms allow the associations of the Quick Ratio and Current Ratio with financial performance to vary across the three pandemic phases.

Table 9. Fixed-Effects Regression Results for Liquidity Management and Financial Performance Across Pandemic Phases

Variable	Coefficient	Clustered SE	t	p-value
Quick Ratio	-0.0223	0.0090	-2.49	0.047
Pandemic Phase: During	-0.0687	0.0159	-4.31	0.005
Pandemic Phase: Post	-0.0911	0.0257	-3.55	0.012
Quick Ratio × During	-0.0203	0.0168	-1.21	0.272
Quick Ratio × Post	0.0422	0.0130	3.24	0.018
Current Ratio	-0.0092	0.0050	-1.82	0.118
Current Ratio × During	0.0218	0.0134	1.63	0.155
Current Ratio × Post	0.0271	0.0177	1.53	0.176
Firm Size	0.0023	0.0043	0.53	0.616
Leverage	-0.0448	0.0347	-1.29	0.244
Constant	0.1161	0.0702	1.65	0.149

Note: Model statistics: Observations = 101; Firms = 7; Within $R^2 = 0.7280$; Between $R^2 = 0.2299$; Overall $R^2 = 0.6173$. Standard errors clustered by firm.

Source: Author's computations using Stata 18

The fixed effects model results indicate that the relationship between the Quick Ratio and financial performance varies across pandemic phases. In the pre-pandemic period, the Quick Ratio is negatively and significantly associated with ROA ($\beta = -0.0223$, $p = 0.047$). The interaction between the Quick Ratio and the pandemic period is negative but statistically insignificant ($\beta = -0.0203$, $p = 0.272$), whereas the post-pandemic interaction is positive and statistically significant ($\beta = 0.0422$, $p = 0.018$). This indicates a substantial change in the Quick Ratio–ROA relationship in the post-pandemic period relative to the pre-pandemic period.

The phase-specific marginal associations provide a clearer interpretation of these interactions. The Quick Ratio has a negative and statistically significant marginal effect before the pandemic ($AME = -0.0223$, $p = 0.013$) and during the pandemic ($AME = -0.0426$, $p = 0.015$). In the post-pandemic period, however, the marginal effect becomes positive ($AME = 0.0199$), although it is not statistically significant at the 5% level ($p = 0.101$). Thus, the results indicate a shift from a negative liquidity–performance relationship before and during the pandemic toward a positive, but statistically imprecise, relationship during the recovery period.

The Current Ratio shows a different pattern. Its phase-specific marginal association is negative before the pandemic ($AME = -0.0092$, $p = 0.068$) and positive during ($AME = 0.0126$, $p = 0.225$) and after the pandemic ($AME = 0.0179$, $p = 0.241$). None of these effects is statistically significant at the 5% level. Likewise, neither the pandemic interaction ($\beta = 0.0218$, $p = 0.155$) nor the post-pandemic interaction ($\beta = 0.0271$, $p = 0.176$) is statistically significant.

Formal joint tests provide further evidence of this distinction. The conventional joint test rejects the null that the Quick Ratio phase-interaction coefficients are jointly zero ($F(2,6) = 5.76$, $p = 0.0402$). More importantly, given the small number of firms, the Webb-weighted wild-cluster bootstrap test also confirms the joint significance of the Quick Ratio interactions ($F(2,6) = 5.8208$, $p = 0.0332$). In contrast, the Current Ratio

interactions are not jointly significant under either the conventional test ($F(2,6) = 1.73$, $p = 0.2559$) or the Webb bootstrap test ($F(2,6) = 1.7444$, $p = 0.2844$). Therefore, the evidence supports pandemic-phase moderation of the Quick Ratio–financial performance relationship, but not of the Current Ratio–financial performance relationship.

Average Marginal Effects of Liquidity Management Across Pandemic Phases

Because interaction coefficients are not directly interpretable as phase-specific effects, Average Marginal Effects (AMEs) were estimated to examine how the association between liquidity management and financial performance varied across the pre-pandemic, pandemic, and post-pandemic periods. The AMEs show the expected change in Return on Assets associated with a one-unit increase in each liquidity measure within each pandemic phase, based on the fixed effects model with firm-clustered standard errors. Table 10 and Figure 2 present the estimated marginal effects and their 95% confidence intervals.

Table 10. Average Marginal Associations of Liquidity Management with Financial Performance Across Pandemic Phases

Variable	Phase	AME	SE	z	p-value	95% CI
Quick Ratio	Pre-pandemic	-0.0223	0.0090	-2.49	0.013	-0.0398 to -0.0048
Quick Ratio	Pandemic	-0.0426	0.0176	-2.42	0.015	-0.0771 to -0.0081
Quick Ratio	Post-pandemic	0.0199	0.0121	1.64	0.101	-0.0039 to 0.0436
Current Ratio	Pre-pandemic	-0.0092	0.0050	-1.82	0.068	-0.0191 to 0.0007
Current Ratio	Pandemic	0.0126	0.0104	1.21	0.225	-0.0078 to 0.0330
Current Ratio	Post-pandemic	0.0179	0.0153	1.17	0.241	-0.0120 to 0.0478

Source: Author's computations using Stata 18

The marginal effects reveal a clear change in the estimated relationship between the Quick Ratio and financial performance across pandemic phases. Before the pandemic, the Quick Ratio was negatively and statistically significantly associated with ROA ($dy/dx = -0.0223$, $p = 0.013$). The negative association became larger during the pandemic ($dy/dx = -0.0426$, $p = 0.015$). In the post-pandemic period, however, the relationship changed direction and became positive ($dy/dx = 0.0199$), although it was not statistically significant at the 5% level ($p = 0.101$). Thus, the results suggest that higher quick liquidity was associated with lower financial performance before and during the pandemic, whereas this negative relationship was no longer evident during the post-pandemic recovery.

The Current Ratio did not show statistically significant phase-specific effects at the 5% level. Its marginal effect was negative before the pandemic ($dy/dx = -0.0092$, $p = 0.068$), but became positive during the pandemic ($dy/dx = 0.0126$, $p = 0.225$) and remained positive post-pandemic ($dy/dx = 0.0179$, $p = 0.241$). The 95% confidence intervals included zero in all three periods.

Overall, Figure 2 reinforces the distinction between the two liquidity measures. The Quick Ratio displays a pronounced phase-dependent pattern, moving from significant negative associations before and during the pandemic to a positive but statistically insignificant association after the pandemic. The Current Ratio shows changes in direction but without statistically significant phase-specific effects. Importantly, the formal Webb-weighted wild-cluster bootstrap test confirms that the Quick Ratio interactions are jointly significant ($F(2,6) = 5.8208$, $p = 0.0332$), whereas those of the Current Ratio are not ($F(2,6) = 1.7444$, $p = 0.2844$). Therefore, the evidence supports pandemic-phase moderation for the Quick Ratio, but not for the Current Ratio.

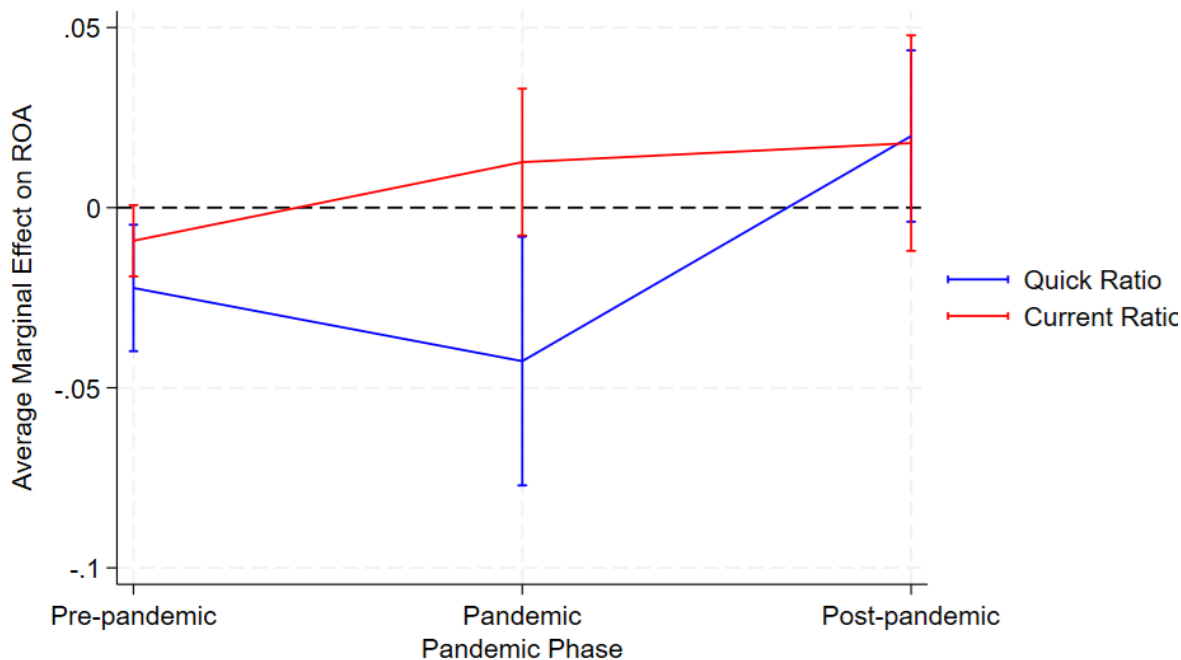


Figure 2. Marginal Effects of Liquidity Management Across Pandemic Phases

Source: Author's computations using Stata 18

Figure 2 illustrates the phase-specific marginal associations of the Quick Ratio and Current Ratio on financial performance. The Quick Ratio shows a pronounced shift from negative associations before and during the pandemic to a positive association in the post-pandemic period. In contrast, the Current Ratio shifts from a negative pre-pandemic association to positive association during and after the pandemic, although its confidence intervals cross zero across all phases. The formal Webb-weighted wild-cluster bootstrap tests confirm that the phase interactions are jointly significant for the Quick Ratio ($F(2,6) = 5.8208$, $p = 0.0332$), but not for the Current Ratio ($F(2,6) = 1.7444$, $p = 0.2844$). Therefore, the results provide evidence of pandemic-phase moderation for the Quick Ratio, but not for the Current Ratio.

Discussion

This study examined whether the relationship between liquidity management and the financial performance of manufacturing firms listed on the Dar es Salaam Stock Exchange differed across the pre-pandemic, pandemic, and post-pandemic periods. The current results reveal an important distinction between the two liquidity measures. For the Quick Ratio, the relationship with ROA changed substantially across the three phases. Its average marginal effect was negative and statistically significant before the pandemic ($dy/dx = -0.0223$, $p = 0.013$) and became more negative during the pandemic ($dy/dx = -0.0426$, $p = 0.015$). In the post-pandemic period, however, the relationship reversed and became positive ($dy/dx = 0.0199$), although the phase-specific effect was not statistically significant ($p = 0.101$). Importantly, the Webb-weighted wild-cluster bootstrap joint test confirmed that the Quick Ratio interactions differed significantly across pandemic phases ($F(2,6) = 5.8208$, $p = 0.0332$). In contrast, the Current Ratio did not show statistically robust phase moderation, with its Webb bootstrap joint test remaining insignificant ($F(2,6) = 1.7444$, $p = 0.2844$).

These results offer a more refined application of the Trade-Off Theory to liquidity management. The framework holds that businesses evaluate the benefits of liquid holdings alongside the costs of keeping assets that tend to generate relatively low returns (Kraus & Litzenberger, 1973; Myers, 1984). The negative Quick Ratio relationship observed before and during the pandemic indicates that higher holdings of highly liquid assets were associated with reduced profitability in these periods. This pattern may reflect the opportunity cost of maintaining resources in liquid form rather than investing them in productive activities (Deloof, 2003; Eljelly, 2004; García-Teruel & Martínez-Solano, 2007; Lazaridis & Tryfonidis, 2006; Raheman & Nasr, 2007). The stronger negative association during the pandemic is particularly relevant because firms facing heightened uncertainty may have increased precautionary liquidity holdings while simultaneously experiencing weaker operating activity. Such precautionary liquidity behaviour was widely observed during the COVID-19 disruption, as firms sought to protect themselves against financing constraints and interruptions in operating cash flows (Acharya & Steffen, 2020; De Vito & Gómez, 2020; Ding et al., 2021; Keynes, 1936). This interpretation is consistent with literature showing that the relationship between liquidity and performance depends on operating conditions and the efficiency with which working-capital resources are managed (Deloof, 2003; Eljelly, 2004; García-Teruel & Martínez-Solano, 2007; Nguyen & Dao, 2022).

The reversal of the Quick Ratio relationship in the post-pandemic period provides further evidence that the role of highly liquid resources may depend on prevailing economic conditions. The marginal effect changed from -0.0426 during the pandemic to 0.0199 after the pandemic. Although the post-pandemic marginal effect itself was not statistically significant at the 5% level, the formal joint interaction test indicates that the overall changes in the Quick Ratio–ROA relationship across phases are statistically supported. One possible interpretation is that the economic role of readily accessible liquidity changed as firms moved from crisis conditions toward recovery. During periods of disruption, excess liquid resources may carry substantial opportunity costs, whereas during recovery they may provide greater flexibility to restore production, finance working-capital requirements, and respond to emerging business opportunities (Fahlenbrach et al., 2021; Oskouei & Borhanib, 2025; Rahmanto et al., 2024). This interpretation is also consistent with evidence that the value and performance implications of working capital and financial flexibility vary with economic conditions (Baños-Caballero et al., 2014; Enqvist et al., 2014). Thus, the results support the broader view that liquidity management should respond to changing economic conditions rather than being treated as a fixed financial policy (Enqvist et al., 2014; Fahlenbrach et al., 2021).

The Current Ratio presents a different pattern. Its marginal effect was negative before the pandemic ($dy/dx = -0.0092$, $p = 0.068$), but became positive during ($dy/dx = 0.0126$, $p = 0.225$) and after the pandemic ($dy/dx = 0.0179$, $p = 0.241$). However, these changes were not statistically supported by the Webb-weighted wild-cluster bootstrap joint test. This difference between the Quick Ratio and Current Ratio highlights the potential importance of liquidity composition. The Quick Ratio focuses on more readily convertible current assets by excluding inventories, whereas the Current Ratio incorporates a broader range of current assets, including inventories. For manufacturing firms, inventories represent an important component of working capital but may not provide the same immediate financial flexibility as more liquid current assets (Gill et al., 2010; Padachi, 2006; Sharma & Kumar, 2010). Excessive holdings of inventories, receivables, and other current assets may also involve carrying and opportunity costs that weaken asset-use efficiency (Almakura et al., 2024; Eldi et al., 2023). The findings therefore suggest that changes in the relationship between liquidity and performance across economic phases may be more evident for immediately accessible liquidity than for broader accounting measures of current assets.

The robustness analyses provide further perspective on this interpretation. The alternative Cash Ratio displayed changes across phases, with its conventional joint interaction test indicating significance, but this evidence did not remain statistically significant under Webb-weighted wild-cluster bootstrap inference. Similarly, the Net

Working Capital Ratio did not show significant phase moderation. These results suggest that the statistically supported phase dependence observed for the Quick Ratio should not be generalized to liquidity management as a whole. Rather, the evidence indicates that the relationship may depend on the particular dimension of liquidity being measured. This interpretation is consistent with evidence that liquidity–performance relationships vary according to the liquidity measure, industry characteristics, institutional setting, and economic conditions (Nguyen & Dao, 2022). More broadly, the mixed empirical literature reports both beneficial and adverse performance consequences of liquidity management (Deloof, 2003; Fahlenbrach et al., 2021; Nguyen & Dao, 2022).

The findings should also be interpreted as associations rather than causal effects. Financial performance may influence firms' liquidity positions just as liquidity conditions may be associated with financial performance, creating the possibility of reverse causality. Although firm fixed effects control for time-invariant firm characteristics and additional robustness tests were conducted, these procedures do not eliminate all sources of endogeneity. Therefore, the observed phase differences should not be interpreted as evidence that changes in liquidity caused the observed changes in ROA.

From a managerial perspective, the findings caution against maintaining a uniform liquidity strategy across substantially different economic conditions. The negative association between the Quick Ratio and ROA before and during the pandemic suggests that maintaining highly liquid resources may involve profitability costs when such resources are not efficiently deployed. At the same time, the positive post-pandemic estimate suggests that readily accessible liquidity may become more useful as firms transition toward recovery, although this individual post-pandemic effect was not statistically significant. Previous crisis evidence similarly emphasizes the role of financial flexibility and liquidity buffers in helping firms respond to severe financing and operating disruptions (Acharya & Steffen, 2020; De Vito & Gómez, 2020; Fahlenbrach et al., 2021). Managers should therefore evaluate liquidity not simply in terms of whether current assets are sufficient to meet short-term obligations, but also in terms of their composition, opportunity cost, operational requirements, and the prevailing economic environment.

The robustness analyses, however, require a cautious interpretation of the main finding. Although the Quick Ratio phase interactions remain significant after introducing calendar-time controls, the evidence becomes weaker after winsorization, where the Webb-bootstrap test is significant only at the 10% level ($p=.0641$). Moreover, the Cash Ratio and Net Working Capital Ratio do not show significant phase variation under Webb-bootstrap inference. The first-difference specification also does not reproduce significant Quick Ratio phase interactions under the Webb procedure. Therefore, the evidence should not be interpreted as showing a general phase-dependent relationship for all forms of liquidity. Rather, the strongest evidence is specific to the Quick Ratio in the main level specification. This sensitivity may reflect differences in what each liquidity measure captures, but it also means that the findings require confirmation using larger samples and alternative empirical settings.

Overall, the findings provide evidence of pandemic-phase variation in the Quick Ratio–financial performance relationship in the main specification, but not for the Current Ratio. However, the robustness analyses show that this evidence is specification-sensitive. The Quick Ratio–financial performance relationship shifted from significantly negative before and during the pandemic to positive, though individually insignificant, after the pandemic, and the Webb-weighted wild-cluster bootstrap confirmed that the interaction terms were jointly significant. By contrast, changes in the Current Ratio relationship were not statistically robust. The findings therefore support a qualified phase-sensitive interpretation of liquidity management: economic conditions appear to matter for the performance implications of more immediately accessible liquidity, but this conclusion does not extend uniformly to all measures of liquidity. This evidence of measure-specificity fine-tunes the application of the Trade-Off Theory by suggesting that when assessing the liquidity – performance relationship,

one should consider both the composition of liquidity and the economic phase (Baños-Caballero et al., 2014; Enqvist et al., 2014; Nguyen & Dao, 2022).

Conclusion

The study examined whether the association between liquidity management and financial performance differed across the pre-pandemic, pandemic, and post-pandemic phases among listed manufacturing firms in Tanzania. The main fixed-effects results provide evidence of phase variation for the Quick Ratio but not for the Current Ratio. However, this evidence is sensitive to model specification. The Quick Ratio pattern remains under calendar-time controls, but its statistical support weakens after winsorization and is not reproduced by alternative liquidity measures or the first-difference sensitivity analysis. The findings therefore do not establish a general phase-dependent relationship between liquidity and financial performance. Instead, they suggest that the relationship may depend on the particular liquidity measure and empirical specification used. Given the seven-firm sample and observational design, these results should be regarded as context-specific associations that require further examination in larger samples.

Theoretical Implications

The results show a phase-sensitive application of the Trade-Off Theory. The negative association between the Quick Ratio and financial performance before and during the pandemic is consistent with the possibility that holding highly liquid assets involves opportunity costs. The positive but statistically insignificant post-pandemic association suggests that the relationship may differ during recovery, although the evidence is not sufficient to conclude that greater liquidity improves financial performance. This pattern was not found for the Current Ratio. The study therefore shows that the trade-off between liquidity and profitability may vary with economic conditions and the composition of current assets. This extends the theory by indicating that liquidity should not be treated as having a uniform performance effect across different economic phases.

Practical Implications

The findings suggest that managers and investors should be cautious when interpreting conventional liquidity indicators across different economic conditions. The Quick Ratio shows the clearest phase variation in the main analysis, whereas the Current Ratio and alternative liquidity measures provide weaker evidence. Therefore, the results do not support a general recommendation that firms should increase or reduce liquidity to improve profitability. Instead, liquidity indicators may be considered together with the composition of current assets, firms' operating conditions, financing constraints, and the broader economic environment. The insignificant post-pandemic marginal association and the sensitivity of the results across robustness specifications further suggest that the findings should not be used as a mechanical liquidity-management rule.

Limitations and Directions for Future Research

The study is limited to seven DSE-listed manufacturing firms, which restricts generalizability and statistical power despite the use of firm-clustered standard errors and Webb-weighted wild-cluster bootstrap inference. Future studies should examine larger samples, additional sectors, and other emerging or frontier markets.

The unbalanced estimation sample also introduces potential selection concerns because the availability of quarterly financial information may not be independent of firms' reporting conditions or financial circumstances.

The results should also be interpreted as associations rather than causal effects because reverse causality between liquidity and performance may remain. The small cross-sectional dimension limits the reliable application of dynamic panel or instrumental-variable methods. Further research with larger panels could apply

stronger causal identification techniques and more liquidity measures to further investigate the phase-sensitive relationships identified in this study.

Declaration

Ethics Statement:

This study received ethical approval from the Institutional Research Review Ethics Committee (IRREC) of the University of Dodoma, Tanzania, on 13 February 2026 (Ref. No. MA.84/261/100/17). Consent for publication was not applicable, as the study used secondary financial data obtained from publicly available financial statements and the Dar es Salaam Stock Exchange and did not involve human participants or personally identifiable information.

Funding:

This research received no external funding.

Acknowledgments:

The authors sincerely thank the Directorate of Postgraduate Studies of the University of Dodoma, Tanzania for providing access to the database and research support. The authors also extend gratitude to the anonymous reviewers of the journal for their valuable suggestions and feedback.

Conflicts of Interest:

The authors declare no conflict of interest.

Data Availability Statement:

The dataset compiled and analyzed during the current study is available from the corresponding author upon reasonable request.

References

- Acharya, V. V., & Steffen, S. (2020). The risk of being a fallen angel and the corporate dash for cash in the midst of COVID-19. *The Review of Corporate Finance Studies*, 9(3), 430–471. doi:10.1093/rcfs/cfaa013
- Agbana, J., Diyo, K., Muritala, T. A., Ibrahim, U. A., & Maitala, F. (2023). Effect of liquidity management on financial performance of manufacturing firms in Nigeria. *Qualitative and Quantitative Research Review*, 8(1), 41–66.
- Akinleye, G. T., & Ogunleye, J. S. (2019). Liquidity and the profitability of manufacturing firms in Nigeria. *Applied Finance and Accounting*, 5(2), 68–73. doi:10.11114/afa.v5i2.4477
- Almakura, F. A., Shiaki, T. K., Gambo, N., & Muhammad, R. A. (2024). Effect of liquidity management on the financial performance of Nigerian oil and gas firms. *International Journal of Business and Management Review*, 12(2), 28–44.
- Almeida, H., Campello, M., & Weisbenner, S. (2004). The cash flow sensitivity of cash. *The Journal of Finance*, 59, 1777–1804. doi:10.1111/j.1540-6261.2004.00679.x
- Baltagi, B. H. (2021). *Econometric analysis of panel data* (6th ed.). Hoboken, NJ: John Wiley & Sons. Retrieved from http://www.mysmu.edu/faculty/zlyang/ECON6031_2025T2Web/BadiBaltagiBook2021.pdf
- Baños-Caballero, S., García-Teruel, P. J., & Martínez-Solano, P. (2014). Working capital management, corporate performance, and financial constraints. *Journal of Business Research*, 67(3), 332–338. doi:10.1016/j.jbusres.2013.01.016
- Bates, T. W., Kahle, K., & Stulz, R. (2009). Why do US firms hold so much more cash than they used to? *The Journal of Finance*, 64(5), 1985–2021.

- Benjamin, M., Boyi, B., Kisaalita, T., Mutungi, W., & Mbabazize, R. (2023). Liquidity management and financial performance of SACCOs in Bushenyi District. *Journal of Economics and Behavioral Studies*, 15(3(J)), 55–69. doi:10.22610/jebbs.v15i3(J).3289
- Campello, M., Graham, J. R., & Harvey, C. (2010). The real effects of financial constraints: Evidence from a financial crisis. *Journal of Financial Economics*, 97(3), 470–487. doi:10.1016/j.jfineco.2010.02.009
- De Vito, A., & Gómez, J.-P. (2020). Estimating the COVID-19 cash crunch: Global evidence and policy. *Journal of Accounting and Public Policy*, 39, 2–14. doi:10.1016/j.jaccpubpol.2020.106741
- Deloof, M. (2003). Does working capital management affect profitability of Belgian firms? *Journal of Business Finance & Accounting*, 30(3–4), 573–587. doi:10.1111/1468-5957.00008
- Ding, W., Levine, R., Lin, C., & Xie, W. (2021). Corporate immunity to the COVID-19 pandemic. *Journal of Financial Economics*, 141(2), 802–830. doi:10.1016/j.jfineco.2021.03.005
- Eldi, E., Ibrahim, L. A., & Haeruddin, H. (2023). Analysis of the effect of liquidity and profitability on financial performance at PT. Mayora Indah Tbk. *Jurnal Ilmiah Indonesia*, 8(1), 29–42.
- Eljelly, A. M. A. (2004). Liquidity–profitability trade-off: An empirical investigation in an emerging market. *International Journal of Commerce and Management*, 14(2), 48–61. doi:10.1108/10569210480000179
- Enqvist, J., Graham, M., & Nikkinen, J. (2014). The impact of working capital management on firm profitability in different business cycles: Evidence from Finland. *Research in International Business and Finance*, 32, 36–49. doi:10.1016/j.ribaf.2014.03.005
- Fahlenbrach, R., Rageth, K., & Stulz, R. M. (2021). How valuable is financial flexibility when revenue stops? Evidence from COVID-19. *The Review of Financial Studies*, 34(11), 5474–5521. doi:10.1093/rfs/hhaa134
- García-Teruel, P. J., & Martínez-Solano, P. (2007). Effects of working capital management on SME profitability. *International Journal of Managerial Finance*, 3(2), 164–177. doi:10.1108/17439130710738718
- Gill, A., Biger, N., & Mathur, N. (2010). The relationship between working capital management and profitability: Evidence from the United States. *Business and Economics Journal*, 10, 1–9.
- Gull, A. A., Mushtaq, R., Nguyen, D. K., & Tran, P. T. (2023). COVID-19 adaptive strategy and SMEs' access to finance. *Applied Economics*, 56(22), 2615–2628.
- Hsiao, C. (2007). *Analysis of panel data* (2nd ed.). Cambridge, England: Cambridge University Press.
- Keynes, J. M. (1936). *The general theory of employment, interest and money*. London, England: Palgrave Macmillan. Retrieved from https://www.files.ethz.ch/isn/125515/1366_keynestheoryofemployment.pdf
- Kim, C.-S., Mauer, D. C., & Sherman, A. E. (1998). The determinants of corporate liquidity: Theory and evidence. *Journal of Financial and Quantitative Analysis*, 33(3), 335–359. doi:10.2307/2331099
- Kraus, A., & Litzenberger, R. H. (1973). A state-preference model of optimal financial leverage. *The Journal of Finance*, 28(4), 911–922.
- Kumar, S., & Zbib, L. (2022). Firm performance during the COVID-19 crisis: Does managerial ability matter? *Finance Research Letters*. doi:10.1016/j.frl.2022.102720
- Lalithchandra, B. N., & Rajendhiran, N. (2021). Liquidity ratio: An important financial metric. *Turkish Journal of Computer and Mathematics Education*, 12(2), 1113–1114.
- Lazaridis, I., & Tryfonidis, D. (2006). Relationship between working capital management and profitability of listed firms. *Journal of Financial Management and Analysis*, 19(1), 26–35.
- Lontchi, C. B., Yang, B., & Shuaib, K. M. (2023). Effect of financial technology on SMEs performance in Cameroon amid COVID-19 recovery: The mediating effect of financial literacy. *Sustainability*, 15(3), 1–15. doi:10.3390/su15032171
- Modigliani, F., & Miller, M. H. (1963). Corporate income taxes and the cost of capital: A correction. *The American Economic Review*, 53(3), 433–443.
- Myers, S. (1984). The capital structure puzzle. *The Journal of Finance*, 39(3), 575–592. doi:10.2307/2327916

- Nguyen, K. Q., Nga Phan, T. H., & Hang, N. M. (2024). The effect of liquidity on firm's performance: Case of Vietnam. *Journal of Eastern European and Central Asian Research*, 11(1), 176–187. doi:10.15549/jeecar.v11i1.1344
- Nguyen, N. P. A., & Dao, T. T. B. (2022). Liquidity, corporate governance and firm performance: A meta-analysis. *Cogent Business & Management*, 9, 1–16. doi:10.1080/23311975.2022.2137960
- Opler, T., Pinkowitz, L., Stulz, R., & Williamson, R. (1999). The determinants and implications of corporate cash holdings. *Journal of Financial Economics*, 52(1), 3–46. doi:10.1016/S0304-405X(99)00003-3
- Oskouei, M. M., & Borhanib, A. (2025). Moderating effect of the COVID-19 pandemic on the relationship between liquidity management and performance of insurance companies. *New Applied Studies in Management, Economics & Accounting*, 8, 169–181.
- Padachi, K. (2006). Trends in working capital management and its impact on firms' performance. *International Review of Business Research Papers*, 2(2), 45–58.
- Paminto, A., Abni Lahaya, I., Iqbal, M., Azizil Yudaruddin, Y., & Yudaruddin, R. (2023). COVID-19 pandemic and firm performance in the insurance industry in developed and emerging markets. *Insurance Markets and Companies*, 14(1), 85–98. doi:10.21511/ins.14(1).2023.08
- Raheman, A., & Nasr, M. (2007). Working capital management and profitability. *International Review of Business Research Papers*, 3(1), 279–300.
- Rahmanto, B. T., Lasmiatun, K., Ar, N., Toalib, R., & Syamsinar. (2024). Analysis of the effect of liquidity, leverage, and profitability on the financial performance of companies in the Indonesian Capital Market. *West Science Business and Management*, 2(4), 1181–1189.
- Sajjiya, S. F., Nusaika, M. F., & Sajeetha, A. M. F. (2023). The impact of liquidity management on financial performance: A study of listed manufacturing companies on Colombo Stock Exchange. *International Journal of Research Publication and Reviews*, 4(3), 4–17.
- Sharma, A. K., & Kumar, S. (2010). Effect of working capital management on firm profitability: Empirical evidence from India. *Global Business Review*, 12(1), 159–173. doi:10.1177/097215091001200110
- Stanić, M., Cita, M., & Prša, D. (2022). The impact of COVID-19 on liquidity management in small and medium-sized trade businesses: The Croatian case. *Review of Contemporary Business, Entrepreneurship and Economic Issues*, 35(2), 261–274. doi:10.51680/ev.35.2.3
- Sumawe, S., & Magoti, L. (2025). The impact of financial risk on financial performance: A case of listed manufacturing companies in Tanzania. *African Journal of Accounting and Social Science Studies*. doi:10.4314/ajasss.v6i2.2
- Wooldridge, J. M. (2020). *Introductory econometrics: A modern approach* (7th ed.). Boston, MA: Cengage Learning.

Appendices

As a baseline analysis, pooled Ordinary Least Squares (OLS) estimation was conducted using the same 101 firm-quarter observations employed in the main panel analysis. The model included the Quick Ratio, Current Ratio, pandemic-phase indicators, their interaction terms, firm size, and leverage. Diagnostic tests were conducted to assess the classical OLS assumptions, and heteroskedasticity-robust standard errors were additionally estimated.

Appendix 1. Baseline Pooled OLS Estimation

Variable	Coefficient	SE	t	p-value
Quick Ratio	−0.0105	0.0148	−0.71	0.481
During-pandemic	−0.0204	0.0271	−0.75	0.455
Post-pandemic	−0.0361	0.0268	−1.35	0.181
During × Quick Ratio	−0.0057	0.0214	−0.27	0.789
Post × Quick Ratio	0.0416	0.0185	2.25	0.027
Current Ratio	0.0061	0.0151	0.40	0.688
During × Current Ratio	−0.0130	0.0208	−0.63	0.533
Post × Current Ratio	0.0004	0.0185	0.02	0.984
Firm Size	0.0011	0.0011	0.96	0.341
Leverage	−0.0312	0.0114	−2.74	0.007
Constant	0.0842	0.0266	3.16	0.002

Model statistics: N = 101; F(10,90) = 16.70, p < 0.001; R² = 0.6498; Adjusted R² = 0.6109; Root MSE = 0.0222.

Appendix 2. OLS Diagnostic Tests

Diagnostic test	Statistic	p-value	Conclusion
Mean VIF ¹	27.51	—	Elevated in interaction specification
Breusch–Pagan/Cook–Weisberg	$\chi^2(1) = 69.38$	<0.001	Heteroskedasticity present
White test	$\chi^2(38) = 67.29$	0.0024	Heteroskedasticity present
Shapiro–Wilk	W = 0.8880	<0.001	Residuals non-normal
Ramsey RESET	F(3,87) = 46.06	<0.001	Evidence of specification inadequacy

¹The high VIF values are concentrated mainly in the pandemic-phase indicators and interaction terms. Firm Size (VIF = 1.67) and Leverage (VIF = 2.62) remain low. Because interaction terms are products of their constituent variables, VIFs from the full uncentered interaction specification should be interpreted cautiously.

Appendix 3. Pooled OLS with Heteroskedasticity-Robust Standard Errors

Variable	Coefficient	Robust SE	t	p-value
Quick Ratio	−0.0105	0.0073	−1.43	0.156
During-pandemic	−0.0204	0.0103	−1.99	0.050
Post-pandemic	−0.0361	0.0147	−2.46	0.016
During × Quick Ratio	−0.0057	0.0105	−0.54	0.589
Post × Quick Ratio	0.0416	0.0158	2.63	0.010
Current Ratio	0.0061	0.0049	1.25	0.213
During × Current Ratio	−0.0130	0.0099	−1.31	0.194
Post × Current Ratio	0.0004	0.0108	0.03	0.973
Firm Size	0.0011	0.0011	1.03	0.307
Leverage	−0.0312	0.0119	−2.61	0.010
Constant	0.0842	0.0099	8.48	<0.001

Model statistics: $N = 101$; $F(10,90) = 36.69$, $p < 0.001$; $R^2 = 0.6498$; *Root MSE* = 0.0222.

The baseline pooled OLS model was statistically significant ($F(10,90) = 16.70$, $p < 0.001$) and explained approximately 65% of the variation in ROA ($R^2 = 0.6498$). The Post-pandemic × Quick Ratio interaction was positive and statistically significant under both conventional OLS ($\beta = 0.0416$, $p = 0.027$) and heteroskedasticity-robust inference ($\beta = 0.0416$, $p = 0.010$), providing baseline evidence that the Quick Ratio–ROA relationship changed in the post-pandemic period. The Current Ratio interaction terms were not statistically significant.

The diagnostic tests, however, identified departures from the classical OLS assumptions. Both the Breusch–Pagan test ($\chi^2(1) = 69.38$, $p < 0.001$) and White test ($\chi^2(38) = 67.29$, $p = 0.0024$) indicated heteroskedasticity, while the Shapiro–Wilk test ($W = 0.8880$, $p < 0.001$) rejected residual normality. The Ramsey RESET test ($F(3,87) = 46.06$, $p < 0.001$) also indicated potential specification inadequacy. Accordingly, pooled OLS is retained as a baseline benchmark rather than the principal estimator. The main analysis relies on the fixed effects panel model with firm-clustered standard errors and Webb-weighted wild-cluster bootstrap inference.

Appendix 4. Fixed-Effects Model with Calendar-Year Controls

Variable	Coefficient	Robust SE	t	p-value	95% CI
Quick Ratio	-0.0228	0.0097	-2.35	0.057	-0.0466, 0.0010
Pandemic phase: During	-0.0713	0.0227	-3.14	0.020	-0.1269, -0.0158
Pandemic phase: Post	-0.1020	0.0282	-3.61	0.011	-0.1712, -0.0329
Quick Ratio × During	-0.0165	0.0126	-1.31	0.240	-0.0473, 0.0144
Quick Ratio × Post	0.0432	0.0133	3.25	0.017	0.0107, 0.0757
Current Ratio	-0.0101	0.0071	-1.43	0.203	-0.0274, 0.0072
Current Ratio × During	0.0171	0.0145	1.18	0.284	-0.0184, 0.0526
Current Ratio × Post	0.0278	0.0161	1.73	0.135	-0.0116, 0.0673
Firm Size	0.0079	0.0067	1.18	0.283	-0.0085, 0.0244
Leverage	-0.0482	0.0322	-1.50	0.185	-0.1271, 0.0307
Calendar-year controls					
2019	-0.0026	0.0061	-0.43	0.686	-0.0174, 0.0123
2020	0.0115	0.0053	2.15	0.075	-0.0016, 0.0245
2021	Omitted	—	—	—	—
2022	0.0122	0.0081	1.51	0.182	-0.0076, 0.0320
2023	Omitted	—	—	—	—
Constant	0.0263	0.1059	0.25	0.812	-0.2328, 0.2855

Model statistics and phase-interaction tests

Statistic	Result
Observations	101
Firms	7
Within R ²	0.7499
Between R ²	0.1231
Overall R ²	0.5324
Quick Ratio interactions, conventional F(2,6)	5.81 (p=.0395)
Quick Ratio interactions, Webb F(2,6)	5.8780 (p=.0339)
Current Ratio interactions, conventional F(2,6)	1.77 (p=.2486)
Current Ratio interactions, Webb F(2,6)	1.7916 (p=.3587)
Firm fixed effects	Yes
Firm-clustered SE	Yes
Calendar-year controls	Yes
Webb bootstrap replications	9,999

Note: The dependent variable is ROA. Pre-pandemic is the reference phase. The model includes firm fixed effects and standard errors clustered at the firm level. Calendar-year indicators were introduced as a robustness check for common time-varying conditions. Because pandemic phases are defined using calendar years, some year indicators are perfectly collinear with the phase indicators and were automatically omitted. Webb-weighted wild-cluster bootstrap tests use 9,999 replications with Webb weights. Bold p-values indicate statistical significance at the 5% level.