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# Does digital transformation improve firm performance? Evidence from Vietnamese VN30 firms during the COVID-19 pandemic

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**Abstract:** Digital transformation is widely promoted as a strategy for enhancing firm resilience during crises, yet rigorous evidence from emerging markets remains limited. This study examines whether digital transformation is associated with improved operational performance among Vietnam's leading listed corporations during the COVID-19 pandemic. We employ a Difference-in-Differences (DiD) framework using panel data for 30 VN30 firms over 2010–2024 (N = 429). Firms are classified into high and low digital transformation intensity groups based on a composite index of credit, operational, and liquidity risk indicators for 2020–2024. Return on assets (ROA) is the primary outcome, with macroeconomic and firm-level risk controls. The DiD estimator for the interaction between the post-COVID period and high digital transformation intensity is positive but not statistically significant (coefficient = 0.0121, p = 0.356), indicating no detectable short-term ROA gains. Formal pre-trend tests show that the parallel trends assumption does not fully hold in this sample (p = 0.008), which limits strict causal interpretation and suggests that estimates should be viewed as descriptive associations. The findings suggest that digital transformation may not translate into immediate profitability improvements for large Vietnamese firms, consistent with the "productivity paradox" and the need for longer adjustment horizons. Credit risk and liquidity management emerge as more important short-run performance drivers than digital investment. The study underscores the importance of explicit assumption testing in DiD applications and highlights that digital transformation benefits in emerging markets may require patient capital and extended implementation periods.
***Keywords:*** *COVID-19, Difference-in-differences, Digital transformation, Emerging markets, Firm performance, Vietnam.*

## 1. Introduction

Corporate performance has emerged as a crucial indicator of firm competitiveness and economic resilience in the context of globalization and increased capital mobility. Firm performance encompasses not only traditional measures of profitability but also managerial capability, adaptability to external shocks, and commitment to sustainable development [1]. Empirical evidence suggests that corporate performance results from complex interactions between endogenous factors, such as capital structure, firm size, and corporate governance, and exogenous elements, including industry characteristics, macroeconomic fluctuations, and global shocks [2-4].

Vietnam's deepening economic integration and rapid capital market development have created both opportunities and challenges for enterprises. The VN30 index, comprising the 30 largest and most liquid companies on the Ho Chi Minh City Stock Exchange, represents the core force driving Vietnam's capital market. These blue-chip firms account for approximately 80% of the market capitalization and serve as a barometer for the overall health of Vietnam's economy [5]. The COVID-19 pandemic, which began in early 2020, created unprecedented disruptions to global supply chains, consumer demand, and business operations [6]. For VN30 firms, the pandemic served as both a crisis and a catalyst, forcing rapid digital transformation across sectors, including banking, retail, telecommunications, and manufacturing [7].


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Despite growing interest in digital transformation and COVID-19's impact on firm performance, several critical research gaps remain. First, while international studies demonstrate that COVID-19 significantly reduced firm profitability globally, Vietnam-specific quantitative evidence using rigorous causal inference methods remains limited [8, 9]. Second, existing studies typically examine individual factors in isolation, such as macroeconomic variables, ownership structure, or financial leverage, without integrating internal firm characteristics with external shocks like COVID-19 [10-12]. Third, most studies focus on short time frames and lack comprehensive datasets spanning pre-crisis (2010-2019), crisis (2020-2022), and recovery periods (2023-2024). This temporal limitation prevents the assessment of both immediate and long-term effects of digital transformation on firm resilience and performance.

This study contributes to the literature in three main ways. First, it provides the first VN30-level evidence on how digital transformation relates to firm performance during the COVID-19 shock in an emerging market, using a long 2010–2024 panel rather than short crisis windows. Second, it explicitly tests the parallel trends assumption underlying the DiD design and shows that it does not fully hold in this context, thereby documenting an "assumption violation problem" that is often ignored in applied work and motivating a more cautious, descriptive interpretation of DiD estimates. Third, it highlights that credit and liquidity risk management explain more short-run variation in ROA than digital transformation intensity, enriching the debate on the productivity paradox of digital investments and the conditions under which digitalization can strengthen firm resilience in emerging markets.

The remainder of this paper is organized as follows: Section 2 reviews relevant literature on firm performance determinants, COVID-19 impacts, and digital transformation. Section 3 describes the data, variables, and methodology. Section 4 presents empirical results and comprehensive diagnostic testing. Section 5 discusses theoretical and practical implications with explicit attention to methodological limitations. Section 6 concludes with limitations and directions for future research.

## 2. Literature Review

### *2.1. Digital Transformation and Firm Performance*

Digital transformation involves integrating digital technologies to fundamentally reshape value creation and delivery [13]. During crises, it enhances resilience through remote operations, customer engagement, and supply chain optimization. The World Economic Forum [6]. Li et al. [14] show that firms with advanced digital deployment experienced smaller performance declines and faster recovery during COVID-19.

However, short-term profitability effects remain contested. The "productivity paradox" [15, 16] documents that IT investments often yield delayed returns due to high implementation costs and organizational change requirements. While some studies find efficiency gains, others emphasize time lags before financial benefits materialize.

### *2.2. COVID-19 and Firm Performance*

COVID-19 created unprecedented shocks across sectors. Bartik et al. [7]. Hu and Zhang [8] analyze 77 countries and find average ROA declines of 2.1 percentage points globally. Shen et al. [9] document similar effects in China, with state-owned firms showing greater resilience due to policy support.

These findings highlight the role of crisis management capabilities and financial buffers, but emerging market evidence using causal methods remains limited.

### *2.3. Emerging vs. Developed Markets*

Performance drivers differ systematically. Developed market firms leverage VRIN resources (valuable, rare, inimitable, non-substitutable), explaining approximately 60% of performance variance, versus around 25% in emerging markets where country-specific advantages dominate [2].

Emerging firms face challenges in digital capability development due to institutional voids, weak IP protection, and financing constraints.


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*2.4. Vietnam Evidence and Research Gaps*

Vietnamese studies examine ownership [17], leverage [17], and COVID impacts [7, 9, 18] but lack VN30-level analysis of digital transformation using causal methods like DiD with parallel trends testing. No prior work integrates 15-year panels spanning pre/post-COVID with explicit assumption validation. This study fills these gaps by providing VN30 DiD evidence on digital transformation during COVID-19, explicitly testing identification assumptions, and combining firm risk indicators with macro controls to reveal short-run performance drivers.

## 3. Materials and Methods

*3.1. Data Sources and Sample*

This study employs a balanced panel dataset comprising 30 firms listed in the VN30 index on the Ho Chi Minh City Stock Exchange, covering 2010-2024. After removing observations with missing values for key variables, the final analytical sample comprises 429 firm-year observations (originally 450, reduced due to missing data). The VN30 index represents blue-chip companies with the highest market capitalization and liquidity, spanning key economic sectors including banking (10 firms in the treatment group), real estate (3 in treatment), energy (3 in control), manufacturing (1 in control), telecommunications (2 in control), retail (2 in control), consumer goods (3 in control), and other sectors.

Financial data were collected from audited annual financial statements from the HOSE database, Thomson Reuters Eikon, and FiinPro Platform. Macroeconomic variables were obtained from the General Statistics Office of Vietnam, the State Bank of Vietnam, and the International Monetary Fund [19]. The 15-year observation period encompasses three phases: pre-pandemic (2010-2019, 329 observations), pandemic period (2020-2024, 100 observations).

*3.2. Treatment and Control Group Classification*

Following established practice in DiD studies, firms are classified into treatment and control groups based on their digital transformation intensity during 2020–2024. In the absence of detailed, consistently disclosed digital investment data, we proxy digital transformation using a composite index that captures how intensively firms rely on digital systems for credit, operations, and liquidity management.

The index combines three dimensions. First, the credit risk ratio (RR_TIN_DUNG), measured by the average collection period, reflects the extent to which firms deploy digital credit and payment platforms to monitor, score, and recover receivables in real time. Second, the operational risk indicator (RR_HOAT_DONG), proxied by changes in operating margins, captures efficiency gains from process automation, online distribution channels, and digitally enabled cost control. Third, the liquidity risk ratio (RR_THANH_KHOẢN), measured by the current ratio, reflects the use of digital tools for inventory, cash, and working capital management.

Firms with the highest composite scores on these three dimensions (Top 15, n = 15) are classified as the treatment group (high digital transformation intensity), while the remaining firms (Bottom 15, n = 15) form the control group (low digital transformation intensity). This classification yields 225 treatment observations and 204 control observations over 2010–2024. Given data limitations, this proxy-based approach inevitably introduces measurement noise and is likely to attenuate true effects, biasing estimated DiD coefficients toward zero and making our null findings conservative.

Treatment Group (High Digital): ACB, BID, CTG, HDB, KDH, MBB, NVL, PDR, STB, TCB, TPB, VCB, VHM, VJC, VTC.

Control Group (Low Digital): BVH, FPT, GAS, GVR, HPG, MSN, MWG, PLX, PNJ, POW, SAB, SSI, VNM, VPB, VRE.

*3.3. Variables and Measurements*

Dependent Variable: ROA = net income after tax / total assets (decimal form)

DiD Variables:
Post = 1 for 2020–2024 (post-COVID), 0 otherwise
Treat = 1 for high digital intensity (Top 15 firms), 0 otherwise
Post × Treat = DiD interaction term
Controls:
GDP = GDP growth (%)
INF = inflation rate (%)
INT_RATE = lending interest rate (%)
ER = VND/USD exchange rate
CREDIT_RISK = average collection period (days) [RR_TIN_DUNG]
OPER_RISK = operating margin change [RR_HOAT_DONG]
LIQ_RISK = current ratio [RR_THANH_KHOAN]
Notes: Variable definitions match Table 5 exactly. Risk ratios proxy digital transformation intensity per Section 3.2.

*3.4. Econometric Model Specification*

The baseline Difference-in-Differences (DiD) model is specified as follows:

$$ROA_{it} = \beta_0 + \beta_1 Post_t + \beta_2 Treat_i + \gamma(Post_t \times Treat_i) + X_{it}'\delta + \epsilon_{it}$$

where $ROA_{it}$ denotes the return on assets of firm i in year t; $Post_t$ captures the post-COVID period effect; $Treat_i$ indicates digital transformation intensity group membership; and the interaction term $Post_t \times Treat_i$ represents the DiD estimator. The coefficient $\gamma$ measures the differential change in ROA for high digital transformation firms relative to low digital transformation firms in the post-COVID period. $X_{it}$ is a vector of control variables, and $\epsilon_{it}$ denotes the idiosyncratic error term.

The DiD coefficient $\gamma$ identifies the average treatment effect under the standard parallel trends assumption. This assumption requires that, in the absence of heterogeneous digital transformation intensity, the treatment and control groups would have exhibited similar pre-COVID trends in ROA. We formally test this assumption in Section 4.2.

*3.5. Identification Strategy and Assumption Testing*

The DiD estimator identifies the average treatment effect of digital transformation on ROA under the standard parallel trends assumption, which requires that, in the absence of differential digital transformation intensity, high- and low-intensity firms would have followed similar ROA trends over time. We assess this assumption using both visual inspection of pre-COVID trajectories and formal pre-trend tests.

First, we plot the average ROA for the treatment and control groups over 2010–2019 and examine whether the gap remains roughly stable before the COVID-19 shock. Second, we regress the annual difference in mean ROA between the two groups on a linear time trend for the pre-treatment period. The slope coefficient from this regression is statistically significant ($p = 0.008$), indicating a declining pre-COVID gap and suggesting that the parallel trends assumption does not fully hold in this sample.

This violation has two important implications. Conceptually, it limits the extent to which the DiD coefficient can be interpreted as a clean causal effect of digital transformation. Practically, it motivates a more cautious interpretation of our estimates as capturing conditional associations rather than definitive causal impacts. Throughout the paper, we therefore emphasize descriptive patterns and treat the DiD estimates as suggestive evidence of how digital transformation intensity correlates with changes in ROA, conditional on observed firm- and macro-level controls.

All analyses were conducted using Python with statsmodels and pandas libraries. We employed OLS regression with standard errors (not clustered, given the balanced panel). Parallel trends tests validated the DiD identifying assumption. Statistical significance was assessed at 1%, 5%, and 10% levels [20]. Diagnostic tests (Jarque-Bera, Breusch-Pagan) assessed residual properties.

*3.6. Robustness and Alternative Specifications*

To assess the robustness of our findings, we considered several alternative specifications commonly recommended for panel DiD designs. First, we estimated models with firm and year fixed effects to absorb time-invariant heterogeneity across firms and common macroeconomic shocks over time. Second, we employed heteroskedasticity-robust standard errors and examined specifications with standard errors clustered at the firm level, following best practices for panel data in finance.

While these alternative specifications do not overturn the main qualitative pattern of a small and statistically insignificant DiD coefficient, they confirm that inference is sensitive to the choice of standard errors and reinforce the need for cautious interpretation given the violated parallel trends assumption. Rather than over-claiming causal effects, we view these robustness checks as supporting the descriptive nature of our conclusions.

# 4. Results

*4.1. Sample Composition and Descriptive Statistics*

**Table 1.**
Descriptive statistics of ROA by group, 2010–2019.

| Group | Mean | ROA | Std. dev. | 95% CI lower | 95% CI upper |
|---|---|---|---|---|---|
| Control (Treat=0) | 165 | 0.0904 | 0.0788 | 0.0784 | 0.1024 |
| Treatment (Treat=1) | 165 | 0.0227 | 0.0344 | 0.0175 | 0.0280 |
| Combined | 330 | 0.0566 | 0.0695 | 0.0491 | 0.0641 |

**Note:** ROA is net income after tax divided by total assets. ROA is reported in decimal form (e.g., 0.068 corresponds to 6.8 percentage points). Treat = 1 for firms with high digital transformation intensity, Treat = 0 otherwise.

Table 1 reports descriptive statistics for ROA by treatment status during the pre-COVID period, 2010–2019. Control firms exhibit an average ROA of 0.0904, while treatment firms record a much lower average of 0.0227, with the combined sample mean equal to 0.0566. An independent samples t-test (not reported in the table) shows that this baseline difference is statistically significant: the mean ROA of control firms is about 0.068 higher, or roughly 6.8 percentage points, than that of treatment firms ($t \approx 10.11$, $p < 0.001$).

**Table 2.**
Test of baseline ROA differences, 2010–2019.

| Statistic | Value |
|---|---|
| Mean difference (Control −Treatment) | 0.0677 |
| Standard error | 0.0067 |
| t-statistic | 10.11 |
| p-value | <0.001 |
| 95% CI lower | 0.0546 |
| 95% CI upper | 0.0808 |

**Note:** The table reports results from an independent samples t-test comparing the mean ROA between control and treatment firms during 2010–2019. ROA is net income after tax divided by total assets and is reported in decimal form. Control and treatment groups are defined as in Table 1.

Table 2 reports the results of an independent samples t-test on the baseline ROA difference between control and treatment firms during 2010–2019. The test confirms a highly statistically significant gap of approximately 0.068 ($t \approx 10.11$, $p < 0.001$), underscoring the importance of the DiD approach, which accounts for these pre-existing performance differences by examining differential changes over time.

### *4.2. Parallel Trends Assumption Test (CRITICAL FINDING)*

**Table 3.**
Pre-COVID mean ROA by group and year, 2010–2019.

| Year | Control mean ROA | Treatment mean ROA | Difference (Control − Treatment) |
|---|---|---|---|
| 2010 | 0.0943 | 0.0191 | 0.0753 |
| 2011 | 0.0791 | 0.0075 | 0.0716 |
| 2012 | 0.0789 | 0.0046 | 0.0743 |
| 2013 | 0.0862 | 0.0078 | 0.0784 |
| 2014 | 0.1045 | 0.0173 | 0.0872 |
| 2015 | 0.0904 | 0.0206 | 0.0697 |
| 2016 | 0.0970 | 0.0202 | 0.0768 |
| 2017 | 0.0990 | 0.0336 | 0.0654 |
| 2018 | 0.0943 | 0.0367 | 0.0576 |
| 2019 | 0.0928 | 0.0378 | 0.0550 |

**Note:** ROA is net income after tax divided by total assets and is reported in decimal form. Control and treatment groups are defined as in Table 1. The "Difference" column reports the yearly gap in mean ROA between control and treatment firms.

Table 3 presents the average ROA for control and treatment firms over the pre-COVID period 2010–2019. The control group consistently outperforms the treatment group, with the ROA gap ranging from approximately 0.0550 to 0.0872. The difference declines from about 0.0753 in 2010 to 0.0550 in 2019, implying a reduction of roughly 0.020, or around 27 percent, over the pre-treatment window. This narrowing gap suggests that treatment and control firms were not on perfectly parallel profitability trajectories before the COVID-19 shock.

**Table 4.**
Pre-trend regression of ROA gap on time trend, 2010–2019.

| Variable | Coefficient | Std. error | t-statistic | p-value |
|---|---|---|---|---|
| Constant | 0.0712 | 0.0061 | 11.67 | <0.001 |
| Time trend | −0.0033 | 0.0010 | −3.35 | 0.008 |

**Note:** The dependent variable is the annual difference in mean ROA between control and treatment firms (Control mean ROA − Treatment mean ROA) over 2010–2019. The time trend is a linear variable taking values from 1 (2010) to 10 (2019). ROA is reported in decimal form. Robust standard errors are reported in parentheses.

Table 4 formally tests the parallel trends assumption by regressing the annual ROA gap between control and treatment firms on a linear time trend for 2010–2019. The estimated slope on the time trend is −0.0033 ($t \approx -3.35$, $p = 0.008$), indicating a statistically significant downward trend in the pre-COVID ROA difference. This result confirms that the profitability gap between the two groups was shrinking over time, and thus,1 the parallel trends assumption does not fully hold in this setting.


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### 4.3. *Difference-in-Differences Regression Results*

**Table 5.**
Difference-in-Differences regression of ROA on digital transformation intensity.

| Variable | Coefficient | Std. error | t-statistic | p-value | 95% CI lower | 95% CI upper |
|---|---|---|---|---|---|---|
| Constant | 0.1588 | 0.0873 | 1.82 | 0.070 | −0.0128 | 0.3303 |
| Post | −0.0159 | 0.0117 | −1.36 | 0.175 | −0.0389 | 0.0071 |
| Treat | −0.0544 | 0.0070 | −7.74 | <0.001 | −0.0682 | −0.0406 |
| Post × Treat | 0.0121 | 0.0132 | 0.92 | 0.356 | −0.0137 | 0.0380 |
| GDP | 0.0014 | 0.0027 | 0.51 | 0.607 | −0.0039 | 0.0067 |
| INF | −0.0016 | 0.0009 | −1.80 | 0.072 | −0.0033 | 0.0001 |
| INT_RATE | 0.0642 | 0.0705 | 0.91 | 0.363 | −0.0744 | 0.2027 |
| ER | 0.0000 | 0.0000 | 0.02 | 0.983 | −0.0000 | 0.0000 |
| CREDIT_RISK | −0.000007 | 0.000002 | −2.95 | 0.003 | −0.000011 | −0.000002 |
| OPER_RISK | 0.0184 | 0.0137 | 1.35 | 0.179 | −0.0085 | 0.0454 |
| LIQ_RISK | −0.4275 | 0.1745 | −2.45 | 0.015 | −0.7705 | −0.0845 |

Model statistics: N = 429; $R^2$ = 0.296; F-statistic = 17.59; p-value (model) < 0.001.
**Note:** The dependent variable is ROA, measured as net income after tax divided by total assets and reported in decimal form. Post = 1 for years 2020–2024 and 0 for 2010–2019. Treat = 1 for firms with high digital transformation intensity and 0 otherwise. Post × Treat is the DiD interaction term. GDP, INF, INT_RATE, and ER denote macroeconomic controls; CREDIT_RISK, OPER_RISK, and LIQ_RISK denote firm-level risk indicators. Robust standard errors are reported. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 5 presents the main Difference-in-Differences regression results. The coefficient on the interaction term Post × Treat, which captures the DiD estimator, is 0.0121 (standard error = 0.0132, t ≈ 0.92, p = 0.356, 95% CI: −0.0137 to 0.0380). This small and statistically insignificant estimate indicates that, conditional on macroeconomic and firm-level controls, high-intensity digital transformers did not experience clearly superior short-run ROA performance relative to low-intensity firms in the post-COVID period.

Among the control variables, CREDIT_RISK is negative and statistically significant at conventional levels, suggesting that longer collection periods are associated with lower ROA. LIQ_RISK is also negative and significant, indicating that weaker liquidity positions correlate with poorer profitability. In contrast, the macroeconomic variables (GDP growth, inflation, lending interest rate, and the exchange rate) are not statistically significant, and the model explains about 29.6% of the variation in ROA ($R^2$ = 0.296).

### 4.4. *Diagnostic Tests*

**Table 6.**
Residual diagnostic tests.

| Test statistic | Value | p-value | Interpretation |
|---|---|---|---|
| Jarque–Bera normality | 42.51 | <0.001 | Residuals non-normal |
| Breusch–Pagan heteroskedasticity | 18.23 | 0.001 | Heteroskedasticity present |

**Note:** The Jarque–Bera test assesses normality of OLS residuals (null: residuals are normally distributed). The Breusch–Pagan test assesses homoskedasticity of residuals (null: error variance is constant). Both tests are conducted on residuals from the baseline DiD specification in Table 5 (N = 429). p-values are reported to three decimal places.

Table 6 reports diagnostic tests on residuals from the baseline DiD specification. The Jarque–Bera test rejects the null hypothesis of normality ($p < 0.001$), indicating outliers or non-linearities. The Breusch–Pagan test also rejects homoskedasticity ($p = 0.001$), showing non-constant error variance.

These violations imply that OLS standard errors may be inefficient and that alternative approaches, such as robust standard errors or clustered standard errors at the firm level, would be preferable for inference. They also suggest potential avenues for model improvement, including transformations of the dependent variable (e.g., log ROA), additional control variables, or non-linear specifications.

## 5. Discussion

### *5.1. Null Finding: What Does It Mean?*

The DiD analysis yields a small and statistically insignificant coefficient on the interaction between the post-COVID period and high digital transformation intensity (approximately 0.012, $p = 0.356$). In other words, firms with higher digital transformation intensity did not exhibit clearly superior short-run ROA performance relative to less digitalized peers during 2020–2024. This pattern is consistent with the well-documented productivity paradox of information technology, whereby substantial digital investments often fail to generate immediate, easily observable gains in accounting profitability.

At the same time, the methodological validity of a causal interpretation is compromised because the parallel trends assumption does not fully hold ($p = 0.008$). The declining pre-COVID gap in ROA suggests that treatment and control firms were on different trajectories even before the pandemic, making it difficult to disentangle the effect of digital transformation from underlying dynamics. We therefore interpret the null result primarily as descriptive evidence that, in this VN30 context, short-term profitability did not diverge markedly between high- and low-intensity digital transformers during the COVID-19 shock.

### *5.2. Sectoral and Market Context*

The composition of the treatment and control groups reveals important sectoral patterns that help explain the observed baseline ROA differences and null DiD results. The high digital transformation group is dominated by banking firms (10 out of 15 firms: ACB, BID, CTG, HDB, MBB, STB, TCB, TPB, VCB, VPB), supplemented by real estate developers and a few others. In contrast, the control group comprises traditional sectors such as energy (GAS, PLX, POW), manufacturing (HPG), consumer goods (VNM, SAB, PNJ), retail (MWG), and financial services (SSI, BVH).

This sectoral imbalance contributes to the substantial baseline ROA gap of approximately 0.068 (Table 1). Banks typically generate stable but lower ROA due to their low-margin, high-volume business model, while consumer goods and retail firms often enjoy higher margins. Moreover, risk-based proxies for digital intensity (credit risk ratios, operating margins) may capture digitalization differently across sectors: banks invest heavily in core banking systems, payment platforms, and AI-driven credit scoring, whereas traditional firms may rely less on these metrics even if they pursue digital initiatives.

These structural differences imply that our DiD estimates capture a mix of digital transformation effects and persistent sectoral profitability patterns. The null result may therefore reflect both the short-term limitations of digital investments and underlying differences in business models between financial and non-financial firms.

### *5.3. Credit Risk as Key Driver*

Among the control variables, CREDIT_RISK emerges as the most robust predictor of ROA (coefficient $\approx -0.000007$, $p = 0.003$), indicating that firms with longer collection periods experience systematically lower profitability. This finding highlights the central role of working capital management in emerging markets, where cash flow constraints and credit market imperfections amplify the importance of efficient receivables collection.

LIQ_RISK is also negative and statistically significant (coefficient $\approx -0.428$, $p = 0.015$), suggesting that weaker liquidity positions, proxied by lower current ratios, are associated with poorer ROA performance. These results align with evidence that financial frictions dominate firm performance in developing economies, where access to external finance is costly, and firms often face binding liquidity constraints.

Notably, neither digital transformation intensity nor macroeconomic variables (GDP growth, inflation, interest rates, exchange rates) are statistically significant, implying that short-run profitability in the VN30 universe is driven more by internal financial discipline than by strategic digital investments


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or broad economic cycles. This pattern suggests that digital transformation may complement, but not substitute for, sound working capital practices.

*5.4. Emerging Market Context*

Several features of the Vietnamese institutional environment may explain both the null DiD result and the methodological challenges encountered. First, data quality issues are pervasive in emerging markets: financial reporting gaps, inconsistent disclosure of digital investments, and reliance on proxy measures introduce substantial measurement error that likely biases coefficients toward zero.

Second, the treatment group's heavy banking composition reflects Vietnam's policy-driven digitalization, where state-owned and private banks received regulatory mandates and subsidies to develop core banking systems and digital payment infrastructure during 2020–2024. However, these investments may prioritize compliance and risk management over revenue generation, explaining the absence of short-term ROA gains.

Third, the parallel trends violation and diagnostic test failures (non-normality, heteroskedasticity) may stem from structural features of emerging market data: high cross-firm heterogeneity, occasional outliers from governance issues or policy shocks, and limited sample size (N=30 firms). These challenges underscore the difficulty of conducting clean causal inference in data-scarce environments and highlight the value of transparent assumption testing.

Finally, the five-year post-COVID window may be too short to capture digital transformation payoffs if, as suggested by the productivity paradox literature, benefits require organizational restructuring and complementary investments that unfold over seven to ten years.

*5.5. When Null Findings Are Valuable*

Null results like ours are informative precisely because they challenge widely held assumptions about digital transformation. First, they caution against the naive view that digital investments automatically boost short-run profitability during crises, even for large, blue-chip firms in fast-growing emerging markets. Second, they highlight methodological pitfalls: the parallel trends assumption, which underpins much of the DiD literature, often fails formal statistical testing even when pre-trends appear visually plausible.

Third, our findings contextualize international evidence. Studies documenting positive digital transformation effects [14, 21] may reflect shorter causal chains, better data, or institutional environments where digital investments more directly translate into revenue gains. In contrast, Vietnamese VN30 firms appear to face longer adjustment periods, possibly due to higher implementation costs, weaker complementary capabilities, or offsetting financial pressures.

Practically, the null result advocates for patient capital in digital transformation strategies: managers, investors, and policymakers should expect delayed payoffs and avoid premature abandonment of digital initiatives. Methodologically, it provides a template for rigorous DiD analysis in emerging markets, combining explicit assumption testing, transparent reporting of violations, and cautious descriptive interpretation rather than overconfident causal claims.

## 6. Conclusion

*6.1. Summary of Findings*

This study examines how digital transformation intensity relates to the operational performance of Vietnamese VN30 firms during the COVID-19 period using a Difference-in-Differences framework on 2010–2024 panel data. The DiD estimator for the interaction between the post-COVID period and high digital transformation intensity is positive but not statistically significant, indicating no robust evidence of short-term ROA improvements for more digitalized firms. Pre-trend tests reveal that the parallel trends assumption does not fully hold, which undermines a strict causal interpretation of the DiD coefficient and motivates a descriptive reading of the results. Credit and liquidity risk indicators emerge as more powerful short-run predictors of ROA than digital transformation intensity, and substantial baseline differences between treatment and control firms highlight structural heterogeneity within the VN30 universe.

### *6.2. Theoretical Contributions*

This study makes three main theoretical contributions. First, it adds emerging market evidence to the debate on the profitability of digital transformation, showing that even large, highly visible firms may not experience immediate ROA gains from intensified digitalization during systemic shocks. Second, it documents an "assumption violation problem" in applied DiD work by explicitly testing and reporting a failure of the parallel trend assumption, thereby highlighting the gap between formal identification requirements and empirical practice. Third, it underscores the central role of credit and liquidity risk management in shaping short-run firm performance, suggesting that in emerging markets, financial frictions and working capital constraints can overshadow the near-term benefits of digital investments and lengthen the horizon over which digital transformation pays off.

### *6.3. Practical Implications*

For corporate managers, the findings caution against expecting rapid ROA improvements from digital transformation alone and emphasize the need to combine digital initiatives with disciplined credit and liquidity risk management. In the VN30 context, digitalization appears more likely to support resilience and process efficiency than to generate immediate accounting profits, implying that managers and boards should adopt longer investment horizons and avoid abandoning digital projects prematurely. For investors, the results suggest that claims about short-term digital transformation payoffs should be scrutinized carefully and evaluated alongside fundamental indicators of working capital quality and risk. For policymakers, the evidence indicates that fostering digital transformation in emerging markets may require complementary policies that ease financial constraints and provide patient capital, so that firms can sustain digital investments long enough for benefits to materialize.

### *6.4. Limitations*

Several limitations should be acknowledged when interpreting our findings. First, the Difference-in-Differences design relies on a parallel trends assumption that does not fully hold in our setting, as pre-trend tests reveal a statistically significant decline in the ROA gap between treatment and control firms before COVID-19. This violation constrains the extent to which our DiD estimates can be interpreted as capturing clean causal effects.

Second, the proxy-based measurement of digital transformation intensity is inherently imprecise. The composite index built from credit, operational, and liquidity risk indicators inevitably contains measurement error and may misclassify firms' true digitalization levels. Such noise is likely to attenuate estimated coefficients toward zero, making our null finding conservative in the sense that any true effects of digital transformation on ROA would be understated rather than overstated.

Third, the sample is limited to 30 VN30 firms, which constrains statistical power and raises questions about generalizability to mid-cap and small-cap firms or non-listed enterprises. The short post-COVID window (2020–2024) further limits our ability to detect longer-term effects, especially if digital transformation benefits materialize over seven to ten years, as suggested by the productivity paradox literature.

Fourth, the empirical models exhibit evidence of non-normal residuals and heteroskedasticity, indicating potential model misspecification and reinforcing the need for robust or clustered standard errors. While robustness checks with alternative specifications do not overturn the qualitative pattern of a small and insignificant DiD coefficient, they underscore that our results should be interpreted cautiously and primarily as descriptive evidence from a specific emerging market context.

### *6.5. Future Research Directions*

Future research can extend and deepen our analysis in several directions. First, extending the observation window beyond 2024 would allow researchers to examine whether digital transformation effects on profitability and resilience emerge over longer horizons, especially if payoffs materialize only after seven to ten years of implementation. Tracking VN30 firms to 2030–2035, and possibly expanding the sample to include mid-cap and small-cap firms, would help assess convergence patterns and heterogeneity across firm sizes.

Second, alternative empirical strategies could address some of the identification challenges documented in this study. Researchers may employ event-study designs, modern multi-period DiD estimators, or matching-based approaches to better account for non-parallel pre-trends and staggered adoption of digital technologies. Quantile regression and distributional methods could also reveal whether digital transformation has asymmetric effects across the performance distribution, benefiting only the most or least profitable firms.

Third, future work should seek richer and more direct measures of digital transformation. Combining financial statement data with information on IT spending, digital platform usage, patenting, or textual analysis of annual reports would reduce reliance on risk-based proxies and mitigate measurement error. Such data would improve the precision of treatment classification and help disentangle different types of digital investments, such as front-end customer-facing technologies versus back-end risk management systems.

Finally, mixed-methods research that integrates quantitative panel analysis with qualitative case studies could shed light on the mechanisms through which digital transformation interacts with governance, organizational capabilities, and institutional constraints in emerging markets. Comparative studies across countries or regions would further clarify whether the patterns observed for Vietnamese VN30 firms are specific to Vietnam's institutional environment or reflect broader emerging market dynamics.

## Transparency:

The author confirms that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

## Copyright:



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