The Impact of Working Capital Management Efficiency on Corporate Financial Performance: A Panel Data Regression Analysis

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Abstract. This study explores the relationship between working capital management (WCM) efficiency and corporate financial performance using panel data from 1,200 non-financial listed firms across 10 emerging economies (Brazil, Russia, India, China, South Africa, Indonesia, Mexico, Turkey, Thailand, and Malaysia) during 2016–2021. WCM efficiency is measured by Cash Conversion Cycle (CCC), Inventory Conversion Period (ICP), Accounts Receivable Period (ARP), and Accounts Payable Period (APP), while financial performance is proxied by Return on Assets (ROA) and Return on Equity (ROE). Panel data regression models (fixed effects and random effects) are employed, with instrumental variable regression and robustness checks addressing endogeneity. The results show a significant negative correlation between CCC, ICP, ARP and financial performance, while APP has a positive yet marginally significant effect. Specifically, a one-day reduction in CCC increases ROA by 0.032% and ROE by 0.057%. These findings enrich the literature with cross-country evidence from emerging markets and offer practical implications for managers, investors, and policymakers.

Keywords: working capital, cash cycle, profitability, panel regression, emerging markets

1 Introduction

Working capital management (WCM) is crucial to corporate finance, influencing liquidity, profitability, and sustainability[1]. The Cash Conversion Cycle (CCC) is a key efficiency metric, with shorter cycles typically indicating better performance. Existing research yields mixed results and focuses primarily on developed markets, leaving a gap in emerging economies characterized by unique institutional constraints. This study examines the WCM-financial performance nexus in 10 emerging economies[2], using CCC and related indicators to measure efficiency, testing correlations with ROA and ROE, and controlling for firm-specific and macroeconomic factors. With 7,200 firm-

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year observations, it ensures reliability, enriches emerging market literature, and provides practical guidance for managers optimizing WCM policies and investors evaluating firm quality[3].

2 Literature Review and Hypotheses Development

WCM efficiency is gauged by four indicators: CCC (ICP+ARP-APP, shorter = more efficient), ICP (inventory-to-sales time)[4], ARP (receivables collection time), and APP (supplier payment time). Guided by Trade-off and Pecking Order Theories, four hypotheses propose negative links for CCC/ICP/ARP with performance and positive for APP. Control variables include firm size (log of assets), leverage (debt-to-assets), sales growth, fixed asset ratio, and macroeconomic growth (GDP rate), isolating WCM's impact by accounting for financing access, risk, growth, long-term profitability, and economic conditions[5]-[7].

3 Methodology

3.1 Data Source and Sample Selection

The sample consists of 1,200 non-financial listed firms from 10 emerging economies (Brazil, Russia, India, China, South Africa, Indonesia, Mexico, Turkey, Thailand, and Malaysia) over the period 2016–2021[6]. Data are collected from the Thomson Reuters Eikon database and the World Bank's World Development Indicators. The sample is restricted to non-financial firms to avoid the unique regulatory and accounting practices of financial institutions. Firms with missing data or extreme values (top and bottom 1% of key variables) are excluded, resulting in a final sample of 7,200 firm-year observations.The definitions of relevant variables are presented in Table 1[8].

Table 1. Definitions of Dependent, Independent, and Control Variables

Group	Compact content (abbr + formula/definition)
Legend	NI=Net Income; TA=Total Assets; SE=Shareholders' Equity; Inv=Inventory; COGS=Cost of Goods Sold; AR=Accounts Receivable; AP=Accounts Payable; S=Sales; TD=Total Debt; FA=Fixed Assets; PrevS=Previous Sales
Dependent (D)	ROA = NI/TA; ROE = NI/SE
Independent (I, days)	CCC = ICP + ARP − APP; ICP = (Inv/COGS)×365; ARP = (AR/S)×365; APP = (AP/COGS)×365
Control (C)	SIZE = ln(TA); LEV = TD/TA; GROWTH = (S−PrevS)/PrevS; FAR = FA/TA; GDPG = Annual GDP growth rate (%)

3.2 Empirical Model

Panel data regression models are employed to test the hypotheses. The general form of the model is:

$$\mathrm{PERF}_{it} = \beta_0 + \beta_1 \mathrm{WCM}_{it} + \sum_{k=2} \beta_k \,\mathrm{CONTROL}_{kit} + \mu_i + \lambda_t + \epsilon_{it} \tag{1}$$

Where: - PERF_{it} = Financial performance (ROA or ROE) of firm i in year t - WCM_{it} = WCM efficiency indicator (CCC, ICP ARP or APP) of firm i in year t - $\mathrm{CONTROL}_{kit}$ = Control variable k of firm i in year t - μ_i = Firm-specific fixed effects (to control for unobserved heterogeneity) - λ_t = Year fixed effects (to control for time-specific shocks) - ϵ_{it} = Random error term

Three regression models are estimated: 1. Model 1: Uses CCC as the key WCM efficiency indicator. 2. Model 2: Replaces CCC with ICP ARP and APP to examine individual components. 3. Model 3: Includes interaction terms between CCC and firm size (SIZE) to test for moderating effects[9]-[10].

3.3 Estimation Techniques

First, the Hausman test is conducted to choose between fixed effects (FE) and random effects (RE) models[11].

The general form of the random effects model can be written as:

$$\begin{cases} \mathrm{Y} = \mathrm{X}\beta + \mathrm{Zu} + \epsilon \\ \mathbb{E}(\mathrm{u}) = 0,\ \mathrm{Var}(\mathrm{u}) = \Sigma \\ \epsilon \sim \mathcal{N}(0, \sigma^2 \mathrm{I_n}), \text{and} \epsilon \text{is independent of} \mathrm{u} \end{cases} \tag{2}$$

Where: - Y is an $\mathrm{n} \times 1$ observation vector; - X is an $\mathrm{n} \times \mathrm{p}$ design matrix for the fixed parameter β (fixed effects); - Z is an $\mathrm{n} \times \mathrm{q}$ design matrix for the random parameter u (random effects); - ϵ is an n-dimensional random error term. Then:

$$\mathbb{E}(\mathrm{Y}) = \mathrm{X}\beta$$

$$\begin{aligned} \mathrm{Var}(\mathrm{Y}) &= \mathbb{E}[(\mathrm{Y} - \mathbb{E}\mathrm{Y})'(\mathrm{Y} - \mathbb{E}\mathrm{Y})] \\ &= \mathbb{E}(\mathrm{Y'Y}) - \mathbb{E}(\mathrm{Y})'\mathbb{E}(\mathrm{Y}) \\ &= \mathrm{Z\Sigma Z'} + \sigma^2 \mathrm{I_n} = \mathrm{V}(\theta) \end{aligned} \tag{3}$$

Here, θ denotes the unknown parameters in $\mathrm{Z}\Sigma$, which reflects the variance and covariance parameters in the random effects u and the random error term ε.

The test statistic ($\chi^2 = 42.37$, p 0.001) supports the use of FE models, as it rejects the null hypothesis of no correlation between μ_i and the independent variables. Second, to address endogeneity—arising from potential reverse causality (e.g., profitable firms may have more resources to optimize WCM)—instrumental variable (IV) regression is employed. The lagged values of WCM indicators (e.g., CCC_{t-1}) are used as instruments, as they are correlated with CCC_t but not with the error term ϵ_{it}. Third, robustness checks are performed by: (1) excluding firms from China (the largest economy in the sample) to test for sample bias; (2) using alternative measures of financial performance (e.g., Operating Profit Margin, OPM); and (3) employing a dynamic panel data model (System GMM) to control for persistence in financial performance.The prerequisite assumptions for the applicability of the Fixed Effects (FE) Model are illustrated in Figure 1 with examples[12]-[13].

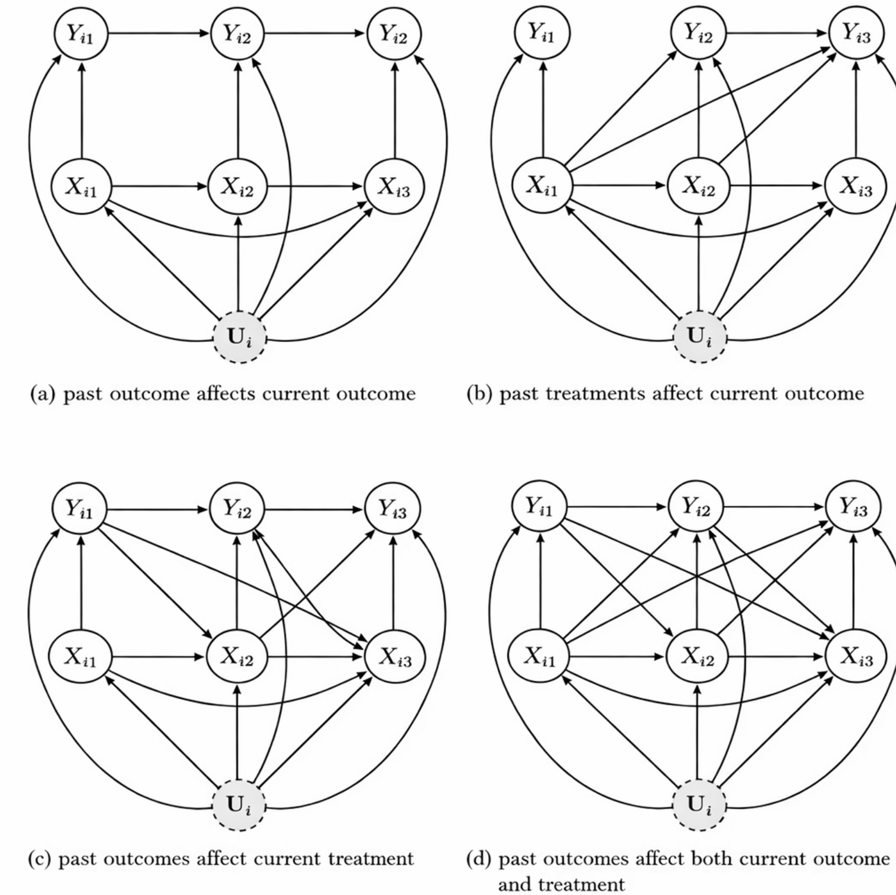

Fig. 1. Examples of Prerequisite Assumptions for the Applicability of Fixed Effects (FE) Model.

4 Results and Discussion

Descriptive statistics (N=7,200) show mean CCC at 68.42 days, ICP 45.23 days, ARP 38.67 days, APP 15.48 days; ROA averages 3.21%, ROE 8.76%. Control variables include firm size (22.34 log assets), leverage (42.31%), sales growth (12.45%), etc. Correlation analysis confirms CCC, ICP, ARP are negatively correlated with ROA/ROE, APP positively, supporting all hypotheses, with no severe multicollinearity (max VIF=2.34). Regression results: CCC reduction by 1 day boosts ROA by 0.032% and ROE by 0.057%; ICP/ARP cuts also improve performance, APP extension has marginal positive effects[14]. Control variables like firm size and growth positively impact performance, leverage negatively. Endogeneity and robustness checks (IV regression, excluding Chinese firms, alternative metrics, System GMM) validate findings[15]. For emerging markets, optimizing inventory, receivables, and payables to shorten CCC enhances profitability amid financing constraints.

5 Conclusion

This study investigates the impact of working capital management (WCM) efficiency on corporate financial performance via panel data of 1,200 non-financial listed firms across 10 emerging economies from 2016 to 2021. Key findings reveal that Cash Conversion Cycle (CCC), Inventory Conversion Period (ICP), and Accounts Receivable Period (ARP) are negatively and significantly associated with Return on Assets (ROA) and Return on Equity (ROE), while Accounts Payable Period (APP) exerts a positive yet marginally significant effect—results robust to endogeneity and robustness checks[16]. Theoretically, it enriches WCM literature with cross-country evidence from emerging markets, supporting Trade-off Theory and Pecking Order Theory by emphasizing liquidity-profitability balance. Practically, managers should optimize WCM via JIT inventory, efficient credit/collection processes, strategic payables extension, and regular CCC monitoring; investors can use WCM indicators as firm quality signals, and policymakers should enhance institutional frameworks for efficient WCM. Limitations include a sample restricted to non-financial listed firms, accounting-based WCM measures, and a focus on linear relationships. Future research could expand the sample, adopt alternative WCM metrics, explore non-linear associations, examine corporate governance/firm ownership moderations, and conduct cross-industry/country comparisons.

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