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KEYWORDS	ABSTRACT
working capital management; cash conversion cycle; firm life cycle; institutional environment; financial constraints; nonlinear performance	This study examines whether the association between working-capital intensity and profitability varies with firm life-cycle stage and the economic-development context of the firm's home country. Using 379,191 firm-year observations for 31,112 listed non-financial and non-utility firms in 134 countries over 2000–2025, we measure working-capital intensity with the cash conversion cycle (CCC) and estimate quadratic CCC–ROA specifications. The empirical design combines pooled models with firm fixed effects and several sensitivity specifications, including lagged regressors, an industry-year instrumental-variable approach, alternative performance measures, and dynamic models. The pooled quadratic specification yields a statistically significant concave CCC–ROA association and an estimated turning point of approximately 133 days. However, this estimate changes materially across estimators, so it is treated as a model-dependent conditional association rather than a structural or universal optimum. Life-cycle subsamples also display different fitted profiles, with the growth estimate exceeding the mature estimate, while the joint development-by-life-cycle results show nonparallel patterns across advanced and emerging/developing economies. Overall, the evidence is most consistent with a contingent and specification-sensitive relationship between working-capital intensity and profitability. The results do not establish a causal or universally transferable CCC target.
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Introduction

Working capital management (WCM) connects operating decisions with corporate finance because inventory, receivables, and payables determine how much capital is committed to day-to-day operations. The cash conversion cycle (CCC), measured as days inventory outstanding plus days sales outstanding minus days payable outstanding, summarizes the time between cash outflow for operations and cash recovery from customers (Johan et al., 2024; Kiyamaz et al., 2024). A shorter CCC can release funds and reduce financing requirements, whereas an excessively lean working-capital position may increase stockout and production-disruption risk or restrict sales supported by trade credit (Sethi & Bapat, 2026; Wang et al., 2020). The relevant empirical question is therefore whether the association between CCC and profitability changes across the observed range rather than whether firms should uniformly minimize CCC.

The existing evidence does not support a universal linear interpretation. Studies report negative average associations between working-capital duration and firm performance, while nonlinear specifications allow operating benefits at lower or moderate levels of working capital before financing and holding costs become more important (Johan et al., 2024; Kiyamaz et al., 2024; Silva & Silva, 2026). Differences across samples, financing conditions, and economic environments motivate examining both the shape of the association and its sensitivity to the empirical specification.

Two contextual factors are central to this question. First, firm life-cycle stage is associated with differences in operating conditions and working-capital requirements (Sethi & Bapat, 2026; Sethi & Dash, 2025). Working-capital requirements may therefore differ as firms move through introduction, growth, maturity, and decline. Second, the external economic environment can affect access to finance, contract enforcement, trade credit, and the costs of holding inventory and receivables. Recent evidence links institutional quality with CCC differences (Chang et al., 2025), while (Sethi & Dash, 2025) document differences in working-capital adjustment across life-cycle stages under firm-level geopolitical risk. Thus, both organizational stage and external environment may moderate the observed CCC–performance relationship.

The literature has generally examined nonlinear working capital, firm life-cycle effects, and institutional or country-level context in separate empirical settings. Recent research has nevertheless begun to connect working-capital management with firm life-cycle heterogeneity and cross-country differences (Kiyamaz et al., 2024; Sethi & Bapat, 2026). This study integrates these dimensions by asking whether the shape and location of the estimated CCC–performance profile vary across life-cycle stages and broad economic-development groups. The goal is not to identify a single optimal CCC, but to determine whether the empirical relationship is context-dependent and if the estimated form of the relationship depends on organizational and economic context.

The empirical sample comprises 134 countries and 31,112 listed non-financial and non-utility firms with a total of 379,191 firm-year observations from fiscal years 2000 to 2025. Life-cycle

stages are constructed using the operating, investing and financing cash-flow signs as outlined by Dickinson (2011) and countries are classified as advanced or emerging market and developing economies based on the IMF classification. The baseline models incorporate year effects and firm-clustered standard errors, whereas additional specifications incorporate firm fixed effects, lagged explanatory variables, an IV design with industry-year instruments, alternative measures of performance, and dynamic models.

The analysis yields three findings. First, the pooled quadratic specification produces a statistically significant concave CCC–ROA profile, but its turning point is not robust across estimators. Second, life-cycle subsamples have different fitted profiles, with the reported growth-stage estimate exceeding the mature-stage estimate. Third, the joint development-by-life-cycle estimates are nonparallel: the fitted profile varies across organizational stages and development groups. These results support a contingent interpretation of working-capital intensity and profitability rather than a universal managerial target.

The remainder of the paper is organized as follows. Theoretical framework and hypotheses are developed in Section 2. Section 3 presents the sample, variable construction and the empirical specifications. Section 4 provides descriptive evidence, baseline estimates, subgroup results, alternative outcomes, component analysis and specification sensitivity analyses. The findings, implications, and limitations are discussed in Section 5 and the conclusion is given in Section 6.

Recent empirical studies reinforce the relevance of working-capital efficiency while identifying important contextual conditions. Evidence from Scandinavian firms associates longer working-capital cycles with weaker performance, and Chinese high-technology manufacturing evidence indicates that foreign ownership moderates the CCC–profitability relationship (Hassan et al., 2023; Zhou et al., 2025). Family governance also conditions working-capital policy and the market value of working-capital investment (Hong et al., 2024). These studies support examining heterogeneity rather than transferring a single fitted threshold across firms.

Financing relationships provide a further source of heterogeneity. Research examines working-capital lending through the banking system, while Japanese small-business evidence shows that young and mature firms obtained different liquidity support from banks during the global financial crisis (Rahman et al., 2024; Tsuruta, 2023). Korean evidence likewise finds that the association between public listing and trade-credit use differs between business-group and other firms (Im et al., 2025). Firm age, listing status, and group affiliation may therefore affect financing choices in ways that a broad development indicator cannot capture.

A second research strand connects working capital with institutions, financial constraints, and economic uncertainty. Silva and Silva (2026) document a nonlinear working-capital–profitability relationship that varies with financial constraints. Chang et al. (2025) examine institutional quality and the CCC, while Sethi and Dash (2025) relate geopolitical risk to working-capital adjustment across firm life-cycle stages. These findings motivate considering organizational stage and the external financing environment jointly.

Digital processes may alter both financing access and working-capital adjustment. Business-process digitalization is associated with more efficient working-capital management, and digital transformation moderates the relationship between product-market competition and adjustment toward working-capital targets (Wang & Nie, 2025; Li & Zhou, 2025). Related research links fintech development with trade-credit access and examines how blockchain-based financing platforms align information-processing capacity with financing requirements (Liu et al., 2025; Jia et al., 2026). These mechanisms are relevant potential controls or moderators in future analyses, rather than mechanisms identified by the present regressions.

The quality and availability of information also influence supplier financing. Evidence on third-party online sales disclosure and annual-report readability links informative disclosures with trade-credit access (Liu et al., 2023; Li et al., 2024). Accounting transparency has also been associated with capital turnover through a trade-credit channel, particularly among younger firms (Sun & Huang, 2025). This literature highlights an information environment that may differ within both advanced and emerging/developing economies.

Recent life-cycle research adds a strategic dimension. Business strategy is associated with trade credit differently across life-cycle stages, while lean and agile supply-chain strategies have different associations with transparency over the firm life cycle (Al-Hadi & Hussain, 2025; Wang et al., 2024). Research on innovation and ESG engagement further examines growth prospects and transitions between life-cycle stages (Paudel & Mukherjee, 2026; Hwang & Liu, 2025). Life-cycle indicators consequently summarize evolving conditions and should not be treated as immutable firm characteristics.

This study integrates these themes by estimating nonlinear CCC-performance profiles across life-cycle stages in a large international panel and reporting sensitivity to estimators and outcome measures. Its contribution is evidence on conditional organizational and economic heterogeneity. The observational design does not establish a structural or causal optimum.

Theoretical Foundation and Hypothesis Development

Working-Capital Trade-Off and Nonlinearity

Working-capital policy balances the operating benefits of current assets against financing costs and the opportunity cost of capital. Research on inventory buffers and volume flexibility illustrates how firms manage uncertain operating environments (Mwangola et al., 2024). Analytical supply-chain studies examine how receivables-backed financing, clearance sales, and loan-payment timing interact with operational decisions under capital constraints (Cheng et al., 2023; Priya et al., 2023). These mechanisms make the benefits of holding working capital dependent on both operating conditions and financing arrangements.

Payment terms can change the allocation of financing burdens within the supply chain. Models compare advance payment, delayed payment, and reverse factoring in pull supply chains; buyer-

intermediated and direct financing; and alternative purchasers of trade-credit insurance (Wang et al., 2025; Chen, 2025; Yan et al., 2025). Such analytical evidence informs the operational-financial trade-off, although model-specific financing solutions do not by themselves imply a common empirical CCC optimum.

The costs of working-capital investment also depend on what firms forgo and how credit risk is distributed. Chinese evidence identifies a strategic substitution between trade-credit provision and innovation, while separate evidence reports a U-shaped association between trade-credit financing and financial distress, moderated by social trust (Huang et al., 2024; Tang et al., 2025). Supply-chain-finance adoption also modifies the trade-payables-performance relationship (Wetzel & Wagner, 2025). A quadratic CCC specification permits a concise assessment of changing conditional slopes, but its turning point remains a mathematical feature of the fitted model rather than a demonstrated causal target.

H1: The CCC-performance relation is concave over the observed support, such that the estimated linear term is positive and the quadratic term is negative, implying an interior turning point within the relevant range.

Firm Life Cycle and Working-Capital Adaptation

The firm life-cycle theory posits that the growth opportunities, operating uncertainties, financing access and organizational routines of the firms vary during introduction, growth, maturity, shakeout and decline phases (Sethi & Bapat, 2026; Wang et al., 2020). Demand uncertainty is likely to be higher for introduction and growth firms and they might maintain inventory buffers or customer credit to support growth. A recent study also indicates that there are systematic differences in working-capital management among the firms in different corporate life-cycle stages, in which the firms in growth and mature stages of the life cycle showed more efficient working-capital management compared with the firms in introduction and decline stages of the life cycle (Sethi & Bapat, 2026). Mature firms may have more consistent demand, have established customer relationships and bargaining power that allow for tighter inventory and collection policies. The expected decline pattern is less clear, as firms can either shorten working capital, or lengthen it due to reduced opportunities or financing constraints, as both increased and reduced working capital increase the likelihood of declining profits. The life-cycle framework, therefore, implies different profiles rather than a uniform progression over the stages (Sethi & Bapat, 2026).

Financing constraints may influence stage-specific responses by limiting expansion and encouraging adaptation. Policy-based lending evidence links additional credit with firm growth and investment, while research on capacity utilization examines how uncertainty and financial constraints interact with expansion opportunities (Dore et al., 2025; Mohades et al., 2026). SME studies also examine credit shocks and R&D financing, and find that cost-saving management innovations can partly offset constraints on revenue growth (Grandi et al., 2024; De Blick et al.,

2024). These findings concern financing and adaptation rather than a direct estimate of the life-cycle-specific CCC turning points tested here.

H2: The estimated CCC turning point varies across firm life-cycle stages; specifically, the reported growth-stage turning point is higher than the reported mature-stage turning point.

Institutional Environment and Financial Constraints

National institutions and financial development can influence the cost and availability of external finance, contract enforcement, trade credit, and the ability to finance receivables. Recent evidence shows that stronger institutional quality is associated with shorter CCC, with the cost of capital and access to external financing identified as important mechanisms (Chang et al., 2025). These mechanisms can change the costs and benefits associated with carrying inventory and receivables. Financial constraints have also been linked to differences in the working-capital level associated with profitability (Silva & Silva, 2026). Cross-country evidence further documents differences between developed and emerging economies, including differences in the effects of CCC components on firm performance (Kiyamaz et al., 2024). In this study, economic-development status is used as a broad contextual indicator rather than as a direct measure of any single institutional mechanism.

Institutional context extends beyond a country's development category. Italian provincial evidence indicates that institutional development limits adverse liquidity transfers through trade credit during financial stress, while international evidence links social capital and institutional conditions with financing constraints (Coricelli et al., 2025; Mertzanis & Houcine, 2026). Research on bankruptcy courts and social-credit reform further examines legal protection, monitoring, and trade-credit access (Wang et al., 2023; Wang et al., 2026). These findings motivate more detailed institutional measures in future work; the advanced-economy indicator cannot identify these channels separately.

H3: Economic-development status moderates the conditional CCC–performance relation.

Integrated Contingency Framework

Firm life-cycle effects need not be independent of the external environment. The financing and operating implications of a given organizational stage can differ where creditor protection, financial depth, factoring markets, and contract enforcement vary. Recent evidence shows that institutional quality is associated with firms' CCC, while cross-country evidence indicates that the CCC–performance relationship differs between developed and emerging economies (Chang et al., 2025; Kiyamaz et al., 2024).

Supply-chain structure creates additional contextual conditions. Supplier concentration and supplier operational inflexibility are associated with less trade credit in recent Chinese evidence, whereas common ownership along supply chains can facilitate supplier credit (Li & Luan, 2025;

Glavee & Yang, 2026; Xu, 2023). Collaboration, information quality, and transaction dependence also condition supply-chain-finance adoption, while transparency can have different associations with bank borrowing and supply-chain financing (Li et al., 2023; Shi et al., 2024). Joint life-cycle and development profiles may therefore reflect multiple interacting financing and operating arrangements.

The joint implication is not that every advanced-economy firm follows one trajectory, or every emerging/developing-economy firm follows another. Rather, development status may condition the association between life-cycle stage and working-capital intensity. This motivates the paper's joint subgroup analysis, while the interpretation remains descriptive and conditional because the design does not identify causal effects of moving between life-cycle stages or development environments.

H4: Economic-development status and firm life-cycle stage jointly condition the estimated CCC-performance profiles, producing different fitted life-cycle patterns across advanced and emerging/developing economies.

Data and Empirical Methodology

Sample Selection and Firm Life-Cycle Classification

The firm-level data are drawn from S&P Capital IQ Global Financials and merged with country classifications from the IMF World Economic Outlook database. Financial institutions (SIC 6000–6999) and regulated utilities (SIC 4900–4949) are excluded because their balance-sheet structures and working-capital processes are not directly comparable with those of operating firms. Following the study's stated sample-cleaning procedure, firm-years with CCC values between –100 and 365 days are retained to limit the influence of extreme observations generated by very small denominators or unusual operating structures.

Firm life-cycle stages are classified from the signs of cash flow from operations, investing, and financing using the reported mapping: Introduction, Growth, Mature, Shakeout, and Decline for the remaining sign combinations. The approach follows the cash-flow-based classification of Dickinson (2011), which continues to be used in recent firm-level research (Sethi & Bapat, 2026; Sethi & Dash, 2025). After observations with missing core regression variables and duplicate firm-year identifiers are removed, the estimation sample contains 379,191 firm-year observations for 31,112 firms in 134 countries over 2000–2025. Because the final fiscal year has fewer observations than 2023–2024, 2025 is treated as the latest available reporting year rather than a complete cross-section.

Winsorization and Variable Definitions

Continuous accounting variables are winsorized at the 1st and 99th percentiles to limit the influence of extreme ratio observations. Variables are retained in economically interpretable

units: days for CCC and its components, percentage points for profitability measures and sales growth, ratios for leverage, capital expenditure, and cash, and natural logarithms for firm size. The winsorization and CCC-range restriction improve comparability and reduce the influence of extreme observations, but they may also exclude economically unusual firm-year observations; accordingly, the results are interpreted for the retained estimation sample.

Performance measures: Return on assets (ROA, %) equals net income divided by total assets multiplied by 100. Return on equity (ROE, %) and EBITDA margin (%) are alternative outcomes. Because these measures capture different aspects of performance, their estimates are interpreted as sensitivity evidence rather than interchangeable measures of the same construct (Johan et al., 2024; Kiyamaz et al., 2024).

Cash conversion cycle = DSI + DSO – DPO, where DSI = days sales of inventory, DSO = days sales outstanding and DPO = days payable outstanding. CCC² is part of the main nonlinear specification. There is a turning point in the estimated quadratic and, if it falls in the observed range, it is interpreted as a mathematical feature of the quadratic, but not as a structural target (Silva & Silva, 2026).

Firm life-cycle stage is determined using the classification of Dickinson (2011) based on cash-flow signs. Economic development is a binary variable that takes the value of one for IMF advanced economies and the value of zero for emerging market and developing economies.

The regressions include firm size (ln total assets), financial leverage (debt/assets), capital expenditure ratio (capital expenditure/assets), cash ratio (cash/assets), and one-year revenue growth. These variables capture scale, capital structure, investment intensity, liquidity, and demand conditions that are plausibly related to both profitability and working-capital policy (Kiyamaz et al., 2024). Their inclusion reduces, but does not eliminate, concerns about omitted-variable bias.

Econometric Specifications and Identification Strategy

The baseline quadratic specification is

$$ROA_{it} = \alpha + \beta_1 CCC_{it} + \beta_2 CCC_{it}^2 + \gamma' X_{it} + \delta_t + \varepsilon_{it},$$

where δ_t denotes fiscal-year effects and X_{it} is the vector of controls. Firm fixed-effects versions additionally absorb time-invariant firm heterogeneity. Standard errors are clustered at the firm level throughout the principal panel specifications. The baseline estimates are therefore interpreted as conditional associations rather than causal effects.

When $\beta_1 > 0$ and $\beta_2 < 0$, the fitted quadratic has an interior turning point $CCC^* = -\beta_1/(2\beta_2)$. The turning point and its standard error are computed using the delta method. Because the turning point can be economically informative only when it lies within the relevant support and is

reasonably stable across specifications, the paper reports estimator sensitivity and avoids treating any single estimate as a structural working-capital target. Recent WCM research similarly employs nonlinear specifications to examine whether the working-capital-performance relationship changes across the observed range Silva and Silva (2026).

Three sensitivity strategies address different sources of potential endogeneity. First, one-year-lagged regressions relate current profitability to lagged CCC and controls, reducing contemporaneous simultaneity but not eliminating omitted-variable bias or longer-run feedback. Second, 2SLS instruments firm CCC and CCC² with the leave-one-out industry-year mean CCC and its square. The instrument is intended to capture common industry working-capital conditions; however, industry-year shocks may also affect profitability directly, so these IV estimates are treated as sensitivity evidence rather than definitive causal identification.

The sensitivity exercises examine lagged explanatory variables, instrumental-variable specifications, alternative outcomes, and dynamic models. Dynamic-panel GMM requires credible moment conditions and satisfactory serial-correlation and overidentification diagnostics (Arellano & Bond, 1991; Arellano & Bover, 1995; Blundell & Bond, 1998; Roodman, 2009). Two-step standard errors are adjusted following Windmeijer (2005). Failure of the reported diagnostics is treated as evidence against interpreting the GMM coefficients as causal or validated robustness evidence.

Empirical Results

Sample Composition and Univariate Distributions

Table 1 describes the sample by development group, firm life-cycle stage, and industry. Advanced economies contribute 212,665 firm-years (56.08%) and emerging market and developing economies contribute 166,526 (43.92%). Mature firms form the largest life-cycle group (178,527; 47.08%), followed by growth (91,025; 24.01%), decline (55,038; 14.51%), introduction (44,600; 11.76%), and shakeout (10,001; 2.64%). The sample is also distributed across industrial, consumer, materials, information-technology, and other non-financial sectors. These proportions describe the composition of the retained sample and should not be interpreted as population shares for all firms globally.

Table 1: Sample Composition Across Economic Groups, Firm Life-Cycle Stages, and Industries

Classification Dimension	Category / Group	Firm-Years (N)	Percentage (%)
Panel A: Economic Group (IMF WEO)	Advanced Economies (AE)	212,665	56.08%
	Emerging Market & Developing Economies (EMDE)	166,526	43.92%
	Total Clean Operating Sample	379,191	100.00%

Panel B: Firm Lifecycle (Dickinson 2011)	Firm Stage	Introduction (FLCS = 1)	44,600	11.76%
		Growth (FLCS = 2)	91,025	24.01%
		Mature (FLCS = 3)	178,527	47.08%
		Shakeout (FLCS = 4)	10,001	2.64%
		Decline (FLCS = 5)	55,038	14.51%
Panel C: Industry Sectors	Industry	Industrials	91,270	24.07%
		Consumer Discretionary	72,085	19.01%
		Materials	59,027	15.57%
		Information Technology	57,596	15.19%
		Consumer Staples	37,654	9.93%
		Health Care	30,144	7.95%
		Communication Services	13,440	3.54%
		Energy	12,229	3.23%
		Real Estate & Other	5,746	1.52%

Note: The estimation sample contains 379,191 firm-year observations for 31,112 listed non-financial and non-utility firms in 134 countries. Financial institutions and regulated utilities are excluded. Economic-development groups follow IMF classifications; firm life-cycle categories use the cash-flow-sign mapping described in Section 3.1. The table reports the composition of the retained sample.

Table 2 reports descriptive statistics. The mean CCC is 90.91 days (median 77.80; SD 83.08), with an interquartile range from 32.60 to 135.30 days. Mean DSI, DSO, and DPO are 85.28, 70.46, and 65.46 days, respectively. Average ROA is 3.41%, average ROE is 5.84%, and average EBITDA margin is 9.83%. There is a high level of dispersion in CCC and its components, allowing for an empirical study of potentially nonlinear conditional profiles.

Table 2: Descriptive Statistics for the Estimation Sample

Variable	N	Mean	SD	p25	Median	p75	Min	Max
Cash Conversion Cycle (CCC, Days)	379,191	90.91	83.08	32.60	77.80	135.30	-100.00	365.00
Days Sales of Inventory (DSI, Days)	378,810	85.28	71.49	32.29	68.40	117.74	0.00	365.00
Days Sales Outstanding	378,827	70.46	53.10	34.70	59.60	92.20	0.00	365.00

(DSO, Days)								
Days Payable	378,671	65.46	50.95	31.00	52.40	84.30	0.00	365.00
Outstanding								
(DPO, Days)								
Return on Assets	379,191	3.41	7.08	1.01	3.52	6.62	-35.40	22.80
(ROA, %)								
Return on	379,162	5.84	30.81	1.46	7.97	16.00	-68.50	49.20
Equity (ROE,								
%)								
EBITDA Margin	376,714	9.83	17.55	4.59	9.83	16.96	-31.80	44.50
(%)								
Firm Size (ln	379,191	12.23	2.04	10.85	12.14	13.51	5.20	19.90
(Total Assets))								
Financial	379,191	0.23	0.19	0.06	0.20	0.35	0.00	0.80
Leverage (Debt								
/ Assets)								
Capital	379,191	0.05	0.05	0.01	0.03	0.06	0.00	0.25
Expenditure								
Ratio (Capex /								
Assets)								
Cash Ratio	379,191	0.17	0.15	0.06	0.12	0.22	0.00	0.68
(Cash / Assets)								
Revenue	379,191	10.85	31.20	-4.80	6.85	19.80	-62.50	185.00
Growth (1-Year								
Sales Growth,								
%)								

Note: N = 379,191 for the full estimation sample, if available. Winsorization at the 1st and 99th percentiles is applied to the continuous variables. CCC = DSI + DSO – DPO. ROA and ROE are reported in percentage points; firm size is the natural logarithm of total assets; leverage, capital expenditure and cash are scaled by total assets and revenue growth is defined as the one-year percentage change in revenue.

Pairwise correlations and variance inflation factors are reported in Table 3. The raw correlation coefficient between CCC and ROA is the smallest negative value ($r = -0.058$), and the largest negative value is between leverage and ROA ($r = -0.238$). Revenue growth ($r = 0.162$), firm size ($r = 0.148$), and the cash ratio ($r = 0.118$) are positively correlated with ROA. The reported VIFs have a low mean value of 1.08 and a maximum of 1.17. These statistics suggest that it is not likely that these regressors are highly correlated with one another, but do not claim that omitted-variable bias, reverse causality, or model specification is not a concern.

Table 3: Correlation Matrix and Variance Inflation Factors

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	VIF
(1) Return on Assets (ROA)	1.000							
(2) Cash Conversion Cycle (CCC)	-0.058*	1.000						1.03
(3) Firm Size (ln (Assets))	0.148*	-0.075*	1.000					1.03
(4) Financial Leverage	-0.238*	-0.041*	0.178*	1.000				1.16
(5) Capital Expenditure Ratio	0.071*	0.022*	0.058*	0.082*	1.000			1.04
(6) Cash Ratio	0.118*	-0.088*	-0.198*	-0.175*	0.012*	1.000		1.17
(7) Revenue Growth	0.162*	-0.015*	0.018*	-0.012*	0.108*	0.051*	1.000	1.02
Mean VIF								1.08

Note: Pearson correlations and VIF statistics for 2000–2025. * denotes statistical significance at the 5% level or better. The maximum VIF is 1.17, and the mean VIF is 1.08. Low VIF values indicate limited multicollinearity among the included regressors but do not establish causal identification.

Baseline Linear and Quadratic Specifications (Testing H1)

Table 4 compares linear and quadratic specifications and illustrates why the nonlinear result must be interpreted cautiously. In the linear models, pooled OLS yields a small positive CCC coefficient (0.0011, $p < .01$), whereas the firm-fixed-effects model yields a negative coefficient (-0.0062 , $p < .01$). In the pooled quadratic model, CCC is positive ($\beta = 0.0152$) and CCC^2 is negative ($\beta = -0.0000571$), both statistically significant, producing a fitted turning point of 133.2 days ($SE = 2.59$). By contrast, the firm-fixed-effects quadratic model yields a near-zero linear coefficient and a negative quadratic coefficient, with an implied turning point of -5.0 days that is not statistically distinguishable from zero ($p = .738$). Thus, H1 is supported by the pooled quadratic specification, but the evidence does not establish an estimator-invariant interior turning point. The pooled estimate is therefore treated as a conditional benchmark rather than a structural optimum.

Table 4: Baseline Linear and Quadratic Regressions of CCC on ROA

Independent Variables	Model (1) Pooled OLS (Linear)	Model (2) Firm FE (Linear)	Model (3) Pooled OLS (Quadratic)	Model (4) Firm FE (Quadratic)
Cash Conversion Cycle (CCC)	0.0011*** (0.0003)	-0.0062*** (0.0003)	0.0152*** (0.0007)	-0.0002 (0.0006)

Cash Cycle (CCC ²)	Conversion Squared			-0.0000571**	-0.0000221**
Firm Size (ln (Assets))				(0.0000023)	(0.0000019)
				0.6771**	0.3279**
				(0.0163)	(0.0392)
Financial Leverage				-7.7224**	-7.0355**
				(0.1589)	(0.1444)
Capital Expenditure Ratio				17.8023**	9.9739**
				(0.4081)	(0.2914)
Cash Ratio				-2.7072**	4.5504**
				(0.2898)	(0.1998)
Revenue Growth				0.0402**	0.0444**
				(0.0007)	(0.0005)
Constant				-4.1045**	0.7248
				(0.2252)	(0.4475)
CCC Turning Point (Days)				133.2 days**	-5.0 days
CCC Turning Point Std. Error / z-stat				(SE: 2.59, p=0.000)	(SE: 15.06, p=0.738)
Firm Fixed Effects	No	Yes		No	Yes
Year Fixed Effects	Yes	Yes		Yes	Yes
Clustered SE (Firm Level)	Yes	Yes		Yes	Yes
Observations (Firm-Years)	379,191	379,191		379,191	379,191
Number of Firms / Groups	31,112	31,112		31,112	31,112
R-squared (Within / Pooled)	0.1227	0.1564		0.1287	0.1573

Note: Dependent variable is ROA (%). Models (1) and (3) are pooled OLS with year effects and firm-clustered standard errors; Models (2) and (4) add firm fixed effects. Turning points are computed as $-\beta_1/(2\beta_2)$ using the delta method. The pooled quadratic specification gives 133.2 days, whereas the firm-fixed-effects specification gives -5.0 days ($p = 0.738$). This contrast is a measure of the sensitivity of the estimators: neither is a causal or universal target.

Figure 1 summarizes the pooled quadratic specification in Table 4. Fitted ROA rises with CCC below the turning point, flattens near the turning point, and falls above it. The confidence band indicates sampling uncertainty about the fitted profile. The firm-fixed-effects specification does

not reproduce the positive interior turning point, so the figure represents the pooled conditional association rather than a universal or causal CCC threshold.

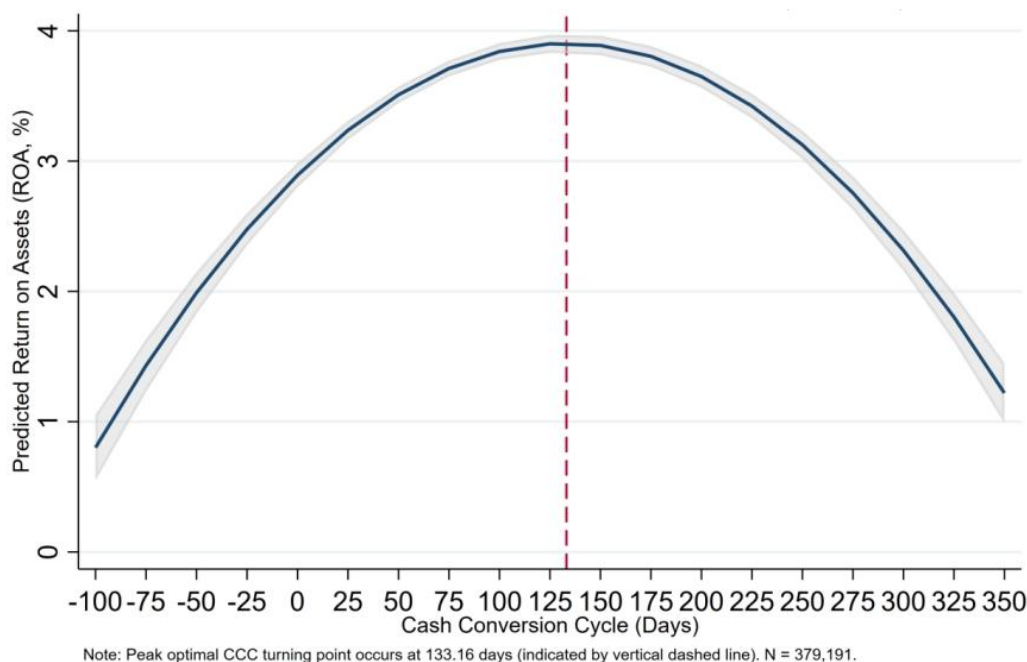


Figure 1: Fitted ROA Across the Cash Conversion Cycle

Firm Life-Cycle Heterogeneity (Testing H2)

Table 5 reports quadratic specifications estimated separately by Dickinson (2011) life-cycle stage. The quadratic terms are negative and statistically significant in all five stages. Fitted turning points are 187.7 days for introduction, 154.2 for growth, 128.2 for maturity, 163.5 for shakeout, and 124.5 for decline. The growth estimate exceeds the mature estimate by 26.0 days, consistent with the direction of H2. This descriptive difference requires a formal cross-model comparison before it can be interpreted as a statistically significant difference between turning points.

There are also differences in the model fit and coefficient magnitudes for the stage-specific regressions. R-squared is highest for introduction firms (0.3064), followed by mature (0.1916), growth (0.1702), shakeout (0.1385), and decline (0.1090). These values reflect explanatory fit in each subsample and should not be interpreted as indicating that working capital plays a greater causal role in one stage. The estimated turning points are also not monotonically ordered, specifically the shakeout and the decline estimates, so caution should be used in interpreting the life-cycle pattern as a uniform sequence.

Table 5: Firm Life-Cycle Subsample Regressions

Variables & Diagnostics	Model (1) Introduction	Model (2) Growth	Model (3) Mature	Model (4) Shakeout	Model (5) Decline
Cash Conversion Cycle (CCC)	0.0468*** (0.0017)	0.0121*** (0.0006)	0.0066*** (0.0007)	0.0103*** (0.0020)	0.0105*** (0.0012)
Cash Conversion Cycle Squared (CCC ²)	-0.0001248*** (0.0000051)	-0.0000392*** (0.0000022)	-0.0000256*** (0.0000025)	-0.0000314*** (0.0000066)	-0.0000423*** (0.0000041)
Firm Size (ln(Assets))	1.7211*** (0.0433)	0.0357*** (0.0133)	0.0967*** (0.0136)	0.8392*** (0.0465)	0.8561*** (0.0266)
Financial Leverage	-5.7387*** (0.3687)	-3.8935*** (0.1469)	-4.4121*** (0.1649)	-5.5568*** (0.4071)	-6.5213*** (0.2593)
Capital Expenditure Ratio	-0.6731 (1.0639)	12.2157*** (0.3557)	26.9639*** (0.6130)	-5.6662* (3.1761)	-0.5547 (1.5083)
Cash Ratio	-27.0981*** (0.5709)	4.6385*** (0.2176)	5.4862*** (0.2363)	-9.1187*** (0.6585)	-2.4813*** (0.4288)
Revenue Growth	0.0255*** (0.0015)	0.0466*** (0.0008)	0.0639*** (0.0008)	0.0363*** (0.0026)	0.0364*** (0.0015)
Constant	-18.6939*** (0.6144)	2.7898*** (0.2189)	2.7961*** (0.2053)	-8.2319*** (0.8058)	-7.4058*** (0.4296)
CCC Turning Point (Days)	187.7 days**	154.2 days***	128.2 days***	163.5 days***	124.5 days***
Optimal CCC Delta-Method SE	(SE: 3.02, p=0.000)	(SE: 3.71, p=0.000)	(SE: 6.24, p=0.000)	(SE: 13.50, p=0.000)	(SE: 5.85, p=0.000)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Clustered SE (Firm Level)	Yes	Yes	Yes	Yes	Yes
Observations (Firm-Years)	44600	91025	178527	10001	55038
R-squared	0.3064	0.1702	0.1916	0.1385	0.1090

Note: ROA (%) is the dependent variable. Life-cycle stages are based on Dickinson (2011). The models all control for year effects and firm-clustered standard errors. Turning points are estimated as: $-\beta_1/(2\beta_2)$. The growth-stage estimate is 154.2 days, which is in line with the direction of

growth indicated in H2, as firms grow and become increasingly similar to the mature firms' estimate of 128.2 days. These are subgroup conditional associations, not a formal equality test between models of the turning points in the table.

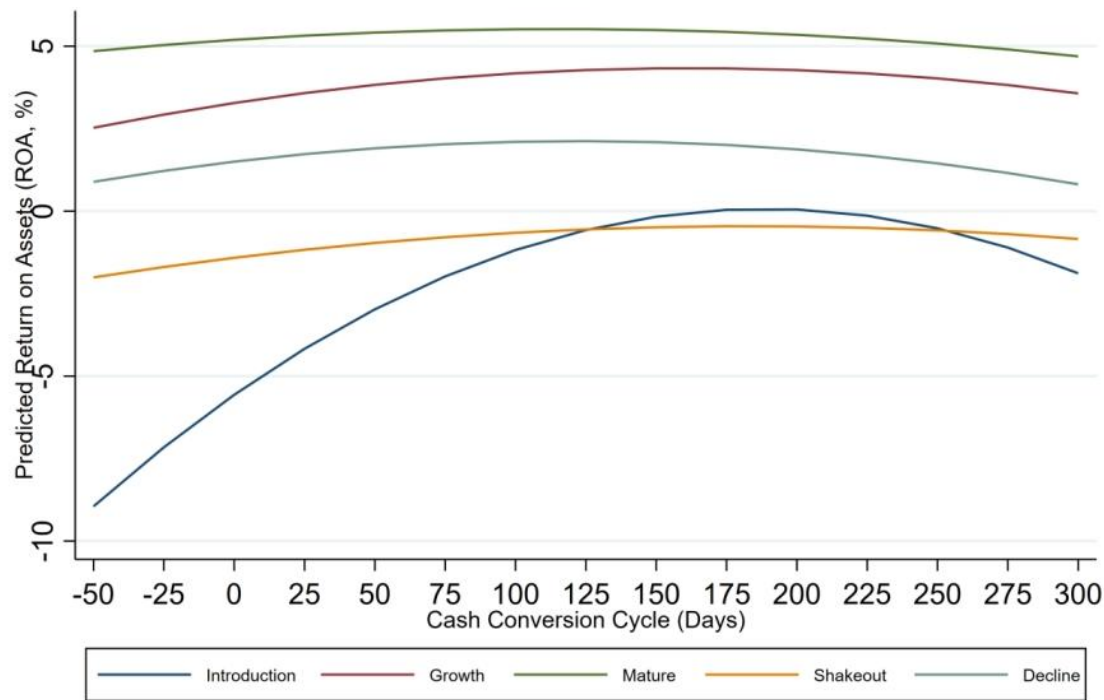


Figure 2: Fitted ROA Profiles Across Firm Life-Cycle Stages

Economic-Development Heterogeneity (Testing H3)

Table 6 compares the advanced economies (AE) with the emerging markets and developing economies (EMDE). In the full interaction model, $CCC \times \text{economic group}$ is negative (-0.0044 , $p < .01$) and $CCC^2 \times \text{economic group}$ is positive (0.0000094 , $p < .05$). The two statistically significant interaction terms suggest that the slope and curvature of the conditional relationship between CCC and ROA vary by development group, thus supporting hypothesis H3. Separate pooled subgroup models yield the fitted turning points of 125.3 days for AE firms and of 120.0 days for EMDE firms. The small magnitude of this turning-point difference should not be used as the primary evidence for H3; the formal interaction coefficients from the full model are the relevant estimates to test differential slope and curvature.

Table 6: Economic-Development Heterogeneity: Advanced vs. Emerging/Developing Economies

Variables	Model	(1)	Model	(2)	Model	(3)
Diagnostics	Full Interaction		Advanced Economies		Emerging Economies	
CCC (Days)	0.0018** (0.0007)		0.0173*** (0.0011)		0.0109*** (0.0008)	
CCC ² (Squared)	-0.0000264*** (0.0000021)		-0.0000691*** (0.0000038)		-0.0000453*** (0.0000025)	
CCC × Economic Group (AE=1)	-0.0044*** (0.0013)					
CCC ² × Economic Group (AE=1)	0.0000094** (0.0000040)					
Firm Size (ln (Assets))	0.3282*** (0.0393)		1.2686*** (0.0248)		0.0664*** (0.0181)	
Financial Leverage	-7.0378*** (0.1444)		-8.1336*** (0.2341)		-6.0469*** (0.1693)	
Capital Expenditure Ratio	9.9884*** (0.2915)		11.0117*** (0.6941)		19.2778*** (0.4343)	
Cash Ratio	4.5516*** (0.1998)		-0.7495* (0.4092)		2.6540*** (0.2882)	
Revenue Growth	0.0444*** (0.0005)		0.0305*** (0.0012)		0.0441*** (0.0007)	
Constant	0.7348 (0.4482)		-12.2059*** (0.3554)		3.3639*** (0.2351)	
CCC Turning Point (Days)			125.3 days***		120.0 days***	
Optimal CCC Delta-Method SE			(SE: 3.61, p=0.000)		(SE: 3.89, p=0.000)	
Year Fixed Effects	Yes		Yes		Yes	
Clustered SE (Firm Level)	Yes		Yes		Yes	
Observations (Firm~Years)	379191		212665		166526	
R-squared	0.1438		0.1626		0.1683	

Note: ROA(%) is the dependent variable. An indicator of economic group is 1 for advanced economies of the IMF and 0 otherwise. The interaction terms are estimated in Model (1) while subgroup quadratic regressions are reported in Models (2) and (3). Interaction coefficients show the variations in slope and curvature. The 125.3 days (AE) and 120.0 days (EMDE) are the turning points of the subgroup and are reported as descriptive conditional estimates.

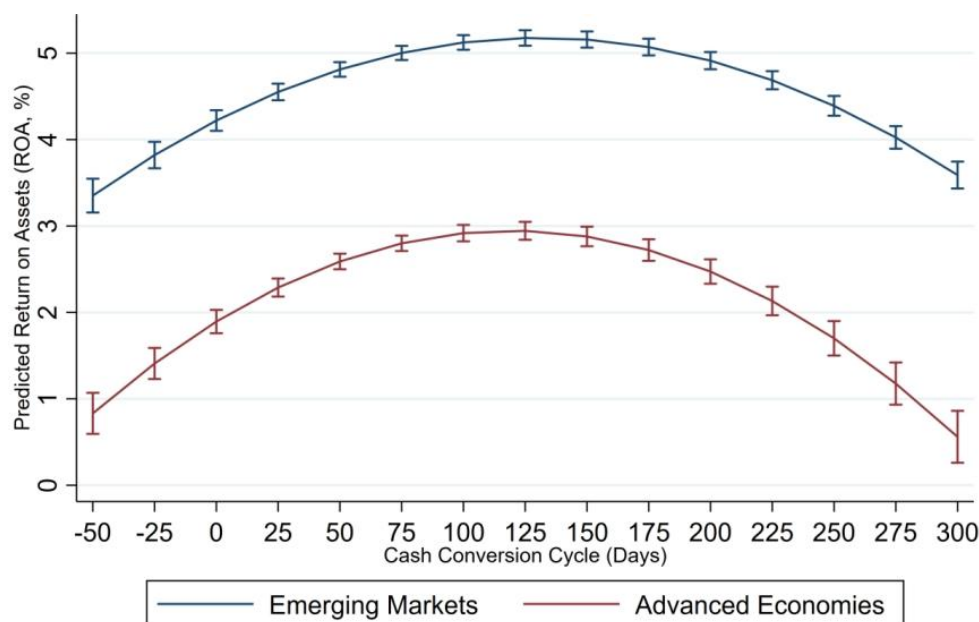


Figure 3: Fitted ROA: Advanced vs. Emerging/Developing Economies

Joint Life-Cycle and Development Heterogeneity (Testing H4)

The development groups are then intersected with three principal life-cycle stages (growth, maturity, and decline) as shown in Table 7 to examine H4. For all of the six subgroup regressions, the quadratic component of the CCC is negative and statistically significant, and so each fitted profile is concave over the range of the model. Estimated turning points do not show a consistent developmental trend between the two groups of development. These patterns are consistent with joint heterogeneity, but each subgroup design is not sufficient as a statistical test to formally test each pair of turning points individually.

In advanced-economy firms, the fitted turning point values are estimated at 160.7 days in growth, 163.8 days in maturity and 116.9 days in decline. The growth and mature estimates are close in magnitude, while the decline estimate is 46.9 days lower than the mature estimate. This pattern is compatible with the possibility that the association changes as firms enter decline, but the subgroup estimates do not establish that life-cycle transitions cause the observed change.

Among emerging/developing-economy firms, the fitted turning point falls from 143.4 days in growth to 107.5 days in maturity and then rises to 118.2 days in decline. The maturity-to-decline difference is consistent with a different conditional profile from that observed in advanced economies, but the subgroup regressions do not identify a specific financing, contracting, or institutional mechanism. Figure 4 therefore provides descriptive evidence of nonparallel fitted profiles rather than a causal explanation of why the profiles differ.

Table 7: Joint Life-Cycle × Development Subgroup Regressions

Variables / Diagnostics	Advanced Growth	Advanced Mature	Advanced Decline	Emerging Growth	Emerging Mature	Emerging Decline
Cash	0.0111***	0.0057***	0.0133***	0.0122***	0.0075***	0.0090***
Conversion Cycle (CCC)	(0.0010)	(0.0010)	(0.0018)	(0.0008)	(0.0010)	(0.0015)
Cash	-0.000034***	-0.000017***	-0.000056***	-0.000042***	-0.000035***	-0.000038***
Conversion Cycle Squared (CCC ²)	(0.0000036)	(0.0000036)	(0.0000063)	(0.0000027)	(0.0000034)	(0.0000046)
Firm Size (ln (Assets))	0.3105***	0.3052***	1.5621***	-0.1973***	-0.0373*	0.1290***
	(0.0197)	(0.0193)	(0.0387)	(0.0185)	(0.0209)	(0.0316)
Financial Leverage	-3.9746***	-3.4036***	-6.4614***	-3.5308***	-5.6730***	-5.0396***
	(0.2154)	(0.2356)	(0.3705)	(0.1926)	(0.2167)	(0.2907)
Capital Expenditure Ratio	8.1469***	21.9800***	-15.0085***	13.6441***	29.1540***	13.3768***
	(0.5667)	(0.9165)	(2.2798)	(0.4487)	(0.8056)	(1.6565)
Cash Ratio	6.2161***	7.8453***	-0.8926	5.0176***	4.4405***	4.0333***
	(0.3392)	(0.3123)	(0.5739)	(0.2764)	(0.3745)	(0.5228)
Revenue Growth	0.0484***	0.0725***	0.0238***	0.0427***	0.0543***	0.0416***
	(0.0013)	(0.0013)	(0.0023)	(0.0010)	(0.0011)	(0.0015)
Constant	-0.4642	-0.4659	-17.0601***	5.1186***	5.1716***	1.2059***
	(0.3310)	(0.2879)	(0.6448)	(0.2879)	(0.3064)	(0.4551)
CCC Turning Point (Days)	160.7 days***	163.8 days***	116.9 days***	143.4 days***	107.5 days***	118.2 days***
Optimal CCC Delta- Method SE	(SE: 7.50, p=0.000)	(SE: 16.39, p=0.000)	(SE: 6.93, p=0.000)	(SE: 4.07, p=0.000)	(SE: 6.97, p=0.000)	(SE: 7.91, p=0.000)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE (Firm Level)	Yes	Yes	Yes	Yes	Yes	Yes
Observations (Firm-Years)	48167	103318	30897	42858	75209	24141
R-squared	0.1600	0.1871	0.1710	0.1985	0.2119	0.1348

Note: Dependent variable is ROA (%). The table reports quadratic subgroup estimates for growth, maturity, and decline firms within advanced and emerging/developing economies.

Advanced-economy turning points are 160.7, 163.8, and 116.9 days; emerging/developing-economy turning points are 143.4, 107.5, and 118.2 days. The nonparallel profiles are consistent with H4, but the separately estimated subgroup models do not establish statistical significance for every pairwise turning-point difference.

Figure 4 translates the Table 7 turning-point estimates into an interaction profile with 95% confidence intervals. The AE series is nearly flat from growth to maturity and then falls to 116.9 days in decline. The EMDE series falls from 143.4 days in growth to 107.5 days in maturity and then rises to 118.2 days in decline. The trajectories are nonparallel in the reported estimates, but overlapping confidence intervals and the separate subgroup estimation mean that the figure should not be interpreted as a formal test that every pairwise difference is statistically significant.

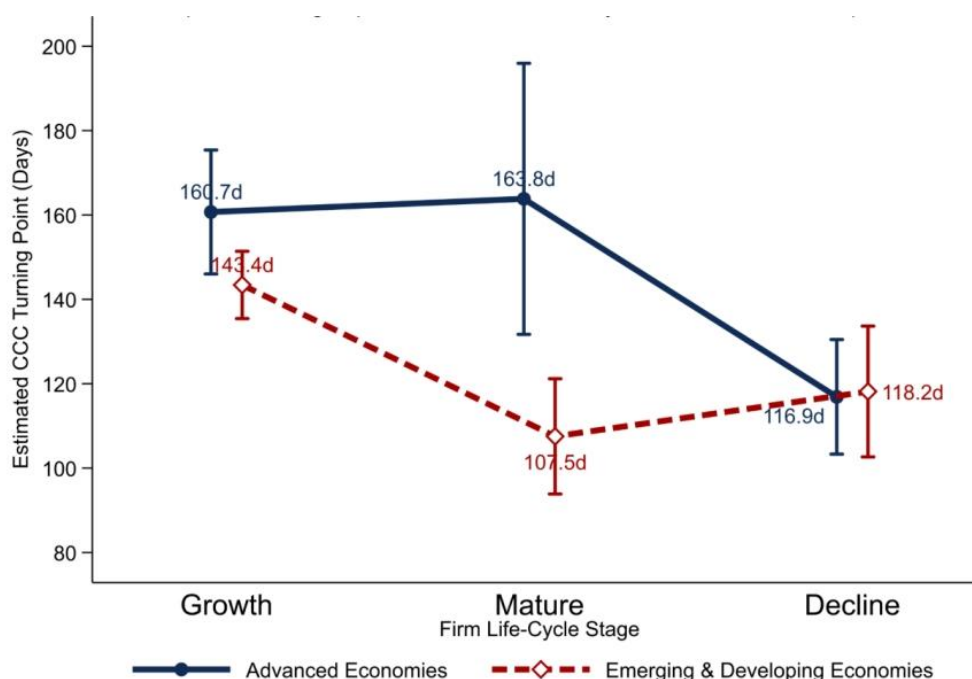


Figure 4: Estimated CCC Turning Points Across Firm Life-Cycle Stages and Economic Development

Alternative Outcomes, Components, and Regional Sensitivity

An assessment of alternative profitability measures is provided in Table 8. The linear firm-fixed-effects specifications indicate negative within-firm linear associations in the specifications for both ROE and EBITDA margin. When quadratic terms are introduced, the pooled ROE specification yields a turning point of 113.8 days, whereas the firm-fixed-effects EBITDA-margin specification yields 70.4 days. Because quadratic specifications use different estimators and

outcomes, the estimates should be interpreted as sensitivity evidence rather than as evidence for one outcome-invariant CCC threshold.

Table 8: Alternative Performance Measures: ROE and EBITDA Margin

Independent Variables	Model (1) ROE (Linear FE)	Model (2) ROE (Quad OLS)	Model (3) EBITDA (Linear FE)	Model (4) EBITDA (Quad FE)
Cash Conversion Cycle (CCC)	-0.0194*** (0.0016)	0.0234*** (0.0025)	-0.0065*** (0.0010)	0.0070*** (0.0018)
Cash Conversion Cycle Squared (CCC ²)		-0.0001026*** (0.0000081)		-0.0000497*** (0.0000054)
Firm Size (ln (Assets))	-0.2928* (0.1656)	1.9271*** (0.0523)	2.5413*** (0.0962)	2.5378*** (0.0961)
Financial Leverage	-21.8470*** (0.9921)	-20.2233*** (0.6242)	-9.4957*** (0.3547)	-9.4658*** (0.3544)
Capital Expenditure Ratio	35.7788*** (1.3725)	45.8404*** (1.4418)	15.5004*** (0.7499)	15.4865*** (0.7492)
Cash Ratio	14.3551*** (0.8647)	-5.2603*** (0.8999)	7.4986*** (0.4934)	7.5011*** (0.4929)
Revenue Growth	0.1514*** (0.0026)	0.1410*** (0.0029)	0.0763*** (0.0013)	0.0757*** (0.0013)
Constant	10.0437*** (1.8667)	-17.7642*** (0.7866)	-17.4572*** (1.0955)	-17.9154*** (1.0966)
CCC Turning Point (Days)		113.8 days***		70.4 days***
Optimal CCC Delta-Method SE		(SE: 5.17, p=0.000)		(SE: 12.48, p=0.000)
Firm Fixed Effects	Yes	No	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Clustered SE (Firm Level)	Yes	Yes	Yes	Yes
Observations (Firm-Years)	379162	379162	376714	376714
R-squared (Within / Pooled)	0.0544	0.0579	0.0799	0.0808

Note: The table re-estimates the working-capital specification using ROE and EBITDA margin. Turning points vary across outcome definitions and estimators. This variation is treated as

evidence of sensitivity in the estimated conditional relationship rather than as evidence for a single universal working-capital optimum.

Table 9 decomposes working capital and compares G7 and BRICS subsamples. In the firm-fixed-effects component model, DSI, DSO, and DPO are each negatively associated with ROA and statistically significant. The negative DPO coefficient is relevant: conditional on the other components and controls, longer supplier-payment periods are associated with lower ROA in this specification, so extended payables should not be interpreted mechanically as a profitability benefit. The fitted turning points in the pooled regional quadratic models are 112.3 days for G7 firms and 112.9 days for BRICS firms. The near equality shows that development-group or estimator comparisons are not necessarily the same pattern as broad regional groupings elsewhere in the paper.

Table 9: Working-Capital Components and Regional Subsamples: G7 vs. BRICS

Variables & Diagnostics	Model (1) Components (Firm FE)	Model (2) G7 Economies (OLS)	Model (3) BRICS Economies (OLS)
Days Sales of Inventory (DSI)	-0.0078*** (0.0005)		
Days Sales Outstanding (DSO)	-0.0158*** (0.0006)		
Days Payable Outstanding (DPO)	-0.0096*** (0.0005)		
Cash Conversion Cycle (CCC)		0.0148*** (0.0016)	0.0100*** (0.0010)
Cash Conversion Cycle Squared (CCC ²)		-0.0000658*** (0.0000060)	-0.0000441*** (0.0000031)
Firm Size (ln (Assets))	0.4488*** (0.0390)	1.3739*** (0.0359)	-0.0386* (0.0216)
Financial Leverage	-6.8579*** (0.1428)	-7.9125*** (0.3452)	-6.5594*** (0.2151)
Capital Expenditure Ratio	9.1286*** (0.2877)	7.1052*** (1.1859)	18.7204*** (0.5131)
Cash Ratio	3.8986*** (0.1986)	-0.8138 (0.5818)	0.3786 (0.3160)
Revenue Growth	0.0385*** (0.0005)	0.0191*** (0.0021)	0.0421*** (0.0009)

Constant	16478*** (0.4378)	-13.4972*** (0.5154)	4.7334*** (0.2873)
CCC Turning Point (Days)		112.3 days***	112.9 days***
Optimal CCC Delta- Method SE		(SE: 5.85, p=0.000)	(SE: 5.04, p=0.000)
Firm Fixed Effects	Yes	No	No
Year Fixed Effects	Yes	Yes	Yes
Clustered SE (Firm Level)	Yes	Yes	Yes
Observations (Firm- Years)	378343	111373	99615
R-squared (Within / Pooled)	0.1734	0.1722	0.1810

Note: Model (1) is a firm fixed effects decomposition based on DSI, DSO, and DPO. Models (2) and (3) present the quadratic specifications of pooled G7 and BRICS firms, respectively. The fitted turning points are 112.3 and 112.9 days, respectively. The component coefficients are associations that are conditional on the other variables and should not be interpreted as effects of a uniform change in payment, inventory or collection days.

Endogeneity Diagnostics and Specification Sensitivity

Table 10 summarizes several approaches for examining reverse causality, omitted heterogeneity and performance persistence. The models do not have a common turning point, with a pooled benchmark of 133.2 days, a specification with a one-year lag of 121.3 days, a 2SLS specification of 74.2 days, and a dynamic OLS specification of 34.3 days. The system-GMM specification is not suitable for obtaining an interior optimum over the positive CCC domain. The interpretation of these estimates is complicated by the spread across these estimates: in some specifications the data exhibit a nonlinear profile, but the location of the profile varies substantially by the choice of the particular estimator.

The one-year-lagged model retains both a positive linear coefficient and a negative quadratic coefficient, and has a turning point of 121.3 days. Lagging the regressors will not account for simultaneity as it was present in the previous year's working capital, but it will not eliminate the possibility of the presence of persistent omitted factors, longer-run feedback or measurement-related endogeneity. The lagged estimate is thus an informative indication of temporal ordering, but does not imply causality.

The 2SLS specification uses leave-one-out industry-year instruments for CCC and its quadratic term and yields a 74.2-day turning point. Interpretation depends on the exclusion restriction and on how the two instruments are constructed. Industry-year conditions may affect profitability directly through demand, input prices, or competition. The IV result is therefore treated as sensitivity evidence rather than conclusive causal identification.

The dynamic OLS model includes lagged ROA and estimates performance persistence ($\rho = 0.7825$) together with a 34.3-day fitted turning point. Because lagged dependent variables can be correlated with fixed effects in finite panels, this specification does not completely resolve dynamic-panel bias (Nickell, 1981). It is therefore interpreted as an additional specification check rather than as a definitive causal estimator.

Model (5) applies two-step system GMM with restricted collapsed instruments and Windmeijer-corrected standard errors. The instrument count is limited to 39 for 29,124 groups, reducing the risk of instrument proliferation. However, the model fails two important specification diagnostics: the Arellano–Bond AR(2) test rejects the null of no second-order serial correlation, and the Hansen overidentification test rejects instrument validity. The failures here make it inappropriate to use the GMM coefficients to draw causal inferences or regard them as successful robustness tests.

Taken together, the sensitivity exercises support one conclusion and qualify another. They reinforce the conclusion that the estimated CCC – performance relationship is a specification-dependent and heterogeneous one. They tend to undermine any arguments that the data can be viewed as a single globally applicable CCC target. The paper then focuses on patterns that repeat within the subgroup analyses, and adopts a descriptive interpretation of exact turning points as quantities that depend on the choice of estimator.

Table 10: Endogeneity Diagnostics and Specification Sensitivity

Variables & Diagnostics	Model (1) Baseline Benchmark (Quadratic OLS)	Model (2) 1-Year Lagged Variables (t-1)	Model (3) 2SLS IV Regression (Ind-Year Instrument)	Model (4) Dynamic Panel (Lagged ROA (t-1))	Model (5) Two-Step System GMM (Blundell-Bond 1998)
Lagged Dependent Variable (ROA_(t-1))				0.7825*** (0.0027)	0.5919*** (0.0087)
Cash Conversion Cycle (CCC)	0.0152*** (0.0007)	0.0099*** (0.0007)	0.0498*** (0.0061)	0.0006*** (0.0002)	-0.0096*** (0.0014)
Cash Conversion Cycle Squared (CCC ²)	-0.000057*** (0.000002)	-0.000041*** (0.000003)	-0.000335*** (0.000030)	-0.000009*** (0.000001)	-0.000014*** (0.000005)
Firm Size (ln (Assets))	0.6771*** (0.0163)	0.5052*** (0.0162)	0.5211*** (0.0211)	0.1460*** (0.0043)	0.1933*** (0.0095)

Financial Leverage	-7.7224*** (0.1589)	-5.6931*** (0.1600)	-7.6569*** (0.1866)	-1.6621*** (0.0514)	-3.5118*** (0.0971)
Capital Expenditure Ratio	17.8023*** (0.4081)	12.7907*** (0.4045)	13.1844*** (0.5702)	-3.4370*** (0.1695)	-1.8225*** (0.2748)
Cash Ratio	-2.7072*** (0.2898)	-3.0014*** (0.2905)	-3.6274*** (0.3289)	-1.2701*** (0.0798)	-1.2852*** (0.1212)
Revenue Growth	0.0402*** (0.0007)	0.0278*** (0.0007)	0.0342*** (0.0009)	0.0545*** (0.0005)	0.0543*** (0.0006)
Constant	-4.1045*** (0.2252)	-2.6286*** (0.2267)	-0.8742** (0.4213)	-1.5144*** (0.0823)	0.5062*** (0.1659)
CCC Turning Point (Days)	133.2 days***	121.3 days***	74.2 days***	34.3 days***	Monotonic Drag (CCC>0)
Optimal Delta-Method Instrument GMM Specification	(SE: 2.59, p=0.000)	(SE: 3.92, p=0.000)	(SE: 3.63, p=0.000)	(SE: 10.23, p=0.001)	(Linear & Quad b < 0)
Number of Instruments	None	None	Leave-One-Out Ind-Y _t	Internal Lags	L (2/3) Collapsed
Arellano-Bond AR (1) Test			2		39 (Collapsed, J < < N)
Arellano-Bond AR (2) Test					z = -40.65*** (p = 0.000)
Hansen Test of Overidentification					z = -3.23 (p = 0.001)
Standard Error Type	Firm Clustered	Firm Clustered	Firm Clustered	Firm Clustered	Windmeijer (2005) Robust
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations (Firm-Years)	379,191	334,020	379,191	334,020	334,020
Number of Firms / Groups	31,112	29,124	31,112	29,124	29,124

Note: Y (dependent variable) is ROA (%). Model (1) is a pooled quadratic benchmark; Model (2) is a 1-year lag of explanatory variables; Model (3) is a 2SLS with leave-one-out instrument of industry-year CCC and its square; Model (4) is a 1-year lag of ROA in a dynamic OLS specification; Model (5) is two-step system GMM with 39 collapsed instruments and Windmeijer standard errors. The turning point ranges from 133.2 days to 34.3 days for the Models (1)–(4), and Model (5) suggests a negative CCC association for positive domain. Model (5) does not pass the AR(2) test (p = .001) and the Hansen overidentification test (p < .001), and is therefore retained only as a diagnostic sensitivity exercise, not as validated causal evidence.

Discussion and Identification Limits

The preferred interpretation is a conservative one. The system-GMM specification is unsatisfactory according to diagnostic tests and the industry-year instrument may contain common shocks that affect profitability directly, which substantially affects the pooled quadratic profile. Accordingly, the estimates are described as conditional associations and sensitivity evidence. The study does not identify a causally optimal working-capital target. Stronger causal inference would require plausibly exogenous variation in financing conditions, payment technology, regulation, or supply-chain shocks.

Theoretical Contributions

The study contributes to international corporate finance in three ways. First, it frames working-capital efficiency as a contingent nonlinear empirical relationship rather than a universal shorter-is-better rule or a single target (Silva & Silva, 2026). Second, it combines firm life-cycle logic with the nonlinear WCM literature by documenting differences in fitted CCC profiles across organizational stages, extending stage-contingent evidence such as Wang et al. (2020) and more recent life-cycle evidence (Sethi & Bapat, 2026; Sethi & Dash, 2025). Third, it connects life-cycle heterogeneity with broad economic-development context, complementing recent evidence on development status, institutional quality, geopolitical risk, and financial constraints (Chang et al., 2025; Kiyamaz et al., 2024; Sethi & Dash, 2025; Silva & Silva, 2026). A further contribution is methodological transparency: variation across estimators is reported as part of the substantive evidence rather than being reduced to a single summary turning point.

Managerial Implications

The results suggest that managers should treat the reported CCC estimates as diagnostic reference points rather than mechanical targets. This relationship is observed at different life-cycle stages and between different development groups and performance measures and estimators. The turning points are reported to be higher for growth firms than for mature firms in the stage-specific models, and different fitted patterns are found in the joint subgroup estimates across the development environments. The estimates are noncausal and sensitive to the specification of the model; in evaluating any operational decision related to inventory, receivables, and/or supplier financing, the firm should consider firm-specific service levels, financing costs, supplier relationships, demand conditions, and industry practices, not just rely on a single estimate from the pooled model.

Operational resilience should be considered alongside liquidity efficiency. Research links supply-chain risk-management capabilities with financing performance and dynamic capabilities with financial performance during disruption (Qiao & Zhao, 2023; Juan & Li, 2023). Other evidence finds that supply-chain finance supports growth and survival without a clear short-run profit benefit, while longer CCCs can weaken the performance benefits of resilience (Cui, 2026; Zhang & Yu, 2025). Evidence connecting supply-chain finance, risk

management, and sustainability similarly suggests evaluating outcomes beyond current accounting profitability (Sun et al., 2025).

The choice of financing instrument should also reflect the firm's position in the supply chain. Case evidence documents different uses of reverse factoring, dynamic discounting, inventory finance, and other instruments across supply-chain stages (Medina et al., 2023). A recent review distinguishes buyer-centric payable financing from supplier-centric receivable financing within a broader stakeholder framework (Liao et al., 2025). Managers should assess who receives financing benefits and who bears liquidity and default risks when changing working-capital terms.

Policy Implications

The cross-country heterogeneity is consistent with a potential role for financial and contracting institutions in shaping working-capital choices. Changes in working-capital adjustment costs may be influenced by policies that enhance receivables financing, the efficiency of payment systems, creditor protection, trade-credit insurance, and access to short-term funds. The present design does not identify the causal effect of any specific reform, however, making it prudent to leave the implications as a matter for policy evaluation in the future, rather than a policy prescription.

Recent regulatory studies illustrate why policy implications require explicit institutional mechanisms. Research examines how regulatory intensity affects trade-credit provision and whether SME-protection legislation changes large buyers' payment behavior toward smaller suppliers (Nguyen, 2025; Feng & Wang, 2026). A regression-discontinuity study of close-call union elections also demonstrates how stakeholder changes can affect supplier credit (Qu, 2024). These designs provide examples of policy or institutional variation that future causal work might investigate, without validating the causal interpretation of the present pooled estimates.

Limitations and Future Research

The results are limited by several factors. First, the reported turning points are reduced-form estimates and differ significantly by estimator and measures of performance. Second, the advanced/emerging/developing classification is a broad contextual classification which obscures substantial institutional and financial diversity within each group. Third, the industry-year instrument has a contestable exclusion restriction, and the reported system-GMM specification fails the AR(2) and Hansen diagnostics. Fourth, the sample is limited to listed firms and generalization is restricted to organizations other than listed firms, and the latest 2025 report year is not a fully representative cross-section. Finally, Dickinson's cash-flow classification offers a useful indicator, but it does not fully capture organizational life cycle. These restrictions suggest that the paper's strongest conclusions are related to conditional heterogeneity and specification sensitivity rather than causal optimization.

Accounting quality is a further measurement concern: earnings management has been associated with longer CCCs and less efficient inventory management (Sawarni et al., 2023). The present study does not directly measure earnings management, supplier concentration, financing-platform adoption, or operational flexibility. Their omission may contribute to residual heterogeneity. Future research should also compare cash-flow-based stages with alternative measures of organizational development and growth opportunities.

Conclusion

Using 379,191 firm-year observations from 31,112 listed firms in 134 countries over 2000–2025, this study examines whether the nonlinear association between the cash conversion cycle and profitability varies with firm life-cycle stage and economic-development context. The pooled quadratic specification is consistent with an association between CCC and ROA that is concave, and yields a fitted turning point of 133.2 days. However, the turning point varies considerably across the alternative specifications of the fixed effects, lagged specification, instrumental variables, alternative outcomes, and dynamic models, and the reported system-GMM specification does not pass the validity diagnostics. The differences also emerge in profiles fitted to the life cycle, with the growth profile showing an increase compared to the mature profile, and nonparallel profiles across the two subgroups across the different economic environments in the development-group analysis. It is thus most defensible to conclude that the profitability observed in the context of working-capital intensity depends on the organizational and economic context and is sensitive to specification. There is no evidence of a universal target or a causal target for the CCC. Future research should use plausibly exogenous variation in credit supply, payment regulation, factoring availability or supply-chain disruption, and refine ongoing institutional and financial-development indicators to account for various country groups. These types of designs would be better suited to distinguish between descriptive nonlinearities and structural working-capital relationships.

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