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Cash Conversion Cycle as an Intelligent Predictor of Persistent Stock Price Dynamics in Artificial Intelligence–Driven Firms: An AI-Based Decision-Making Framework

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ABSTRACT

The research demonstrates that effective management of working capital, examined through the cash conversion cycle (CCC), provides economic relevant information which is not yet reflected in stock market. Researchers predicts that CCC stock price dynamics in the face of informational complexity and intangible intensity in these settings, focusing on leading large-cap companies in the field of artificial intelligence (AI): Meta, Tesla, Alphabet, Amazon, Microsoft, Apple, and Nvidia. The data period ranges from December 2012 to September 2025 with a monthly frequency, which provides a comprehensive overview of the interplay between operational efficiency and equity valuation over time. We present evidence of long-memory dependence and persistent equilibrium relationships between operational efficiency and market valuation using ARFIMA and fractionally cointegrated VAR (FCVAR) models. The continuity of CCC and stock prices is highly heterogeneous among firms, as confirmed by the unit root and fractional integration tests. The Granger causality analysis reveals that in a few companies, the CCC has a significant influence on stock price movements; in other companies, stock price movements influence the CCC; and in Tesla, no such significant relationship is found. The long-run equilibrium linkages between working capital efficiency and equity valuation are confirmed by the FCVAR estimates, which are all between very negative and moderately positive values of the cointegrating coefficients. The results imply that information is slowly embedded in prices, which plays a role in informational frictions. This research adds value to the prior studies about the relationship between working capital efficiency and stock prices. This study serves as an empirical basis for an AI-based decision-making system where the CCC has been used as an intelligent stock price dynamics predictor.

1. Introduction

This research built on how information about a firm is incorporated into stock prices. This study shows the efficiency of working capital, captured by the cash conversion cycle (CCC), carries an information component in the stock price that cannot be captured by other components. We focus on large-cap companies near the technological frontier of artificial intelligence (AI) and find that CCC forecasts when and how companies' stocks will move in settings where complexity is high and the intensity is intangible. Overall, these results match the informational friction observed to reduce the speed of incorporating operational information into market valuations and hence provide a justifiable basis for employing an AI-based decision-making process.

Richard and Laughlin (1980), states that cash conversion cycle (CCC) is a metric that tracks net amount of cash-in on purchases to cash-out on sales and it has been the major indicator of firm's operational efficiency in day-to-day systems. Hence, it reflects the interaction between purchasing, production, sales, and cash with receipts. The CCC differs from traditional snapshot-shaped liquidity ratios because it provides an operating cash flow-based yardstick for measuring liquidity that considers the timing of cash flows and the synchrony of operating cash flows (Largay and Stickney, 1980; Moss and Stine, 1993; Farris and Hutchison, 2002). CCC is the central role in working capital management. Shin and Soenen (1998) and Deloof (2003) states that empirical studies address the relationship between cycle length and profitability, and suggests higher operational efficiency which will develop firm value, and the outcomes varies across different business and market settings (Gill et al., 2010; Lin and Lin, 2021; Mandalaputri et al., 2021; Chang, 2022). However, more recent studies have tended to focus on the trade-off between a firm's holding and opportunity costs (Nobanee and AlHajjar, 2014), highlighting the economic significance of working capital decisions. Although this has resulted in a large volume of studies, most use the CCC as an information set at the time of its operation and not as a variable that provides forward-looking information. However, more recent studies indicate that operating parameters may have predictive information on stock returns. Wang, (2019) suggests that all firms with the less cash conversion cycle significantly enhance abnormal returns. The long-short strategy around the CCC exhibits economically meaningful alphas that are also statistically significant relative to typical asset pricing models such as Fama and French (1993, 2015), Carhart (1997), and Hou et al. (2015). The results imply that the CCC incorporates unanticipated variation in expected returns, which is unrelated to the expectations of risk factors.

This study is related to Wang (2019), but there are some important differences between them. First, while the cross-sectional asset pricing perspective is adopted in Wang (2019) and return predictability object has the examination of dynamic relationship between working capital efficiency and stock prices over time. This enables us to define and study how the timing of operational information is reflected in market valuations, not whether it anticipates expected returns. Second, we explicitly address the issue of long-memory dependence and fractional integration in both operational and financial variables and identify persistence phenomena not considered in the standard asset pricing literature. Third, we limit our sample to large-cap companies that appear in industries particularly oriented toward AI because valuations in such companies are even more uncertain, and the issue of friction over information is likely to be even more important. Combined,

our approach offers a complementary view, as it emphasizes one aspect of the cross-section of pricing, namely, the temporal dimension has operational information which is reflected by the stock prices.

Fama (1970) shows that Market efficiency theory has stock prices which will capture all relevant information and operational metrics such as CCC to forecast future price behaviour. The results were being intrigued. However, if information is added over time as a result of informational frictions, limited attention, or limits to arbitrage (Shleifer and Vishny, 1997), then working capital measures may have incremental predictive value. In line with this, Wang (2019) documents that CCC forecasts future earnings, and investors are under reactive to the information received in working capital dynamics. This study extends the literature on firms working at the technological frontier in terms of artificial intelligence (AI), an area that has been sparsely studied in the area of working capital and asset pricing. AI-focused companies exhibit significant intangible capital, fast innovation rates, and complex business models (Corrado et al., 2009; Eisfeldt and Papanikolaou, 2013), which can further increase the level of valuation uncertainty and drive-up informational friction for the company. These characteristics render these types of firms a preferable laboratory for analyzing the assimilation of working details into stock pricing. In particular, when the study looks into the CASH CONVERSION CYCLE, the firm's performance may manifest aspects that are hard to digest, and hence only slowly discernible from the market. Methodologically, this approach, in which both persistence and LRD in operational and financial variables are explicitly considered. Granger and Joyeux (1980), Hosking (1981) and Diebold and Rudebusch (1991) states that economic and financial time series shows long-memory behaviour and fractional integration. These processes can often be inadequately represented by standard econometric methods. To overcome this problem, we use the ARFIMA models for the univariate characterization of persistence and the Fractionally Cointegrated VAR (FCVAR) studies which is the long-term collaboration among CCC and the stock prices.

The three main contributions of this study are: First, this study demonstrates that working capital efficiency has predictive information for stock price dynamics in large-cap companies that rely heavily on artificial intelligence (AI) in their operations, thus adding to the growing literature on the predictive power of operational measures of stock price dynamics. Second, we document that this relationship varies across firms—is heterogeneous—and is predictive and feedback, suggesting the influence of firm complexity and information frictions. Third, we show that EF and market valuation are long-memory dependent and fractional cointegrated, which adds to the works on the persistence of financial time series. All of these contributions converge into an intelligent prediction framework which measures the equity markets' behaviour on the dynamics of CCC.

2. Materials and Methods

Data are STORED from: Refinitiv Eikon (Reuters) firms' financial statements and market data for publicly listed firms. It includes firms from seven major companies with large market caps that operate at the cutting edge of artificial intelligence (AI) and whose past and current performance is the most relevant in terms of affecting the economy: Meta (formerly Facebook), Tesla, Alphabet (formerly Google), Amazon, Microsoft, Apple, and Nvidia. The operating characteristics of these firms

include high intangible capital, high innovation, and complex operational structures, and they are among the more attractive to analyze the operational efficiency and the dynamics of the stock price. This sample includes observations between December 2012 and September 2025 at a monthly frequency. The time intervals between accounting and market variables were synchronized to current conventions to make the information comparable and lessen the risk of look-ahead bias.

The duration of working capital will reflect cash and measures the cash conversion cycle as a key variable. The CCC is defined, as per Richards and Laughlin (1980), as follows: CCC = Days inventory outstanding + Days receivables outstanding - Days payables outstanding (DPO).

$$CCC = DIO + DRO - DPO \quad (1)$$

This information is sourced directly from Refinitiv Eikon and are based on companies' financial statements. Corporate actions are closed from the monthly adjusted actions. In main specification, stock returns were calculated as the first differences of price taken in the logs. A key initial modeling consideration, whether in statistical or econometric analysis, prior to model implementation, is understanding the basic characteristics of the time series under consideration. The first important feature has the series of a unit root, is checked by the stationary (I (0)) or not (I (1)) (Nelson and Plosser, 1982).

In the collaboration of each variable, conventional unit root tests are used. Dickey-Fuller test is the most popular test (Dickey and Fuller, 1979). The basic model has certain level of autocorrelation in their error terms, the augmented version provides greater confidence than the basic model (Dickey and Fuller, 1981). Non-parametric method measures spectral density at zero frequency Phillips (1987) and Phillips and Perron (1988). However, another way of thinking was proposed by Kwiatkowski et al. (1992) and this introduces a new argument in testing for the presence of a deterministic trend, which is a complementary alternative to the conventional unit root tests. Kwiatkowski et al., 1992 states that complementary method assess the deterministic trends on traditional unit frameworks. The study then moves on to an advanced analytical method after determining the methods of integration for each series using standard tests for the presence of unit roots in these series. In the spirit of the work accomplished by Adenstedt (1974), Granger and Joyeux (1980), Granger (1980 and 1981) and Hosking (1981), we make use of a concept of fractional integration $I(d)$. This approach is different from conventional models, which only allow the differencing parameter d to be set as an integer because, in this approach, the differencing parameter d sets the real number, thus rendering a model stationary under more flexible conditions. These two advantages can be exploited by fractional differencing, which is a technique non-stationary series stationery as well as to better capture the long-range dependences between the series members than the conventional methods of differencing. It also exhibits increased statistical power, and so is especially suitable for cases with fractional integration such as those of Diebold and Rudebusch (1991), Hassler and Wolters (1994), and Lee and Schmidt (1996).

The ARFIMA (p,d,q) framework captures a long-term memory feature which is present in the data. The formal representation is that of a time series, which is fractionally integrated with an order of fractional integration that can be any real number d , referred to as $x_t \sim I(d)$.

$$(1 - L)^d x_t = u_t, \quad t = 1, 2, \dots \quad (2)$$

The estimation of the memory properties of a time series, with $d=0$ has short memory, $0 < d < 0.5$ long-memory stationarity and $d \geq 0.5$ non-stationarity. The degree of persistence and fractional integration calculates the methodology of Sowell (1992) together with information criteria (Akaike, 1973, 1979). To investigate the long-run relationship between the variables, Johansen and Nielsen (2012) developed the Fractionally Cointegrated Vector Autoregressive (FCVAR) model.

$$\Delta^d X_t = \alpha \beta' L^b \Delta^d (d - b) X_t + \sum_{i=1}^n \Gamma_i \Delta^b L^b (bi) Y_t + \varepsilon_t \quad (3)$$

The matrices α and β ($p \times r$, $0 \leq r \leq p$) shows the adjustment mechanism and long-run co-integration relationship, while Γ_i captures short-run dynamics. Granger causality among CCC and stock prices tests the VAR model with lag length is chosen by the Akaike Information Criterion (AIC).

Two causality hypotheses are tested: (i) CCC is not a Granger cause of stock prices, and (ii) stock prices are not a Granger cause of the CCC.

$$\begin{aligned} CCC_t &= \alpha_1 + \sum_{i=1}^n \beta_i SP_{t-i} + \sum_{j=1}^m \delta_j CCC_{t-j} + \varepsilon_{CCC,t} \end{aligned} \quad (4)$$

$$\begin{aligned} SP_t &= \alpha_2 + \sum_{i=1}^n \theta_i SP_{t-i} + \sum_{j=1}^m \psi_j CCC_{t-j} + \varepsilon_{SP,t} \end{aligned} \quad (5)$$

The FCVAR methodology is particularly appropriate for the firms examined in this study because there is a spectrum of persistence and long-range dependence among firms regarding their process of valuation in the market.

3. Results and Discussion

Table 1 shows the results of the ADF and PP unit root tests for the CCC and stock price variables across the selected firms.

Table 1. Unit Root Results

	ADF		PP		
	(i)	(ii)	(iii)	(ii)	(iii)
Cash Conversion Cycle					
Meta	– 0.2147	–0.8557	–2.604	–0.91	
Tesla	– 1.0711	–1.7872	–2.5959	–1.7914	
Alphabet	– 0.1786	– 3.1052*	–3.461*	–	3.9352*
Amazon	– 0.6527	– 3.0228*	– 4.9354*	–	5.2771*

Microsoft Corp	−1.398	−1.2023	− 3.9617*	−2.2449	
Apple	− 0.6186	−6.087*	− 6.1636*	− 5.7053*	
Nvidia	− 0.0273	−2.497	−3.228	−2.0014	
Stock Prices					
Meta	2.021	0.8907	−0.7058	1.0279	− 0.7344
Tesla	0.7295	−0.1912	−2.1918	−0.004	−2.4
Alphabet	2.2816	1.1449	−1.1988	1.3376	− 1.1188
Amazon	1.5444	−0.0682	−2.1808	−0.2997	− 2.7152
Microsoft Corp	2.4772	1.0335	−1.7239	1.4394	− 1.5451
Apple	1.9921	0.5374	−2.0832	1.1311	− 2.0076
Nvidia	3.4572	2.8442	1.2793	4.318	2.083

*Note: * denotes rejection of the null hypothesis of a unit root at the 5% significance level.*

Results shows that considerable asymmetry in the stochastic characteristics of the operational and market variables, even for this well-chosen sample of leading AI companies. Equity prices of all seven firms show extreme cases of non-stationarity, all of which has asset pricing theory, which proposes that equity prices are integrated processes continuously absorbing information on long-term growth opportunities, innovations in technologies, and cash flows from future profits that result from any newly acquired investment. However, differences in the time-series properties of these leading AI companies are apparent in the cash conversion cycle. The CCC exhibits mean-reverting behavior around firm-specific long-run targets for Alphabet, Amazon, Microsoft, and Apple, as evidenced by the rejection of the unit root null hypothesis when deterministic components are included. However, for Meta, Tesla, and NVIDIA, the CCC is not stationary, and the changes in working capital are more persistent, which would be expected under structural shifts driven by high levels of capital investments and a fast pace of innovation.

Figure 1. ARFIMA Long-Memory Estimates: CCC vs. Stock Prices Across AI-Intensive Firms

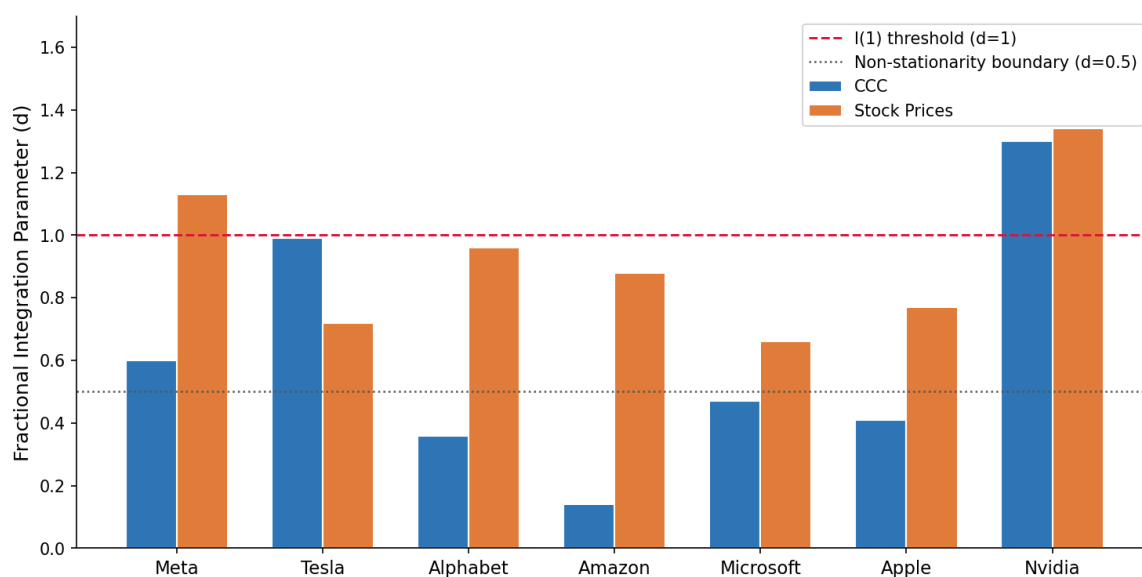


Table 2 reports the fractional integration parameter (d) which measures CCC and stock prices using Sowell's (1992) exact maximum likelihood approach.

Table 2. Long Memory Results

Data Analyzed	Sample Size	Model Selected	d	Std. Error	Interval	$I(d)$
Cash Conversion Cycle						
Meta	52	ARFIMA (0, d , 0)	0.60	0.121	[0.40, 0.80]	$I(d)$
Tesla	52	ARFIMA (0, d , 0)	0.99	0.115	[0.80, 1.18]	$I(d)$, $I(1)$
Alphabet	52	ARFIMA (0, d , 0)	0.36	0.096	[0.20, 0.52]	$I(d)$
Amazon	52	ARFIMA (1, d , 2)	0.14	0.082	[0.00, 0.27]	$I(0)$, $I(d)$
Microsoft Corp	52	ARFIMA (0, d , 2)	0.47	0.046	[0.39, 0.54]	$I(d)$
Apple	52	ARFIMA (2, d , 2)	0.41	0.053	[0.32, 0.49]	$I(d)$
Nvidia	52	ARFIMA (0, d , 0)	1.30	0.134	[1.08, 1.52]	$I(1)$
Stock Prices						
Meta	52	ARFIMA (0, d , 0)	1.13	0.117	[0.94, 1.32]	$I(d)$, $I(1)$
Tesla	52	ARFIMA (0, d , 0)	0.72	0.137	[0.49, 0.94]	$I(d)$

Alphabet	52	ARFIMA (0, d, 0)	0.96	0.170	[0.68, 1.24]	I(d), I(1)
Amazon	52	ARFIMA (0, d, 0)	0.88	0.130	[0.67, 1.10]	I(d), I(1)
Microsoft Corp	52	ARFIMA (2, d, 2)	0.66	0.127	[0.45, 0.87]	I(d)
Apple	52	ARFIMA (0, d, 0)	0.77	0.124	[0.57, 0.97]	I(d)
Nvidia	52	ARFIMA (2, d, 2)	1.34	0.107	[1.16, 1.51]	I(1)

Note: Confidence intervals are reported at the 95% level. The model is selected using AIC and BIC criteria.

The results suggest significant variation in the persistence of cash conversion cycles from firm to firm among leading AI companies. The fractional integration d estimates of the working capital efficiency of Alphabet, Microsoft, Apple, and Meta fall between 0 and 1, suggesting the presence of long memory in these processes. Amazon's estimated value of d is fairly low ($d = 0.14$) and near the barrier between stationarity ($d \geq 0$) and fractional integration ($d < 0$), indicating that its working capital practices are very flexible and constantly change. However, Tesla and Nvidia are far more persistent. Structural shifting, where working capital dynamics are non-mean reverting, is related to fast technological innovation, and this is observed for Tesla with its estimated d close to one, and for Nvidia with its estimated d exceeding unity. Long memory estimates for stock prices show that the behavior of the series is closer to being near-unit-root or unit-root across all companies, except for META, Alphabet, Amazon, and Nvidia. A graphical summary of all these long-memory estimates is given in Figure 1 for all firms and both variables.

Figure 2. Granger Causality p-Values: CCC and Stock Prices Across AI-Intensive Firms

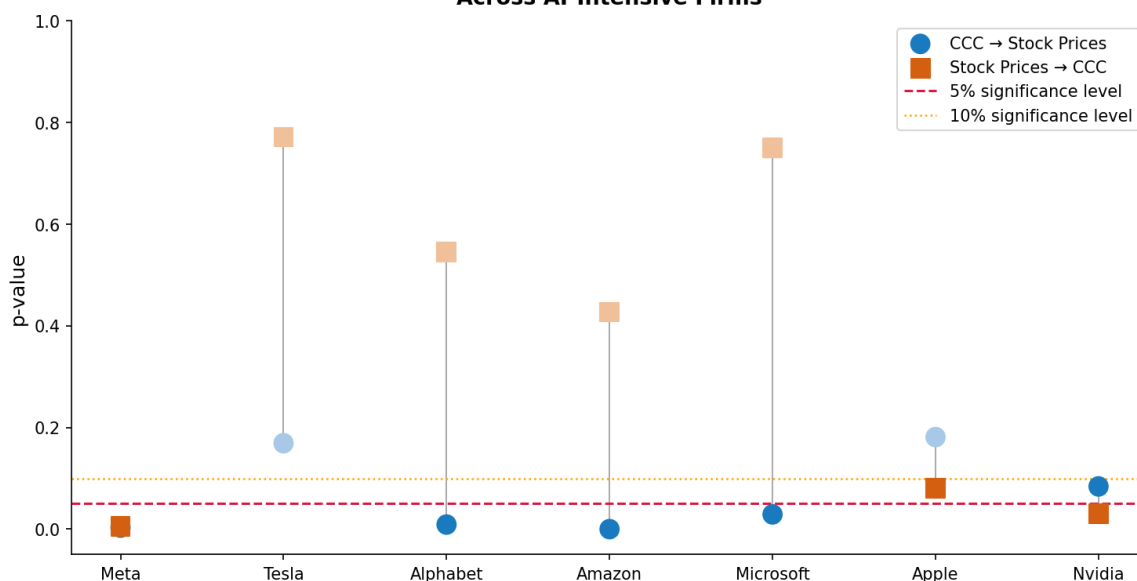


Table 3 has multivariate Granger causality test which is carried out on a vector autoregressive (VAR) model sequentially for each firm after conducting the univariate analysis.

Table 3. Results of Granger Causality Test

Direction of Causality	Lags	Prob.	Decision
CCC → Stock prices	4	0.003*	Reject Null H ₀
Stock prices → CCC	4	0.005*	Reject Null H ₀
CCC → Stock prices	1	0.169	No reject null H ₀
Stock prices → CCC	1	0.771	No reject null H ₀
CCC → Stock prices	1	0.009*	Reject Null H ₀
Stock prices → CCC	1	0.545	No reject null H ₀
CCC → Stock prices	4	0.000*	Reject Null H ₀
Stock prices → CCC	4	0.427	No reject null H ₀
CCC → Stock prices	4	0.029*	Reject Null H ₀
Stock prices → CCC	4	0.750	No reject null H ₀
CCC → Stock prices	4	0.181	No reject null H ₀
Stock prices → CCC	4	0.080*	Reject Null H ₀
CCC → Stock prices	1	0.084*	Reject Null H ₀
Stock prices → CCC	1	0.031*	Reject Null H ₀

*Note: * denotes significance at the 5% and 10% levels. Lag lengths selected using the Akaike Information Criterion.*

Results shows that significant variation among firms regarding whether and to what degree there is temporal predictability. We have evidence of positive causality in the case of Amazon, Alphabet, and Microsoft in the sense that their changes in the cash conversion cycle Granger-cause stock prices; the reverse causalities are not statistically significant. This trend suggests that historical biases in working capital efficiency have predictive value for the stock price path, suggesting progressive pricing of working capital efficiency gains over time, as in AI-based decision models utilizing historical working capital factors. For Apple, the cash conversion cycle Granger-causes changes in stock market valuation before any such adjustments in a way how Apple manages its money. For Meta and Nvidia,

the results suggest bidirectional Granger causality, suggesting a dynamic feedback mechanism whereby the value of Meta stocks influences the efficiency of their operations and vice versa. Finally, in the case of Tesla, there is no statistically significant Granger causality in either direction. The distribution of the p-value for all causality directions for every firm is shown in Figure 2 to provide an intuitive visualization of the pattern of significant and insignificant relationships.

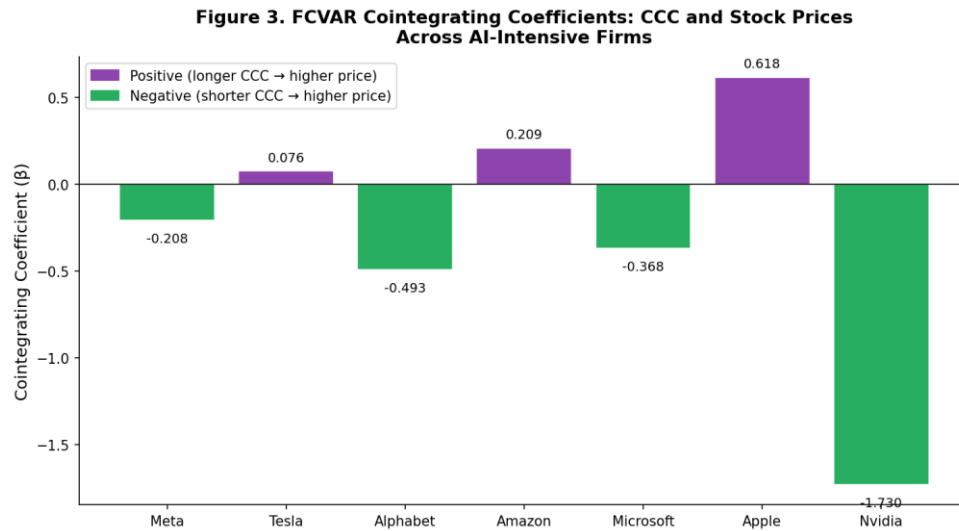


Table 4 reports FCVAR values which estimates long-term CCC and stock prices.

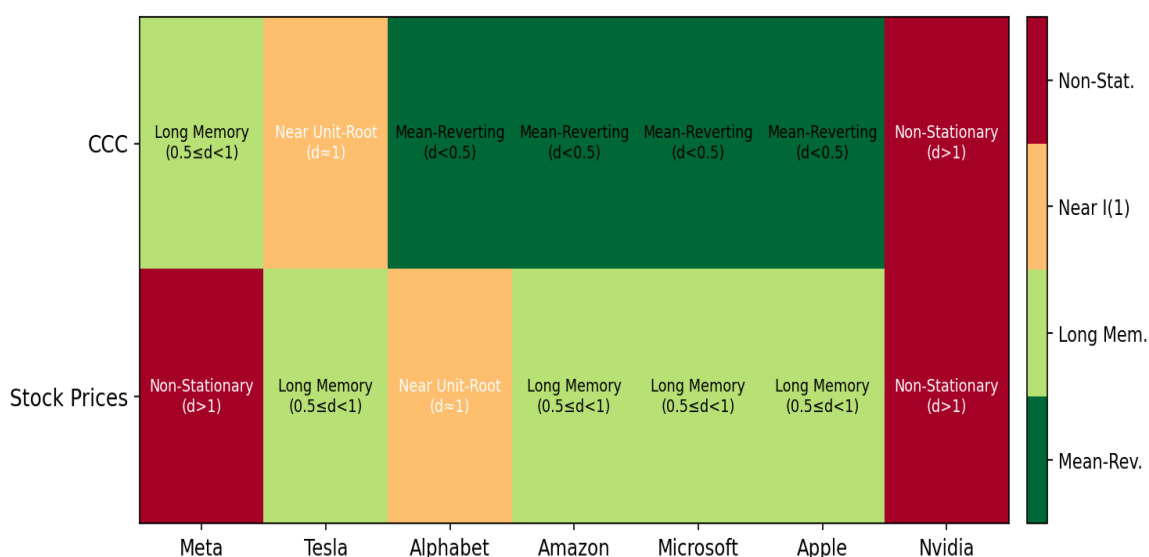
Table 4. Results of the FCVAR Model

Firm Pair	d and b Estimates (Std. Error)	CCC (β)	Stock Prices (β)
Meta: CCC vs Stock Prices	d=0.010 (0.174) b=0.010 (0.000)	1.000	−0.208
Tesla: CCC vs Stock Prices	d=0.011 (0.130) b=0.011 (0.001)	1.000	0.076
Alphabet: CCC vs Stock Prices	d=0.010 (0.160) b=0.010 (0.000)	1.000	−0.493
Amazon: CCC vs Stock Prices	d=0.080 (0.154) b=0.080 (0.009)	1.000	0.209
Microsoft Corp: CCC vs Stock Prices	d=0.010 (0.156) b=0.010 (0.001)	1.000	−0.368
Apple: CCC vs Stock Prices	d=0.813 (0.451) b=0.424 (0.416)	1.000	0.618
Nvidia: CCC vs Stock Prices	d=0.010 (0.118) b=0.010 (0.000)	1.000	−1.730

Note: Standard errors in parentheses. The cointegrating vector is normalized on the CCC coefficient.

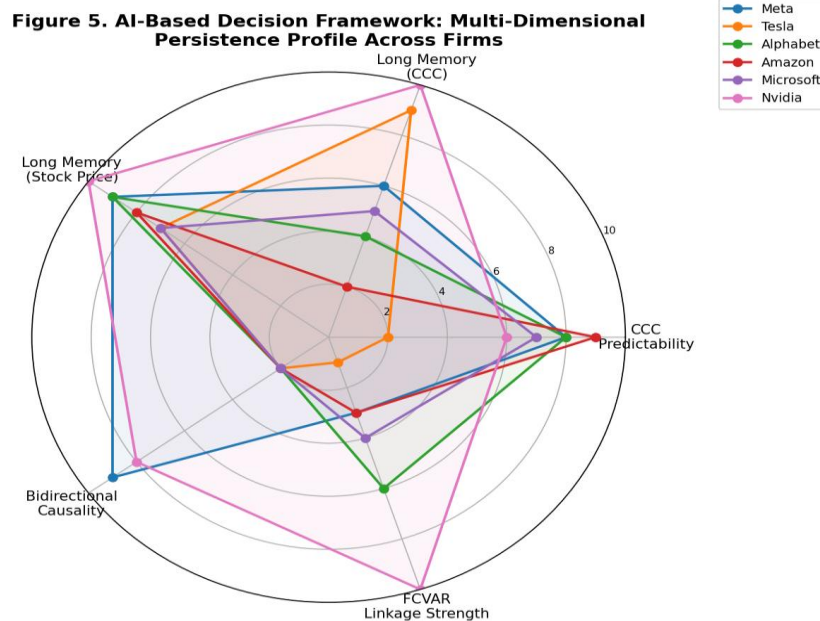
Above FCVAR results shows the long-term relationship between efficiency and market valuation. The magnitude and direction of this relationship vary in many companies. The coefficients are negative and significantly larger than the null coefficient for Meta Inc., Alphabet Inc., and Microsoft Corp. of approximately 15.6, 11.4, and 8.9, respectively, of these estimated coefficients implying that improvements in working capital efficiency have a positive relationship with long-run stock value for these companies. Such companies also have fractional integration parameters $d \approx 0.01$, which has long-run equilibrium level and corrected quickly. Apple and Amazon show positive operational values (0.618 and 0.209, respectively), suggesting a mechanism that has been built up as the norm in the activities of these companies that have a longer working capital cycle, and not necessarily due to inefficiency, but due to strategic investment or bargaining power. The strongest correlation is for Nvidia, with analysts forecasting a negative correlation of -1.730 , suggesting a very strong link between operational measures and the market forecasts. Unlike most previous evidence, Tesla has a very small positive coefficient (0.076), suggesting that its value is based more on the longer-term growth prospects than on the up-and-down nature of its operations. The cointegrating coefficients are visualized in Figure 3, which demonstrates the strength and direction of each CCC's price linkage.

Figure 4. Persistence Classification Heatmap: CCC and Stock Prices Across AI-Intensive Firms



A persistence classification heatmap that captures the stochastic characteristics of all seven firms' stock prices and CCC behavior is displayed in Figure 4, where X is shown in dark gray if it is above 40% and light gray if it is below 40%. Each variable is identified as being either mean-reverting, long memory, near unit-root, or non-stationary, as shown in the heatmap, using the estimated fractional integration values indicated in Table 2. This visualization process helps identify the concurrent persistence model structure of the CCC and stock data to provide an AI-based decision-making diagnostic tool. These results, which align with the Granger causality and FCVAR outcomes, reveal that firms within the mean-reverting regime or long memory regime (Alphabet, Microsoft, Apple, and Meta) are more likely to have operational efficiency signals that would consist of predictive information with respect to stock prices. In contrast, companies characterized by non-stationary CCC

dynamics (Tesla and Nvidia) have fewer or more nuanced connections between price and efficiency, in line with structural and not cyclical working capital dynamics.



The AI-based decision-making framework is represented in this multi-dimensional radar chart, with five dimensions of this framework being shown: CCC predictability of the stock price, long-memory intensity of CCC, long-memory intensity of stock price, strength of the bidirectional causality, and the magnitude of the FCVAR linkage. This framework condenses all empirical evidence into one visualization for investors and analysts to determine the most favorable companies for implementing prediction strategies based on CCC. The companies that do well in terms of both persistence and linkage are Nvidia and Tesla, with Nvidia being one of those with the highest score and Amazon being one of the companies that scored the lowest on the operational predictability scale. As shown in Figure 5, there is sufficient empirical and visual evidence to support the proposed framework for AI-based decision-making system in AI-driven companies, which supports the CCC as an intelligent predictor of persistent stock price dynamics.

4. Limitations and Future Perspective

These results consider several constraints, which has study's concentration on seven large-cap firms that are integral to the artificial intelligence ecosystem. This narrow stream of information provides scope for a detailed and methodologically sound research study of the CCC-stock price relations in an environment of AI but may not necessarily provide wider conclusions for other industries, firms, or size groups. These results may not apply to smaller or less technically advanced companies, where operational efficiency and valuation may vary significantly. Second, all analyses are based on market and accounting data from Refinitiv Eikon, which contain limitations inherent in financial statements that are sometimes reported: the definition of components of working capital is sometimes firm-specific and time-varying; there can be measurement lags; and some financial statements use standards of representation that do not lead to consistency. To cope with this restriction, future studies may consider using other variables such as analyst forecasts, investor attention using text

analysis, or transaction-based data on supply chains. Third, the fractional integration and FCVAR models are useful and powerful models for describing persistence and long-run relationships; however, the underlying sample size (52 quarterly observations) of the model is relatively small, which might impact the estimates of long memory and cointegrating parameters. A longer sample size or more frequent data would have increased statistical reliability, especially for firms with low sample variation for CCC. Fourth, the proposed AI decision-making framework in this study is conceptual in that it combines all the empirical results into a multidimensional profile and does not directly optimize any investment or management decision rule.

This work could be extended to the integration of machine learning or reinforcement learning algorithms, which could continuously adjust the CCC-based predictive signals based on new observations to operationalize the framework in support of real-time investment decisions. Fifth, this study lacks a clear model of the effect of macroeconomic shocks, interest rate cycles, and geopolitical events that could impact working capital and stock price dynamics. Adopting the same considerations in a model that is of the structural type of VAR formulation, or a factor model can potentially expand the knowledge of the relationship between CCC stock prices and enhance their stability in different national policies of the economy. There are many aspects that can be investigated. This could be expanded to a broader sample of AI-intensive and non-AI companies to gain a systematic understanding of the scope of working capital efficiency across different technological intensities and institutional environments. An interesting avenue for future research is to combine a return-based asset pricing model with fractional dynamics to investigate the connection between operational characteristics and expected returns in a risk-return framework. Furthermore, studying the impact of market microstructure, investor interest, and information processing costs would offer further insights into the mechanisms contributing to the slow integration of operational information into stock prices and how this could reveal new aspects of the AI-driven decision framework introduced in this study.

5. Conclusion

Large-cap companies play a crucial role in shaping the development of artificial intelligence technologies. This research investigates how operational efficiency reflects the cash conversion cycle (CCC) which relates to stock market performance. To identify economically meaningful information that is not reflected in market valuations, we use a time-series model which considers the working capital efficiency persistence, long memory, and fractional cointegration. This research supports AI-based decision making by utilizing the CCC as a predictor of stock price dynamics. We find that the effect of operational efficiency on stock prices is persistent and heterogeneous among firms. In certain instances, there are price reaction delays with respect to changes in the CCC because information regarding its operations is signalled by price changes first. The coexistence of fractional cointegration also reveals long-run efficiency–valuation relationships that change gradually over time. Combined, these findings suggest an evolving process of information absorption by financial markets, such that signals known about a firm's operations are absorbed only gradually by markets. Thus, the type of information absorption that will be enabled by machine learning frameworks and AI-based processes in investing. This research aims on how operational information is incorporated

into asset prices over time. The combination of working capital management and asset pricing highlights the short-term choices by affecting companies' operational performance which not only impact company performance but also affect market valuation in the short and long term. At a broader level, the findings show that it is important to consider persistence and long-memory phenomena for broader economic financial analyses, especially in settings with high complexity and strictly increasing intangibility among the factors.

This study also contributes from a methodological perspective. In the context of corporate finance, we use ARFIMA and Fractionally Cointegrated VAR models to present a framework for the properties of the data that are often neglected by conventional empirical methods. This can reveal more subtle relationships and adjustment processes that cannot be seen in standard econometric specifications, providing deeper insights into the interactions between operational and financial variables in the longer term. The results have practical relevance for investors and corporate managers. The results indicate that for investors, working capital efficiency carries additional information compared to official financial statements that is not instantaneously reflected in stock prices, especially for companies with high AI intensity. This creates the potential for crafting tactics that take advantage of delayed information diffusion. The results reinforce the importance of working capital policies for corporate managers; they are not only for their effect on liquidity and operating performance, but also on the timing and dynamics of the process of market valuation. In summary, this study presents new evidence that operational efficiency is a key, yet under-researched, part of the information set influencing asset prices. The findings provide empirical support for understanding how the markets value a firm and process its long-term-but-continuous-and-periodic working capital management information, and a tangible empirical foundation for designing intelligent and CCC-based investment and managerial decision frameworks in information-rich and dynamic AI environments.

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