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Capital Expenditure Decisions in the Private Sector and Their Impact on Uk Stock Market Performance A Fractional Integration Analysis

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Abstract

This paper examines the relationship between capital expenditures (CAPEX) in the private sector and the performance of the UK stock market, specifically focusing on the manufacturing and non-manufacturing sectors. Using quarterly CAPEX data for UK private sector firms and FTSE index data spanning from Q1 1997 to Q1 2024, we employ a robust methodological framework that integrates fractional integration analysis, Granger causality tests, and Continuous Wavelet Transform (CWT). The findings reveal sector-specific dynamics. CAPEX in the non-manufacturing sector exhibits a significant positive causal relationship with FTSE index movements, particularly in short- and medium-term horizons, highlighting its role as a leading indicator of market performance. In contrast, CAPEX in the manufacturing sector demonstrates weaker and less immediate correlations, reflecting its long-term, structural nature and sensitivity to economic cycles. Persistence analysis confirms the long memory behavior of both CAPEX series, with non-manufacturing investments displaying higher stability and predictability. These results underscore the heterogeneity of CAPEX impacts across sectors and emphasize the importance of distinguishing between short-term and long-term investment responses when evaluating stock market dynamics.

Keywords: *Capex, Non-Manufacturing Companies, Manufacturing Companie, Market Capitalization, United Kingdom, ARFIMA (P,D,Q) Model, Causality Test, Wavelet Analysis*

JEL Classification: ***R30, C22, C32***

Introduction

Organizations worldwide depend on capital expenditure (CAPEX) investments to achieve strategic objectives, enhance operational capabilities, and ultimately create organizational value while maximizing shareholder wealth. These investments are intrinsically tied to the expectation of future returns, which should translate into improved financial performance and a higher overall valuation of the firm.

CAPEX occupies a central role in financial decision-making, with implications at both macroeconomic and microeconomic levels. From a macroeconomic perspective, CAPEX influences critical indicators such as aggregate demand, gross domestic product, and economic growth, playing a vital role in shaping business cycles (Dornbusch and Fischer, 1987). At the firm level, CAPEX directly impacts operational capacity (Nicholson, 1992), informs strategic planning (Bromiley, 1986), and enhances competitive positioning (McConnell and Muscarelle,

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1985). This dual relevance underscores CAPEX as an essential element in economic and corporate analysis, connecting national economic performance with organizational growth.

The study of CAPEX determinants has spanned decades, resulting in a robust body of literature. Foundational works by Kuh and Meyer (1957), Dusenberry (1958), and Jorgenson (1963) introduced CAPEX's role in economic behavior and investment dynamics. Subsequent studies by Jorgenson and Siebert (1968), Grabowski and Mueller (1972), and Elliot (1973) expanded on these insights by analyzing CAPEX drivers in varying economic contexts. More contemporary research, such as that by Nair (1979), Berndt et al. (1980), Larcker (1983), and Fazzari et al. (1988), extended the discussion to include financial constraints, managerial incentives, and macroeconomic conditions. Together, these studies form the basis for understanding how CAPEX allocation influences firm performance and long-term value creation.

CAPEX investments can be broadly categorized into two types: expansionary investments and sustaining capital outlays. Expansionary investments focus on acquiring or creating new assets to increase a firm's operational scale, while sustaining capital outlays are directed at maintaining or improving the efficiency of existing assets (Vogt, 1997). Both types are essential for ensuring operational stability and growth, with their success measured by their ability to deliver returns that justify the resource allocation and align with shareholder interests.

As one of the most significant uses of a firm's resources, CAPEX reflects its strategic priorities and long-term goals. The availability of internal funds often determines a firm’s capacity to undertake substantial investments. When firms generate ample cash flow, they are better positioned to fund capital projects internally, avoiding the higher costs or constraints associated with external financing (Gitau, 2012). This dynamic positions CAPEX as a direct consequence of a firm's ability to reinvest its profits into growth or maintenance activities (Fazzari et al., 1988).

The scale of CAPEX allocations highlights its importance in corporate finance. For instance, Hennessy and Whited (2005) found that U.S. publicly traded firms allocate an average of 13% of their assets annually to CAPEX, while the global average stands at 7.5%. Li (2004) noted the immense scale of these investments, citing that U.S. firms spent $1.3 trillion on CAPEX in 2001 alone. However, despite the significant resources allocated to CAPEX, there is a notable gap in the literature exploring how these expenditures affect future profitability and market valuation.

CAPEX investments are inherently forward-looking, allocating current resources with the expectation of generating future returns. These returns are anticipated to exceed the initial investment, thereby enhancing the firm's value and maximizing shareholder wealth. This principle aligns with financial theory, which postulates a positive correlation between strategic investments and a firm's financial performance. Empirical evidence supports this premise; for example, Al Farooque et al. (2005) found a significant positive impact of CAPEX on corporate performance.

The central question this paper seeks to answer is whether strategic investment decisions, particularly CAPEX, influence stock valuation. Strategic investment decisions are critical drivers of a firm's overall performance (Kannadhasan and Nandagopal, 2010a). These decisions hold dual importance: they are vital for the future operations of individual firms and for the functioning of the broader economy. At the firm level, they shape operational efficiency, survival, profitability, and growth by requiring significant financial, human, and organizational resources. Consequently, their impact is long-term and far-reaching, often determining the success or failure of the firm (Kannadhasan and Nandagopal, 2010b).

Strategic investments encompass a wide range of initiatives, including organizational restructuring, adoption of new technologies, technical projects, joint ventures, diversification, and, most prominently, capital expenditures. CAPEX is frequently regarded as the most visible and impactful form of strategic investment due to its direct role in creating future economic benefits. These expenditures involve acquiring or enhancing fixed assets such as equipment, property, and industrial facilities, which are integral to the productive capacity of a firm.

By examining the relationship between CAPEX and market valuation, this article aims to fill the gaps in the literature. Specifically, we employ advanced econometric techniques to analyze the statistical properties of key variables and examine the link between CAPEX by private sector manufacturing and non-manufacturing firms and the FTSE index, which serves as a proxy for the performance of the UK stock market. By doing so, this research seeks to contribute novel insights into the dynamic interplay between investment decisions and market valuation.

The importance of CAPEX in shaping market valuation has been the focus of several research papers. For instance, Woolridge and Snow (1990) employed the market-adjusted returns approach to assess the stock market's reaction to 767 strategic investment announcements, including capital expenditures. They found that capital expenditures yielded positive stock market reactions, reinforcing their importance as value-enhancing investments. Similarly, Kerstein and Kim (1995) analyzed the incremental information content of unexpected CAPEX using pooled and cross-sectional regression models. Their findings highlighted the ability of CAPEX changes to signal future growth opportunities, particularly when firm-specific factors were incorporated into the analysis.

Subsequent studies expanded on this perspective. Park and Pincus (2003) examined the informational value of annual and quarterly CAPEX changes using pooled and cross-sectional regression models. Their findings underscored the significance of CAPEX timing, showing how market-adjusted abnormal returns are sensitive to the periodicity of CAPEX announcements. Jiang et al. (2006) further supported the value-relevance of CAPEX, demonstrating that investment ratios positively predict future earnings for manufacturing firms listed on the Taiwan Stock Exchange. This study emphasized the long-term benefits of CAPEX, aligning with the traditional view that strategic investments enhance profitability.

More recently, researchers have investigated the behavioral and market dynamics surrounding CAPEX disclosures. Brown et al. (2006) explored herding behavior in voluntary CAPEX announcements, revealing that industry dynamics and managerial reputational concerns drive disclosure patterns. Their findings highlight the role of inter-firm informational flows in shaping disclosure practices. On a related note, Özbebek et al. (2011) applied event study methodology to analyze the Turkish stock market's reaction to CAPEX announcements. Their results challenged the shareholder value maximization hypothesis, suggesting that skepticism about firms' strategic investments may temper market reactions.

Research in emerging markets has also added valuable perspectives. Pakmaram et al. (2013) utilized multivariate regression analysis to examine CAPEX impacts on Tehran Stock Exchange-listed firms, concluding that CAPEX investments linked to growth opportunities significantly improve market performance. Similarly, Mwangi (2014) analyzed firms listed on the Nairobi Securities Exchange and demonstrated that CAPEX positively influences financial performance, emphasizing the need for alignment between investment strategies and long-term growth objectives. Samarajeewa and Perera (2020) explored CAPEX impacts in Sri Lankan firms, highlighting the trade-offs between long-term capital investments and short-term liquidity, and underscoring the necessity of balancing growth opportunities with financial stability.

Building on this extensive body of literature, our study introduces innovative quantitative methods to deepen the understanding of CAPEX dynamics and their relationship with the UK stock index. Unlike previous research, we employ a comprehensive methodological framework that integrates fractional integration, causality tests, and wavelet analysis. This combination of approaches allows us to capture the nuanced behavior of CAPEX and the FTSE index over time, providing valuable insights into their stability, predictability, and responsiveness to exogenous shocks.

To the best of our knowledge, the quantitative techniques utilized in this study represent a novel contribution to the field, introducing methodological innovations not previously explored in the literature. These methods offer a robust framework for analyzing the statistical properties and interactions of the variables under investigation, delivering significant contributions to both theoretical understanding and practical applications. By bridging gaps in the existing research, this study enhances the understanding of how CAPEX decisions influence market performance and provides actionable insights for policymakers, investors, and corporate decision-makers.

Our analysis begins with the application of long memory techniques, that are particularly valuable for examining the persistence and mean-reverting behavior of time series data. The importance of this analysis is threefold. First, it allows us to differentiate between short-memory and long-memory characteristics in the data. Long memory implies sustained effects of past values, enhancing the data's reliability for forecasting and pattern recognition, while short memory indicates that historical data quickly lose their influence. Second, the determination of stationarity or non-stationarity in the series provides a foundation for accurate data transformation. Fractional differencing techniques enable us to capture the underlying dynamics of the data with precision, ensuring that its statistical properties remain consistent over time. Third, understanding how the time series reacts to exogenous shocks sheds light on its stability. If the series reverts to its mean following a shock, it suggests resilience, whereas deviations requiring external interventions may signal vulnerabilities, guiding potential managerial or policy actions.

From a multivariate analysis perspective, we conducted causality tests. These tests are instrumental in determining whether one variable can effectively predict another, establishing a directional and meaningful relationship. Identifying such causality ensures that our subsequent analysis focuses on relationships with genuine predictive value, avoiding the pitfalls of spurious correlations. This step is critical for ensuring the validity of the findings and their applicability to real-world decision-making.

Finally, we conducted a wavelet analysis using the Continuous Wavelet Transform (CWT).

This advanced technique allows us to decompose the time series and analyze its behavior across multiple time scales simultaneously. Unlike traditional econometric methods, CWT provides a nuanced understanding of both local (short-term) and global (long-term) relationships, capturing patterns and trends that evolve over time and across frequency domains. This is particularly valuable for identifying time-varying interdependencies and cyclical dynamics, which are essential for understanding the intricate relationships (correlation) between CAPEX and market performance.

The integration of these methodologies creates a robust analytical framework for examining the complex dynamics underlying CAPEX and market valuation. Each technique contributes unique insights, enabling a multi-dimensional exploration of the data that extends beyond the limitations of traditional approaches.

The structure of this paper is organized as follows. Section 2 provides a detailed description of the dataset, outlining its sources, key characteristics, and relevance to the research objectives. Section 3 explains the methodologies employed, offering a thorough discussion of their theoretical underpinnings and practical applications. The results of the study are presented and analyzed in Section 4, where we delve into the implications of the findings for theory and practice. Finally, Section 5 concludes the paper by summarizing the key contributions, addressing limitations, and proposing directions for future research.

Data

The data used in this study were sourced from Thomson Reuters Eikon. The dataset includes quarterly capital expenditures (CAPEX) for both manufacturing and non-manufacturing private sector firms in the United Kingdom.

The CAPEX for manufacturing sector reflects investments in physical assets, machinery, and infrastructure aimed at enhancing production capacity and operational efficiency. On the other hand, CAPEX for non-manufacturing sector represents expenditures in intangible and service-oriented assets, including infrastructure modernization, technology, and service delivery improvements.

To represent the aggregate performance of listed firms on the the UK stock market, we obtained the FTSE index data, initially reported at a monthly frequency. The index serves as a benchmark for market valuation trends and investor sentiment over time.

To ensure consistency with the CAPEX data, the FTSE index values were transformed into a quarterly frequency by selecting the closing values at the end of each quarter.

The period analyzed is from the first quarter of 1997 to the first quarter of 2024.

Figure 1. Capital expenditures by private sector manufacturing and non-manufacturing companies and the FTSE index.

Figure 1 illustrates the CAPEX trends for non-manufacturing and manufacturing sectors, respectively, against the FTSE index.

The data reveal distinct sectoral differences in CAPEX behavior. The non-manufacturing sector shows a stable, upward trajectory, reflecting a steady increase in investments. The FTSE index, in contrast, demonstrates notable volatility, particularly during periods of economic crises, such as the 2008 Global Financial Crisis and the 2020 COVID-19 pandemic. However, post-2009, both CAPEX and the FTSE index appear to exhibit a stronger positive co-movement, suggesting a potential alignment between private sector investments and market recovery.

The manufacturing sector, however, is characterized by greater sensitivity to economic cycles and market fluctuations, particularly between 1997 and 2005. The observed decline during this period may reflect economic downturns and reduced investments in physical infrastructure. Post-2009, CAPEX in the manufacturing sector recovers gradually, displaying a stronger relationship with the FTSE index, particularly after 2013, when both series trend upward in tandem.

Methodology

Unit Roots

Tests for unit roots can be conducted in numerous ways. In this study, Dickey and Fuller's ADF test is employed (1979). Numerous alternative tests, like Phillips and Perron (1988), which employ a non-parametric estimation of the spectral density of u_t at the zero frequency, can be used to compute unit roots with higher powers. Additionally, we employ the methods based on Kwiatkowski et al. (1992) and Elliot, Rothenberg, and Stock (1996), which yield nearly identical results when taking deterministic trends into account.

ARFIMA (P, D, Q) Model

Thanks to authors such as Lee and Schmidt (1996), Hassler and Wolters (1994), Diebold and Rudebusch (1991), and others, it is now widely accepted that all unit root algorithms have incredibly low power if the real data creating process is fractionally integrated or has long memory. Fractional orders of differentiation are thus permitted in the following.

Because of this, we employ the ARFIMA (p, d, q) model, using the following mathematical notation:

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

According to equation (1), u_t denotes I(0), L is the lag-operator ($Lx_t = x_{t-1}$), d is any real number, and x_t is the time series with an integrated process of order d ($x_t \approx I(d)$). The Bayesian information criterion (Akaike 1979) and the Akaike information criteria (Akaike 1973) were used to determine the models' correct AR and MA ordering.

For the time series and the subsamples, the d parameter has been estimated for each possible combination of AR and MA terms ($p;\ q < 2$), accounting for their 95% confidence bands.

Granger Causality Test

After estimating the VAR model, the Granger causality test is run to determine the direction of causation between two stationary series, x_t and y_t. The vector autoregressive representation (VAR) used in the Granger test is made up of the following two series:

$$x_t = a_1 + \sum_{i=1}^{k} a_i x_{t-i} + \sum_{i=1}^{k} \beta_i y_{t-i} + \epsilon_{1t}$$

$$y_t = a_2 + \sum_{i=1}^{k} \gamma_i x_{t-i} + \sum_{i=1}^{k} \delta_i y_{t-i} + \epsilon_{2t}$$

K represents the lag length of the variables x_t and y_t. The null hypothesis can be tested "x is not a consequence of y", which can be described as $H_0^1 = \gamma_1 = \cdots = \gamma_k = 0$. The result reflects that the causality goes from y_t to x_t when the null value is rejected; in the same way as in the second case $H_0^2 = a_1 = \cdots = a_k = 0$ the causality from x_t to y_t occurs when the null value is rejected. Both hypotheses can be rejected. The Chi-square distribution has been chosen to perform the statistical tests.

Continuous Wavelet Transform (CWT)

A time series is a collection of elements that function at various frequencies. Therefore, the frequency content of the signal contains the most notable information contained inside. This approach makes a lot of sense because of this.

The time-frequency domain of this research has been further explored through the application of wavelet coherence and wavelet phase difference. This research eliminates the need for the time series to meet the stationarity criterion in order to analyze the interaction of the time series in the time domain and show structural changes.

Many writers have used nonlinear approaches to analyze the consequences of oil shocks using wavelet analysis, based on the research of nonlinear dependencies and energy markets carried out by Kyrtsou et al. (2009). Many authors have used wavelets to test and study business cycle synchronization, such as Aguiar-Conraria and Soares (2014) and Crowley and Mayes (2009).

To uncover hidden patterns or information, we use the wavelet coherency plot, which calculates the correlation between the time series in the time-frequency domain. In order to obtain this outcome, we compute the wavelet transform of a time series $x(t)$, or $WT_x(a,\tau)$, by projecting the mother wavelet ψ onto a function of τ and a.

$$WT_x(a,\tau) = \int_{-\infty}^{+\infty} x(t) \frac{1}{\sqrt{a}} \psi^* \left(\frac{t-\tau}{a}\right) dt, \quad (5)$$

We use the Morlet wavelet as the mother wavelet to measure the synchronism across time series since it is a complex sine wave enclosed in a Gaussian envelope (see Following Aguiar-Conraria & Soares, 2014).

Considering the outcomes of the Wavelet Transform, Wavelet Coherence aids in our comprehension of the relationship between one time series and the other. This term can be defined as:

$$WCO_{xy} = \frac{SO\left(WT_x(a,\tau) WT_y(a,\tau)^*\right)}{\sqrt{SO(|WT_x(a,\tau)|^2) SO\left(\left|WT_y(a,\tau)\right|^2\right)}}, \quad (6)$$

As the wavelet coherence for all scales and times would be one if the SO parameter were eliminated, it is significant because it reflects the smoothing operator in time (Aguiar-Conraria et al., 2008). The codes created in Matlab for the CWT solution are available on the Aguiar-Conraria website.

Empirical Results

We present our findings in Table 1 after performing the common unit root tests (ADF, PP, and KPSS) on the aforementioned time series.

	ADF			PP		KPSS	
	(i)	(ii)	(iii)	(ii)	(iii)	(ii)	(iii)
Original Data							
FTSE	0.6998	–1.4274	–2.7954	–1.5826	–3.1796	1.7599	0.1567
CapEx non-manufacturing	2.5417	0.3746	–1.5093	0.1518	–2.1474	2.0638	0.3064
CapEx manufacturing	1.4314	0.3059	–1.7895	0.0966	–1.7833	1.7381	0.4888

Table 1. Unit Root Tests

The results suggest that the market capitalization of companies in the United Kingdom and the CAPEX of private non-manufacturing and manufacturing companies present a non-stationary I(1) behavior.

Given the low power of the unit root methods under fractional alternatives and in line with the aforementioned methodology, the ARFIMA (p,d,q) models are used in order to analyze the persistence of the time series that we are analyzing. To select the AR and MA orders in the models, the AIC (Akaike, 1973) and BIC (Akaike, 1979) criteria have been used.

Table 2 shows the estimates of long memory test following Sowell (1992) and the maximum likelihood estimator for the three time series. Various ARFIMA specifications (p, d, q) have been considered with all combinations of $p, q \leq 2$ for each time series.

Data analyzed	**Sample size (days)**	**Model Selected**	**d**	**Std. Error**	**Interval**	**I(d)**
Original Data						
FTSE	108	ARFIMA (0, d, 0)	0.82	0.152	[0.57, 1.07]	I(1)
CapEx non-manufacturing	108	ARFIMA (1, d, 1)	1.05	0.170	[0.77, 1.32]	I(1)
CapEx manufacturing	108	ARFIMA (2, d, 1)	1.11	0.235	[0.73, 1.50]	I(1)

Table 2. Results of Long Memory Tests

Table 2 highlights distinct behaviors for each variable, all demonstrating high persistence or long memory characteristics.

The FTSE (London Stock Exchange Index) exhibits long memory ($d = 0.82$), indicating that market shocks have persistent effects that gradually diminish over time. The ARFIMA(0, d, 0) model reveals no significant autoregressive or moving average components, suggesting that persistence is fully captured by the d parameter. This implies that shocks, such as changes in market capitalization, can have prolonged effects. For investors and portfolio managers, this highlights the need for long-term strategies to address these sustained market dynamics.

The CAPEX in private non-manufacturing sectors shows extreme persistence or unit root behavior ($d = 1.05$), suggesting a strong dependence on past levels and an almost non-stationary trajectory. The ARFIMA(1, d, 1) model indicates that both autoregressive and moving average components contribute alongside persistence. This extreme persistence implies that investment decisions in these sectors, such as technology and services, are heavily influenced by previous levels of CAPEX, likely due to their cumulative or strategic investment patterns.

The CAPEX in private manufacturing sectors also demonstrates long memory, with a slightly higher persistence value ($d = 1.11$). This reflects a stronger dependence on historical levels compared to the other variables. The ARFIMA(2, d, 1) model suggests a more complex dynamic, incorporating two autoregressive terms and one moving average term. This higher dependence may indicate that manufacturing CAPEX is influenced by structural constraints or rigid investment cycles, making this sector less responsive to immediate economic changes.

For all three series, the confidence intervals for d include values close to or above 1, reinforcing the high persistence and non-stationarity across variables. These findings highlight the long-term influence of historical trends on market performance and sectoral investment behaviors, underlining the importance of considering persistence when making policy or investment decisions.

Once we have studied the statistical properties of each time series, we use the Granger causality test to examine the interactions between capital expenditures in manufacturing and non-manufacturing private sector companies and their market capitalization.

Direction of Causality	Lags	Prob.	Decision	Outcome
d_non-manufacturing → d_FTSE	1	0.0035	Reject Null	CapEx in non-manufacturing companies is causing behavior on company returns in United Kindom.

d_FTSE → d_non-manufacturing	1	0.9865	Do not reject Null	Company returns in United Kindom do not cause CapEx behavior in non-manufacturing companies.
d_manufacturing → d_FTSE	4	0.2125	Do not reject Null	CapEx in manufacturing companies is not causing behavior on company returns in United Kindom
d_FTSE → d_manufacturing	4	0.5901	Do not reject Null	Company returns in United Kindom do not cause CapEx behavior in manufacturing companies.

Table 3. Results of Granger Causality Test

The results of the Granger causality test presented in Table 3 reveal interesting dynamics between capital expenditure (CAPEX) in private non-manufacturing and manufacturing sectors and the behavior of company returns on the London Stock Exchange, represented by the FTSE index. These findings provide insights into the direction and nature of causality, highlighting the varying influence of sectoral investment decisions on market performance and vice versa.

One of the key findings is the significant causal relationship from CAPEX in non-manufacturing companies to FTSE returns. The probability value of 0.0035 leads to the rejection of the null hypothesis, confirming that CAPEX in the non-manufacturing sector exerts a measurable influence on market performance. This outcome underscores the strategic importance of investment decisions in sectors such as technology and services, which dominate the non-manufacturing space. As these investments drive growth and innovation, they appear to have a direct impact on market capitalization and investor confidence. This highlights non-manufacturing CAPEX as a critical driver of stock market dynamics, making it a valuable indicator for both policymakers and market participants.

In contrast, the data do not corroborate the inverse relationship, i.e., causality between FTSE returns and capital goods investment in the non-manufacturing sector. With a probability value of 0.9865, the null hypothesis cannot be rejected. This suggests that investment decisions in the non-manufacturing sector are not directly influenced by short-term fluctuations in stock market returns. Instead, these decisions may be driven by longer-term strategic objectives or sector-specific factors, such as technological advancements or consumer demand trends. The independence of CAPEX decisions from market volatility emphasizes the forward-looking nature of investment planning in non-manufacturing industries.

The findings related to CAPEX in manufacturing sectors present a different narrative. Unlike the non-manufacturing sector, there is no evidence of causality between manufacturing CAPEX and FTSE returns in either direction. The probability value of 0.2125 indicates that manufacturing CAPEX does not cause changes in FTSE returns, while the probability of 0.5901 confirms that FTSE returns do not influence manufacturing CAPEX. These results suggest a weaker or more indirect link between manufacturing investment and stock market performance. Manufacturing CAPEX may be constrained by structural factors, such as fixed production capacities, regulatory requirements, or global supply chain dependencies, which limit its responsiveness to market trends. Furthermore, the lack of causality from FTSE returns to manufacturing CAPEX suggests that investment in this sector is likely guided by long-term considerations, such as technological upgrades or capacity expansions, rather than immediate market signals.

Overall, the Granger causality test results reveal that CAPEX in non-manufacturing sectors has a significant impact on market returns, positioning it as a leading indicator of stock market performance in the United Kingdom. Conversely, manufacturing CAPEX shows no direct influence on market behavior, reflecting the structural and strategic differences between these two sectors. Additionally, the lack of causality from FTSE returns to CAPEX in either sector highlights the independence of investment decisions from short-term market fluctuations.

After determining with the causality test and obtaining robust results that there is a relationship from CAPEX in non-manufacturing companies to FTSE returns, and that it is not spurious (the relationship between the two variables in the direction indicated above is significant), we want to determine the correlation that exists between both variables. To do so, we use Continuous Wavelet Transform (CWT) that is a multivariate analysis based on time-frequency domain. This methodology is very useful to identify periods of high correlation (relationship that exists between two variables over time), and to know if this relationship is located in the short, medium or long term through the frequency domain.

Wavelet Coherency	**Phase difference**

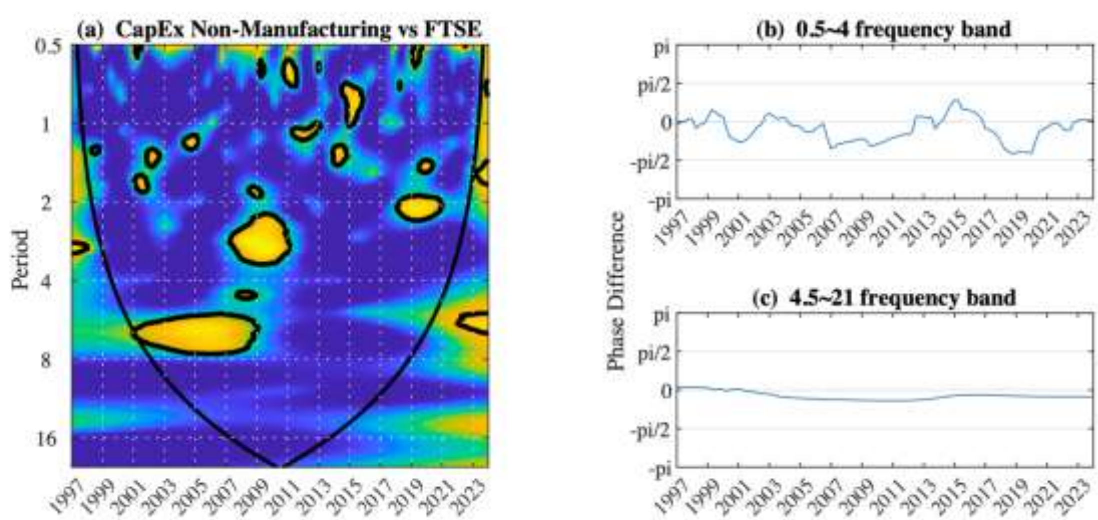

Figure 2: Wavelet Coherency and Phase Difference Results.

Section (a) of Figure 2 illustrates the wavelet coherence between CAPEX in non-manufacturing companies and the London Stock Exchange (FTSE) over time (horizontal axis) and across different frequencies or periods (vertical axis, measured in quarters). This representation provides insight into when and at which frequencies significant interactions occur between the two time series, as well as the periods where these interactions are strongest. Statistically significant coherence regions at the 5% significance level were identified using Monte Carlo simulations (n=1000). These regions, where coherence levels are highest, are highlighted in yellow on the graph.

The results reveals two main areas of high coherence: 1) short-term cycles that corresponds to the frequency band of 2–4 quarters (approximately 6 months to 1 year); 2) medium-term cycles that are observed in the frequency band of 4–8 quarters (approximately 1 to 2 years).

The vertical axis indicates these frequency bands, while the horizontal axis represents the analyzed period, allowing us to identify specific timeframes with significant coherence.

To interpret these regions of high coherence, the partial phase difference results in section (b) were examined. For high-frequency zones, the phase difference analysis reveals that during the period from 2014-2017, at the 5% significance level, the phase difference lies within the range $[0, \frac{\pi}{2}]$. This indicates a positive correlation between CAPEX in non-manufacturing companies and market performance in the FTSE, particularly within the short-term frequency band (0.5–2 quarters, corresponding to approximately 1.5 to 6 months). The concentration of coherence in the short- and medium-term frequency bands implies that CAPEX impacts on market performance are more pronounced over shorter time horizons. This aligns with the understanding that investment decisions and their effects on market valuation often manifest within these cycles.

Economically, this means that capital expenditures acted as a leading indicator of short-term market capitalization performance. For the rest of the period, the relationship was negative, showing that the increase in market capitalization of non-manufacturing companies was not the result of higher capital investment.

Concluding Remarks

This study provides novel insights into the relationship between capital expenditures (CAPEX) in private sector manufacturing and non-manufacturing firms and the market performance of the UK stock market, represented by the FTSE index. By employing a robust methodological framework integrating fractional integration analysis, Granger causality tests, and the Continuous Wavelet Transform (CWT), we capture the nuanced behavior, persistence, and interactions of these variables over time and across frequencies.

Our findings reveal distinct sectoral differences in how CAPEX influences market performance. CAPEX in the non-manufacturing sector exhibits a significant positive causal relationship with FTSE returns, confirming its role as a leading indicator of short-term stock market performance. Wavelet analysis further demonstrates that this relationship is concentrated in short- and medium-term frequency bands (6 months to 2 years), highlighting the immediate and measurable impact of non-manufacturing investments on market valuation. This outcome underscores the importance of sectors such as technology and services in driving investor confidence and enhancing market capitalization.

In contrast, CAPEX in the manufacturing sector shows no significant causal relationship with FTSE returns, as confirmed by Granger causality tests. This lack of influence suggests that manufacturing investments are characterized by structural constraints, rigid timelines, and long-term strategic considerations that reduce their responsiveness to short-term market signals. Furthermore, the absence of causality in the reverse direction in which FTSE returns influence CAPEX decisions indicates that both sectors operate with some degree of independence from short-term market fluctuations.

The persistence analysis through ARFIMA models further reinforces these findings. All three series (FTSE, non-manufacturing CAPEX, and manufacturing CAPEX) demonstrate long memory characteristics, with non-manufacturing CAPEX exhibiting extreme persistence. This behavior reflects the cumulative and strategic nature of investments in this sector, which remain strongly dependent on historical trends. In contrast, while manufacturing CAPEX also exhibits long memory, its greater dependence on structural and cyclical factors limits its immediate impact on market performance.

The wavelet coherence analysis enriches these conclusions by revealing dynamic interactions between CAPEX and market performance across different time horizons. The results highlight that non-manufacturing CAPEX has a greater short-term correlation with market movements, aligning with its forward-looking nature and its role in signaling growth and innovation to market participants. Conversely, the weak relationship observed in the manufacturing sector underscores the challenges inherent in translating large-scale capital investments into immediate market value.

This study contributes to the existing literature by highlighting the sectoral heterogeneity in CAPEX impacts on stock market performance. For investors, the findings underscore the importance of monitoring non-manufacturing CAPEX as a reliable indicator of short-term market dynamics. For corporate managers, the results emphasize the need to align capital investment strategies with market expectations, particularly in sectors where immediate value creation is more transparent. Policymakers can leverage these insights to promote investment-friendly environments that drive economic growth and enhance market stability.

Future research could extend this analysis to other markets and sectors, incorporating additional macroeconomic variables to explore the broader determinants of CAPEX behavior. Further, refining the methodologies with non-linear models or higher-frequency data could offer deeper insights into the complex interactions between capital investment and market performance.

In conclusion, this study bridges an important gap in the literature by demonstrating that CAPEX in non-manufacturing sectors in United Kingdom acts as a significant driver of short-term market performance, while manufacturing CAPEX remains more constrained by structural and cyclical factors. These findings provide a comprehensive understanding of the dynamics between strategic investment decisions and stock market valuation, with valuable implications for theory, practice, and policy.

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