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Cash Conversion Cycle and Corporate Performance: Evidence from the United States

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Master's in Finance

Supervisor:
PhD, Rui Manuel Meireles dos Anjos Alpalhão, Full Invited Professor,
Iscte-Iul

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Resumo

A Duração Líquida do Ciclo de Exploração é considerada uma das mais importantes medidas de gestão de fundo de maneio. Este estudo analisa a relação entre a Duração Líquida do Ciclo de Exploração, bem como os seus componentes (Prazo Médio de Clientes, Prazo Médio de Inventários, e Prazo Médio de Fornecedores), e rentabilidade económica numa amostra de 987 empresas cotadas na bolsa de valores de Nova Iorque, por um período de 6 anos de 2017 a 2022. O estudo procura investigar até que ponto diferentes políticas de gestão de fundo de maneio impactam a rentabilidade, focando em empresas que operam em setores com mais abertura para negociação de prazos de pagamento e recebimento, pois assumimos que nesses setores a gestão de fundo de maneio faz maior diferença. Para isso usamos análise de correlação e regressão linear. Os resultados sugerem que os diferentes setores têm realidades bastantes distintas. Em linha com estudos anteriores, em alguns setores existe uma relação negativa entre rentabilidade—medida através da Rendibilidade Operacional dos Ativos e do rácio da Margem Bruta sobre Ativo Total—e o ciclo de exploração, o que indica que a performance empresarial pode melhorar caso as empresas acelerem recebimentos de clientes, reduzam inventários, e atrasem pagamentos a fornecedores. No entanto, para outros setores a relação é positiva ou insignificante. Assim, gestores devem perceber a realidade do setor em que operam antes de procurarem aumentar ou diminuir a Duração Líquida do Ciclo de Exploração.

Palavras-chave: Necessidades de Fundo de Maneio, Duração Líquida do Ciclo de Exploração, Rentabilidade

Classificação JEL: G30, G31

Abstract

The Cash Conversion Cycle is considered the most important measure of working capital management. This paper studies the relationship between the Cash Conversion Cycle and corporate profitability on a sample of 987 companies operating in the Energy, Materials, Industrials, and Health Care sectors, listed on the New York Stock Exchange, for a period of 6 years from 2017 to 2022. We aim to find to what extent different working capital management policies impact profitability, with a focus on companies operating in sectors where it is more common to negotiate payment and receiving terms, as in these sectors working capital management policy likely makes a bigger difference. We study the relationship between profitability and the Cash Conversion Cycle, as well as its components (Days of Sales Outstanding, Days Payable Outstanding, and Days of Inventory Outstanding) through correlation and regression analysis. The results of our research vary a lot across the sectors. In line with previous literature, in some sectors there is a negative relationship between profitability—measured through Return on Assets and Gross Operating Profit—and the Cash Conversion Cycle, which suggests corporate performance improves when companies collect payments from clients faster, avoid stocking too much inventory, and delay payments to suppliers. However, in other sectors the relationship is positive or insignificant. As such, managers should understand very well the reality of the sector in which they operate before attempting to shorten or lengthen their Cash Conversion Cycle.

Keywords: Working Capital Management, Cash Conversion Cycle, Corporate Profitability

JEL Classification: G30, G31

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Glossary

B2B – Business to Business

B2C – Business to Consumer

BLUE – Best Linear Unbiased Estimator

CCC – Cash Conversion Cycle

COGS – Cost of Goods Sold

DCF – Discounted Cash Flow

DIO – Days Inventory Outstanding

DSO – Days Sales Outstanding

DPO – Days Payable Outstanding

EBIT – Earnings Before Interest and Taxes

EBITDA – Earnings Before Interest, Taxes, Depreciation, and Amortization

FE – Fixed Effects

GICS – Global Industry Classification Standard

GMM – Generalized Method of Moments

GOP – Gross Operating Profit

IFRS – International Financial Reporting Standards

MSCI – Morgan Stanley Capital International

NYSE – New York Stock Exchange

OLS – Ordinary Least Squares

ROA – Return on Assets

RE – Random Effects

ROCE – Return on Capital Employed

VIF – Variance Inflation Factor

WCM – Working Capital Management

1. Introduction

At the heart of a company's annual financial reports lies a fundamental metric—revenue, which is often a barometer for the firm's success. However, the revenue figure in the income statement is not the actual cash the company received that year because the company may allow clients to pay later. The same applies to the costs, as not all of them are actual cash outflows because the company may be granted trade credit by its suppliers.

Actual cash inflows and outflows are reflected in the cash flow statement, but not in the income statement. The same revenue figure can have different cash flow statements. While taking longer to pay suppliers and receiving money faster from clients improves the cash flow from operations in the cash flow statement, it does not impact the revenue figure *directly*. The goal of this study is to see if the extra cash results in an *indirect* increase in revenues (possibly due to more money being available for investments in growth opportunities).

On one hand, giving clients trade credit boosts sales as the ability to pay later not only attracts new clients, but also likely increases the quantities purchased by existing ones. On the other hand, as the cash inflows from clients are delayed, the company needs financing to bear the costs of fulfilling sales. The financing can either be through bank loans or suppliers' trade credit.

Suppliers typically offer discounts when they are paid upfront and fully (Wilner, 2000). This is why allowing companies to pay later is a form of financing. In a bank loan, the cost of the money is the interest. With suppliers' trade credit the cost is the discount for paying upfront, as the company loses the right to that discount when it decides to pay later. Thus, finding a balance between boosting sales by offering trade credit to clients and reducing upfront costs of fulfilling those extra sales is crucial to maintaining a healthy cash balance.

This is the main objective of Working Capital Management (WCM)—to negotiate payment terms that allow the company to have cash available to take advantage of new growth opportunities, but also guarantee there is enough cash to cover daily operations.

With clients, the goal is to grant trade credit to boost sales but at the same time avoid excessive cash tied up in accounts receivable. With suppliers, to delay payments so more cash is available within the company for other investments, but to avoid deteriorating the business relationship with them (Ng, Smith, and Smith, 1999). As to inventories, the goal is to have enough to fulfill sales and cover daily operations as well as potential increases in demand, but to avoid excessive amounts so as to reduce storage costs and free up cash for better investments.

The Cash Conversion Cycle (CCC) is the most popular measure of working capital management (Prasad et al., 2018). Developed by Richards and Laughlin in 1980, it is the time length between the purchase of raw materials used to produce products and the payment received for the sale of finished goods. The longer the CCC length, the bigger the investment in working capital.

A long cash conversion cycle fueled by higher sales on trade credit and growing accounts receivable might translate into increased profitability, as clients enjoy the option of paying later for goods. However, most of the literature points in the opposite direction—the lower the CCC length, the higher the profitability (Prasad et al., 2018). This is because if a company allows clients to pay later but avoids difficulties fulfilling those sales by negotiating equally long payment terms with its suppliers, it has a low cash conversion cycle length. Conversely, receiving payments from customers upfront and paying suppliers later is also optimal, and also results in low CCC length. Therefore, working capital management is wholly captured by the Cash Conversion Cycle metric, and typically, good working capital management is synonymous with a low CCC (Wang, 2019). As such, in this paper we will aim to study if low CCC (i.e., good WCM) leads to higher profitability.

The goal of this work is to compare the performance of companies with different CCC lengths but operating within the same sector. This is because companies operating in different industries have distinctive and significantly different working capital management policies (Weinraub and Visscher, 1998). Also, we limit the review to sectors where giving clients credit is the norm. Working capital components in the balance sheet of business-to-business (B2B) companies have more significance, making them more suitable for the purposes of this research, in contrast with business-to-consumer (B2C) industries where companies can quickly transfer sales into cash (i.e., have low accounts receivable). For instance, retailers get immediate payment when a client buys goods.

B2B companies have a different asset structure compared to B2C companies due to differences in their working capital needs, sales cycles, and inventory turnover (Filbeck and Krueger, 2005). They often have longer sales cycles and may require larger inventories, leading to a higher proportion of current assets in their total assets, and more days of sales outstanding as a result (J.P. Morgan Working Capital Index, 2019). In contrast, B2C companies operate in industries with shorter sales cycles and faster inventory turnover (Filbeck, 2005), resulting in a lower proportion of current assets relative to total assets due to the very nature of the business and industry, not due to the managers' ability to negotiate favorable terms with clients, or to use financial debt in a way that frees up cash for other investments, or any other strategy to decrease CCC length and manage working capital optimally.

We also focus on listed companies, given they must adopt the International Financial Reporting Standards (IFRS) when preparing financial reports, as opposed to domestic accounting standards which may differ from country to country, rendering the data incomparable. This mitigates differences caused by accounting methods and not strategy. Additionally, unlisted firms may have an incentive to hide profits to pay lower taxes (Lazaridis and Tryfonidis, 2006).

We aim for the paper to contribute to the literature by enhancing the understanding of the impact of working capital management (measured through the CCC) on profitability—proxied by Gross Operating Profit (GOP) and Return on Assets (ROA)—by analyzing six years of data from 2017 to 2022 of companies listed in the New York Stock Exchange (NYSE).

This paper is structured as follows: In the next chapter we go over the characteristics of the sectors of the companies studied. Section three consists of an explanation of all the theoretical key concepts needed to understand this study. Section four reviews previously published literature on the relationship between working capital management and corporate profitability. The fifth section outlines the methodology, describes the data, and details the hypotheses along with the models used. In section six we go over the results of the study and discuss the findings of our univariate, bivariate, and multivariate analysis. Section seven presents the main conclusions relevant to managers and closes the paper with its limitations and suggestions for future research.

2. Sectors Overview

The New York Stock Exchange organizes publicly traded companies into different sectors based on their primary business activities. Developed by MSCI and Standard & Poor's in 1999, the Global Industry Classification Standard (GICS) framework is commonly used to categorize companies into sectors. The GICS sectors on the NYSE are: Energy, Materials, Industrials, Consumer Discretionary, Consumer Staples, Health Care, Financials, Information Technology, Communication Services, Utilities, and Real Estate.

This paper aims to focus on companies where all three components of the Cash Conversion Cycle (accounts receivable, inventories, and accounts payable) play a key role in the working capital management of a company. As such, we focus on companies operating in four sectors: Energy, Materials, Industrials, and Health Care.

The Energy sector covers companies that do business in the oil and natural gas industry. It includes oil and gas exploration and production companies, as well as producers of other consumable fuels like coal and ethanol. This sector also includes the related businesses that provide equipment, materials, and services to companies that explore and produce oil and gas. It also includes companies primarily involved in the production and mining of coal, related products, and other consumable fuels related to the generation of energy.

The Materials sector includes companies that provide various goods for use in manufacturing and other applications. It includes makers of chemicals, construction materials, containers, and packaging, along with mining stocks and companies specializing in making paper and forest products. It caters to a diverse range of clients and customers, as it encompasses companies involved in the production and distribution of raw materials, chemicals, and other basic materials used in various industries.

The Industrials sector encompasses a wide range of different businesses that generally involve the use of heavy equipment and the construction of heavy machinery that other companies will use in their activities. Transportation businesses such as airlines, railroads, and logistics companies are also part of the Industrials sector, as are companies in the aerospace, defense, construction, and engineering industries. Companies making building products, producing electrical equipment, building facilities, and providing security and protection services to businesses and governments also fall into this sector, as do many conglomerates. It also includes firms that provide professional services to other firms, such as human resources management and management consulting.

The Health Care sector has two primary industries. One industry includes companies that develop pharmaceuticals and treatments based on biotechnology, as well as the analytical tools and supplies needed for the clinical trials that test those treatments. The other encompasses manufacturers of health care supplies and medical devices, instruments, and products, including hospital supplies, safety equipment, and diagnostic tools. It also encompasses distributors and wholesalers of these products and companies providing information technology services primarily to health care providers.

We exclude Consumer Discretionary and Consumer Staples sectors for the very nature of the business, as accounts receivable may have a relatively lower impact on the cash cycle given the characteristic of immediate client payments. In the Information Technology sector, inventories do not play a crucial role as technology is an intangible asset. Our focus is on industries where the management of receivables, inventory, and payables are all key factors influencing working capital dynamics. This targeted approach aims to provide insights into sectors where the interplay between inventory turnover and payment/collection terms with suppliers/clients significantly contributes to operational efficiency and overall profitability.

Of course within each sector, there can be a mix of business models, and some companies may serve both consumers and businesses. Additionally, the landscape can change over time due to industry dynamics and evolving business strategies. For instance, working capital management for distributors within the Consumer Staples sector is certainly important as they deal with retail companies as opposed to the final consumer. Accounts receivable will certainly be a crucial component of WCM for producers of food products that do not package and market them to the final consumer. However, for this study we emphasize whether the broader sector is B2B-focused or not.

Due to the differing nature of working capital across industries (Hawawini, Viallet, and Vora, 1986), we only compare companies operating within the same sector, as opposed to comparing all companies in the four chosen sectors together.

3. Key Concepts

The following section aims to theoretically support this study. It will explain the concepts considered necessary for a clear understanding of the paper, as well as some important considerations about working capital and how firms manage each component separately.

3.1. Working Capital

Working capital is the amount of current assets (assets expected to be converted into cash or used up within one year) minus the current liabilities (obligations expected to be settled within one year). It is a measure of a company's short-term liquidity and its ability to meet its short-term obligations. Positive working capital means the company has more current assets than current liabilities, which is generally seen as a healthy financial position as it means it has enough resources to cover its short-term obligations.

The main items of working capital are accounts receivable, inventory, and accounts payable. They can be found in the balance sheet of a company. Accounts receivable are amounts clients owe a company for products or services that have been delivered but have not been paid for yet. Inventory comprises the goods or materials a company holds for consumption, production, or sale. It includes raw materials, work-in-progress products, and finished goods. Accounts payable are amounts a company owes its suppliers for goods or services received but not yet paid for.

The main objective of working capital management is to maintain an optimal balance between each of the working capital components. Companies can manage working capital using an aggressive or conservative approach, reflecting their attitude towards risk, liquidity, and investment in working capital. A conservative approach involves maintaining higher levels of current assets, resulting in a higher ratio of current assets to total assets (Weinraub and Visscher, 1998). This helps the company meet its short-term obligations even in unexpected adverse conditions. However, while conservative WCM provides a safety net, it may result in a lower Return on Assets, as a significant portion of resources is tied up in less profitable, highly liquid assets. Aktas, Croci, and Petmezas (2015) found firms with excessive working capital can use corporate investment as a channel through which the decrease in unnecessary working capital translates into higher firm performance. This decrease through time increases a firm's financial flexibility not only in the short term thanks to the release of unnecessary cash invested in working capital, but also in the long term thanks to less financing needs to fund day-to-day operating activities. Additionally, financially flexible firms have a greater ability to take investment opportunities (Denis and Sibilkov, 2010).

Conversely, aggressive WCM implies minimizing current assets to increase efficiency, as lower levels of cash, receivables, and inventory free up resources for more profitable investments. The lower the ratio of current assets to total assets, the more aggressive the WCM policy (Weinraub and Visscher, 1998). By keeping a leaner balance sheet, companies adopting an aggressive WCM strategy can get better returns on invested capital. However, this approach has a higher risk of being unable to meet short-term obligations if unexpected downturns arise. Per Weinraub and Visscher (1998), aggressive working capital policies prefer lower-cost short-term debt over long-term capital. Although lower capital costs increase the risk of a short-term liquidity problem. A more conservative policy uses more expensive capital but delays the principal repayment of debt or avoids it entirely by using equity.

Different firms will have different optimal levels of working capital that maximize their value. Giving clients generous trade credit may lead to higher sales, as it gives them more time to pay and the opportunity to assess product quality before paying (Long, Maltiz, and Ravid, 1993). Maintaining high levels of inventory reduces the cost of possible interruptions in the production process, reduces the risk of running out of stock and losing potential business, reduces supply costs, and protects against unfavorable price fluctuations, among other advantages (Blinder and Manccini, 1991). However, uncollected accounts receivables and excessive inventories can lead to liquidity problems i.e., insufficient funds to run the daily operations of the business and settle short-term obligations (Van-Horne and Wachowicz, 2008). As such, companies that invest heavily in inventory and give plenty of trade credit can also see reduced profitability. This is because the greater the investment in current assets, the lower the risk, but also the lower the profitability. Delaying payments to suppliers works as a flexible source of financing, but it can be expensive when they offer discounts to a company for paying early (Wilner, 2000). Paying early will also improve the business relationship with suppliers (Wilner, 2000).

Companies may use static and dynamic metrics to evaluate working capital management. Static measures include traditional liquidity ratios such as the current ratio, quick ratio, and cash ratio. These metrics compare balance sheet items at a single point in time. However, static measures of liquidity have been questioned by many researchers. Canina and Carvell (2008) point out these measures include both liquid financial assets and operating assets in their formulas. Thus, if the goal is to measure the liquidity a company has, the inclusion of operating assets essential to its ongoing activity is not useful because the company cannot sell those assets without impacting its operations negatively. Additionally, current assets include financial resources that are not easily convertible into cash without loss of value. On a broader scale, Canina and Carvell (2008) also state another problem with standard liquidity ratios is the assumption that a higher current ratio is a good thing. But a high current ratio may be caused by an increase in accounts receivable generated not by increased sales, but rather by an increase in clients not paying. In this case, the company is actually less likely to cover its current liabilities even though its current ratio is increasing. The same applies to inventories. If inventory is increasing due to more unsold goods, then their fair market value is likely substantially lower than the stated book value.

These shortcomings of working capital and liquidity ratios have led researchers and analysts to advocate for other measures of liquidity that better indicate cash availability, the main one being the Cash Conversion Cycle (Richard and Laughlin, 1980). The Cash Conversion Cycle is a more comprehensive and dynamic measure of WCM, combining data from both the balance sheet and the income statement. It is the subject of the following section.

3.2. Cash Conversion Cycle

The Cash Conversion Cycle (CCC) was introduced by Richards and Laughlin in 1980 as a measure of working capital management that details the time interval between the cash outflow to purchase inventories and the cash inflow from the sale of the final product. Its calculation consists of adding up the number of days in accounts receivable plus the number of days of inventories minus the number of days in accounts payable.

$$CCC = DSO + DIO - DPO \tag{3.1}$$

Days Sales Outstanding (DSO) is the average number of days it takes for a company to collect payment from its clients after a sale. It is calculated as follows:

$$DSO = \frac{Accounts\ Receivable}{Sales} \cdot 365 \tag{3.2}$$

Days Inventory Outstanding (DIO) is the average number of days it takes for a company to sell its entire inventory. It is calculated as follows:

$$DIO = \frac{Inventory}{Cost\ of\ Goods\ Sold} \cdot 365 \tag{3.3}$$

Days Payable Outstanding (DPO) is the average number of days it takes for a company to pay its suppliers. It is calculated as follows:

$$DPO = \frac{Accounts\ Payable}{Cost\ of\ Goods\ Sold} \cdot 365 \tag{3.4}$$

A shorter Cash Conversion Cycle is generally favorable, as it indicates a company is able to quickly convert its resources into cash. This efficiency can lead to improved liquidity and a reduced need for external financing (Molina and Preve, 2012). However, there are a number of factors that determine the optimal CCC of a company, including its industry, business model, size, maturity, country of operation, and overall economic environment.

Two similar companies may have completely different CCC lengths. It all depends on the WCM approach each company chooses, which is dependent on their risk appetite. A company that wants to maximize efficiency will invest in effective inventory control systems to better forecast demand, manage its supply chain, and plan its production accordingly in an attempt to shorten its CCC (at the cost of more risk). Negotiation power with both customers and suppliers also plays a significant role in WCM (Ng, Smith, and Smith, 2002). A company with a single big client responsible for most of its revenues will hesitate to demand early payment, which could lead to liquidity problems. Analogously, if the company is the biggest customer to its suppliers, it will have an easier time delaying payments—decreasing CCC length—because suppliers will not want to lose the relationship with the company, so they will be more lenient as a result. As such, DSO and DPO are a good proxy for the bargaining power of companies. These two metrics help validate the hypothesis that companies that enjoy more favorable conditions with suppliers and customers have better performance—the goal of our study.

Another determinant of CCC is the financing options a company has available. When a supplier allows the company to pay later, it is effectively granting the company a form of financing. However, a company should not pay later without having a purpose for the extra available cash because it may be losing out on a discount for paying upfront (Wilner, 2000). In essence, delaying payments is only useful if the extra available cash is used to generate a higher return than the percentage of the discount for paying early. That potential discount lost for not paying early is effectively the cost of the financing granted by suppliers, just as the interest rate is the cost of financing in a loan granted by a bank. As such, this trade credit received from suppliers is especially important for smaller firms that typically have less access to cheap bank loans (Wilson and Summers, 2002). Companies that benefit from better relationships with banks will have more favorable loan terms, especially in times of financial distress. As a result, they do not depend on trade credit from suppliers as much as firms with less bargaining power do, which will impact WCM policy and CCC length (Coeuré, 2013).

3.3. Profitability

In this study, profitability is proxied by Return on Assets (ROA), as suggested by Nazir & Afza (2009). Since this study aims to understand the relationship between the CCC and corporate profitability, and the components that make up the calculation of the Cash Conversion Cycle are purely business-related, we modify the numerator of the ROA calculation to Earnings Before Interest and Taxes (EBIT) as opposed to the net income. This way, the results focus solely on operational activity, as capital structure and taxes do not impact the results.

$$ROA = \frac{EBIT}{Total\ Assets} \tag{3.5}$$

ROA will function as a measure of firms' operating income in proportion to the value of their total assets, reflecting how efficiently a firm is using its assets to generate operating profits.

Besides ROA, we also use Gross Operating Profit (GOP) as a measure of profitability. It is calculated by subtracting the cost of goods sold from total sales and dividing the result by total assets (Karadag, 2015):

$$GOP = \frac{Sales - COGS}{Total\ Assets} \tag{3.6}$$

GOP assesses performance in relation to a company's asset base, making it easier to compare companies of different sizes on a level playing field. It focuses on the operational core business of a company, excluding profits from financial activities, as well as the impact of capital structure and taxes on profitability. Since the numerator is calculated by subtracting purchases from suppliers from sales to customers, it offers a direct look at the relationship between these two key components of CCC.

4. Literature Review

The following section is a review of the existing empirical literature about the relationship between WCM and profitability. The literature is extensive. Many authors have used different methodologies to analyze different samples of companies across the globe operating in all kinds of industries. Although the results are not consensual, most of them point in the direction of a negative relationship between the two variables, meaning lower CCC length is associated with higher profitability.

In his landmark study, Deloof (2003) analyzed the relationship between working capital management and corporate profitability for a sample of 1,009 large Belgian non-financial firms between 1992-1996. Trade credit policy and inventory policy are measured by the number of days accounts receivable, accounts payable, and inventories, and the CCC serves as a comprehensive measure of WCM. The results suggest managers can increase corporate profitability by reducing the number of days accounts receivable and inventories. Deloof also finds a negative relationship between days accounts payable and profitability, suggesting less profitable firms take longer to pay their bills. Nonetheless, Deloof stresses we cannot rule out the idea that a negative relationship between CCC and profitability stems from profitability affecting CCC, and not vice versa.

The results of Lazaridis and Tryfonidis (2006) are also relevant. They found a negative relationship between CCC length and gross operating profit on a sample of 131 companies listed in the Athens Stock Exchange during the period of 2001 to 2004. They also find a negative relationship between the number of days in inventory and profitability, suggesting decreases in sales and inventory mismanagement lead to excess capital tied up in inventories and less profits. In addition, they suggest listed companies in Greece can raise financial debt to decrease their CCC and increase their profitability as a result.

With a focus on four specific manufacturing sectors, namely automobile and parts, cement, chemical, and food producers, Attari and Raza (2012) looked at data from 31 companies listed in the Karachi Stock Exchange over the period 2006-2010. The data analysis was conducted by using one-way ANOVA and Pearson correlation. As expected, they found a significant negative relationship between CCC and profitability, measured through ROA.

In Spain, Baños-Caballero, García-Teruel, and Martínez-Solano (2010) sampled 4,076 small and medium-sized enterprises over the period 2001-2005 and found that older firms and companies with greater cash flows maintain a longer CCC, while firms with more leverage, growth opportunities, investment in fixed assets, and higher ROA maintain a more aggressive working capital policy and hence lower CCC length. This indicates the cost of financing has a negative effect on firms' cash cycles. It also indicates better access to capital markets might increase investments in working capital. García-Teruel and Martínez-Solano (2011) found similar conclusions on a sample of over 8,000 small and medium-sized Spanish firms covering the period 1996-2002. Their results were robust to the presence of endogeneity and showed managers can create value by reducing their firm's days of sales outstanding and inventories. Additionally, shortening the Cash Conversion Cycle also improves the firm's profitability.

Högerle et al. (2020) investigated the impact of working capital management on profitability and shareholder value in Germany. They analyzed data from 115 firms listed on the German Prime Standard from 2011 to 2017 and found that efficient working capital management, indicated by a shorter Cash Conversion Cycle, has a positive impact not only on Return on Capital Employed (ROCE) as a measure of profitability but also on shareholder value.

However, there are also research studies suggesting the opposite relationship. In a study of the relationship between WCM and the profitability of 88 American firms listed on the New York Stock Exchange, Gill, Biger, and Mathur (2010) found a positive relationship between CCC and gross operating profit for a period of three years from 2005 to 2007. Additionally, unlike Lazaridis and Tryfonidis (2006), they found no statistically significant relationship between days of accounts payable and profitability. The same applies to the days the inventory is held. They did find a negative relationship between accounts receivable and corporate profitability, in line with previous research. This suggests managers can improve profitability by reducing the credit period granted to their customers.

Thuvarakan (2013) used correlation and regression analysis to study data from manufacturing, construction, and telecommunication companies listed on the London Stock Exchange covering the period of 2006-2011. They found no significant relationship between the working capital components and firms' profitability, measured through gross income.

The results of Sharma and Kumar (2011) also go against the previous studies. They looked at a sample of 263 Indian firms divided into 15 industrial groups for the period 2000-2008, and used OLS multiple regression models. The study found a negative linear relationship between profitability and the number of days of accounts payables and days of inventory, and a positive relationship between profitability and the number of days of accounts receivables. This suggests companies can increase their profitability by offering extended credit to customers. They also found a positive relationship between CCC and profitability, suggesting the shortening of the cash cycle negatively impacts the profitability of Indian companies.

In a comprehensive review of the literature on working capital management, Prasad et al. (2018) looked at articles with over 50 citations and found most of the highly cited articles have studied the relationship between the WCM and the profitability of the firms. The review includes most of the studies detailed above. They found the majority of the studies (79%) reported a negative and significant relationship between the measure of WCM and profitability, suggesting firms' profits increase with an improvement in their working capital efficiency. As to the individual components of CCC, Prasad et al. found most studies indicate firms can increase their profits by reducing their average collection period, reducing the average inventory holding period, and delaying payments to suppliers. However, they also point out most researchers repeatedly use the same proxies (such as CCC or ROA) while new innovative proxy measures are rare, which is why many highly cited articles are published in relatively lower-category journals.

In conclusion, while many studies show a negative relationship between CCC and profitability, contradictory results exist. Therefore, this research aims to extend the existing body of literature and contribute to increasing the clarity around the topic.

5. Empirical Research

This section describes the hypotheses and research questions, the data sample, and the dependent and independent variables along with the methodology we use to conduct the empirical analysis.

5.1. Hypotheses

As previously mentioned, this study aims to understand if the working capital management of companies listed on the NYSE has an impact on their profitability. As such, the hypotheses are defined as follows:

H0 (Null Hypothesis): There is no statistically significant relationship between the Cash Conversion Cycle and the performance of companies in the NYSE.

H1: There is a statistically significant relationship between the Cash Conversion Cycle and the profitability of companies listed in the NYSE, meaning working capital management impacts profitability.

H2: There is a negative relationship between the Cash Conversion Cycle and the profitability of companies listed in the NYSE.

There is a negative relationship between Days Sales Outstanding and profitability.

There is a negative relationship between Days Inventory Outstanding and profitability.

There is a positive relationship between Days Payable Outstanding and profitability.

5.2. Methodology

We use standard descriptive statistics, a Person correlation matrix, the Ordinary Least Squares (OLS) multiple regression model, the Fixed Effects (FE) regression model, and the Random Effects (RE) regression model to investigate the relationship between the Cash Conversion Cycle and corporate performance.

The dependent variable is the *Return on Assets (ROA)*. The independent variable is the *Cash Conversion Cycle (CCC)*.

We run an additional model in which the dependent variable is the *Gross Operating Profit (GOP)* and the independent variables explaining the behavior of the dependent variable are the components of the cash cycle: *Days Sales Outstanding (DAYS_AR)*, *Days Inventory Outstanding (DAYS_I)*, and *Days Payable Outstanding (DAYS_AP)*.

In addition to the dependent and independent variable(s) for both models, we also include a set of control variables in the regression equation that may influence firms' profitability and working capital management:

Size (TOT_ASSETS): Large companies have historically performed better when it comes to working capital management as they are able to collect payments faster than their smaller counterparts (J.P. Morgan Working Capital Index, 2019). As such, we use the total assets (in millions) as a proxy for company size. Smaller companies have a harder time getting access to low-interest credit from banks, so WCM is more crucial whereas with large firms it is not as critical to have bargaining power with suppliers because they have better relationships with banks (Petersen and Rajan, 1997).

Market capitalization (MARKET_CAP): Market capitalization (in millions) is another measure of a company's size and value. Additionally, there is a direct link between working capital management and the most common approach to corporate valuation—the Discounted Cash Flow model (Högerle et al., 2020). In the Discounted Cash Flow approach changes in working capital impact the cash flow calculation. Increases in working capital are subtracted as cash outflows and discounted to the present, while decreases are added. This presents an incentive for companies to create shareholder value by optimizing working capital (Högerle et al., 2020). Market capitalization reflects the market's current valuation of the firm and is a useful benchmark for comparing a company's intrinsic value derived from the DCF analysis.

Age (AGE): We expect that as a company matures and builds relationships with customers and suppliers, it can better manage working capital and increase profitability. Mature companies are in general more creditworthy, and hence have easier access to additional financing alternatives at more favorable conditions than their younger counterparts. Baños-Caballero et al. (2010) found a positive significant relation between firms' age and CCC.

EBITDA Multiple (EBITDA_MULTP): The EBITDA multiple is a measure of a company's value often used in comparison to its peers. It compares the enterprise value of a business to its earnings before interest, taxes, depreciation, and amortization (EBITDA). Enterprise value is the sum of a company's market capitalization and any debts, minus its cash. Efficient working capital management, which shortens the CCC, means a company is better at turning its resources into cash quickly. This efficiency improves cash flow, reduces the need for external financing, and enhances profitability, which can lead to a higher EBITDA multiple.

Leverage (DEBT_TO_ASSETS): We measure leverage through the ratio of total debt to total assets. Deloof (2003), Lazaridis and Tryfonidis (2006), and Baños-Caballero et al. (2010) all found a negative relationship between profitability and leverage. Additionally, according to Petersen and Rajan (1997), smaller companies are more reliant on trade credit from suppliers because they cannot easily access other sources of financing.

Effective interest rate (EFF_IR): Companies with access to cheap external financing may be incentivized to use that when they need cash, as opposed to negotiating better terms with suppliers in an attempt to increase the amount of cash available. These companies may also be able to extend more credit to clients because they can get their liquidity from external financing. As such, we also look at the effective interest rate (interest expenses divided by financial debt) to study its impact on the relationship between the CCC and profitability, if any.

Revenue growth (SALES_GROWTH): Extending more trade credit to clients may increase sales, but at the same time it ties up cash in accounts receivable that could be used for investments that would bring more revenue to a company. Given this conundrum, we include revenue growth in the regression model as a control variable by taking a year's revenue, subtracting the previous year's revenue, and dividing that by the previous year's revenue.

Cash (CASH_ASSETS): Per Denis and Sibilkov (2010), greater cash holdings are associated with higher investment, especially for constrained companies. More cash allows companies to invest in value-increasing projects even if external financing is costly. As such, we consider cash as a percentage of the total assets of the company as a control variable.

Federal funds rate (FEDFUNDS): The federal funds rate is often considered a useful indicator of economic conditions. During economic downturns demand decreases, profitability shrinks, clients take longer to pay, and banks become more cautious about lending. When interest rates rise, companies whose WCM strategy involves extending a lot of trade credit to clients and getting liquidity through external financing will want to collect payments faster than usual. Given this, we look at how monetary policy—proxied by the Federal Funds Effective Rate—impacts the relationship between WCM and profitability throughout the years. We retrieved monthly data from the Federal Reserve Bank of St. Louis website. For each year in the study (2017-2022), we calculate FEDFUNDS as the average rate across all 12 months of that year.

Furthermore, we introduce a dummy variable to capture the impact of categorical data in the regression model.

Recession year (RECESSION): This dummy variable (1 for 2020, 0 otherwise) accounts for year effects, meaning time-specific factors that may influence the dependent variable. As the unique conditions of that year are accounted for thanks to the dummy variable, this enables the regression to focus on how other independent variables affect profitability, the dependent variable, without those effects being mixed with or distorted by the significant economic impact of the Covid-19 pandemic.

5.3. Data Description

In order to obtain relevant results from the study, we aimed to collect financial data from the annual financial statements of all companies as uniformly as possible, so that the sample data is comparable between different companies and sectors. To meet this requirement, we retrieved all data used in this study from Bloomberg.

The data sample is retrieved from the balance sheet and income statement. From the balance sheet, we look at accounts receivable, inventories, accounts payable, cash and cash equivalents, and total assets. From the income statement, we look at revenues, cost of goods sold, EBIT, and EBITDA. Some variables are taken from Bloomberg as is, specifically market capitalization, enterprise value, year of incorporation (to calculate companies' age), effective interest rate, and the total debt to total assets ratio. This financial data is retrieved for every year from 2017 to 2022 for each company in the NYSE operating in the Energy, Materials, Industrials, and Health Care sectors.

This period allows us to identify industry differences over time. It also creates a multi-year comparison that allows us to study the impact of Covid-19 in 2020, as well as how the recovery years after the pandemic compare to before, as there are three years of data before Covid and two years after.

The original data set is composed of 2,124 companies (12,744 rows of data in total). Due to missing data and outliers, 1,137 companies are excluded. To arrive at the final sample, all data points for a company were eliminated if there were three or more years of key data (i.e. the dependent and independent variables ROA, GOP, CCC, and days of receivables, payables, and inventory) missing during the six-year total period. The goal of this is to maintain the integrity of the figures for each company as a whole. We also excluded companies for being extreme outliers and errors in the data such as negative numbers in variables where it does not make sense (for example, market capitalization or total assets), as this could lead to problems in the analysis and result in misinterpretations. As a result of all adjustments, the final sample size is composed of 987 companies and 5,922 rows of data points in total. This still includes some missing observations for some control variables in some companies, which were automatically removed when using R, the programming language for statistical estimation we chose to use for this study.

While most studies use cross-sectional data and time series data for analysis, in this study we use panel data. Panel data combines both cross-sectional data and time series data (Wooldridge, 2013). Unlike cross-sectional data, which gives us a snapshot at one point in time, panel data (also called longitudinal data) tracks many variables across many time periods, enabling us to study trends and causal relationships more effectively. As panel data follows the same units (such as individuals, firms, or regions) over time, it allows us to control for unobserved factors that are constant over time but may vary across entities. This is especially important because these unobserved factors can bias the results if we do not account for them.

6. Presentation and Analysis of Results

This section presents the results of the data analysis and an examination of the findings with potential reasons behind them. We divide the analysis into three subsections for clearer interpretation.

We start by looking at the Descriptive Statistics of the dataset to get an overview of the central tendencies, variability, and distribution of each variable individually. Next, we run a bivariate analysis to explore the strength and direction of the linear relationships between pairs of variables. Lastly, we estimate multiple regression models to study how the variables together explain the behavior of profitability, along with robustness tests to verify the reliability of the results.

6.1. Descriptive Statistics

As detailed before, we will estimate separate multiple linear regression models for each of the four sectors. As such, to get an initial sense of the reality of the variables present in the model, the tables below present the descriptive statistics of the sample of companies in the model for each BICS sector, extracted from Bloomberg.

Table 6.1: Descriptive statistics across all sectors and variables, 2017-2022

Energy				
Variable	Median	Mean	StDev	No. Obs.
ROA	0.02012	-0.01481	0.196067	886
GOP	0.11513	0.14372	0.131324	886
CCC	32.536	46.957	87.67553	882
DAYS_AR	52.4	56.97	45.79318	868
DAYS_AP	42.89	54.4	47.42496	883
DAYS_I	21.826	44.429	61.3538	884
TOT_ASSETS	2036.2	13705.7	38549.07	892
MARKET_CAP	1264.9	10525.2	35032.03	853
AGE	17.862	22.965	18.73357	834
EBITDA_MULTP	0.08383	-0.03344	5.00341	846
DEBT_TO_ASSETS	27.94	31.84	26.19028	886
EFF_IR	5.546	9.897	51.81504	727
SALES_GROWTH	16.53	108.78	2425.128	876
CASH_ASSETS	0.05505	0.09489	0.123871	886

Materials				
Variable	Median	Mean	StDev	No. Obs.
ROA	0.07395	0.06926	0.10656	876
GOP	0.1793	0.20283	0.126238	874
CCC	72.25	84.85	68.77754	870
DAYS_AR	47.21	53.11	37.95228	873
DAYS_AP	42.5004	48.7803	35.57004	871
DAYS_I	69.49	80.79	52.09257	874
TOT_ASSETS	2367.9	6451.21	11249.62	877
MARKET_CAP	2038.35	6863.12	14793.86	860
AGE	25.6836	36.2949	32.45479	864
EBITDA_MULTP	0.09541	0.07346	0.540713	860
DEBT_TO_ASSETS	30.85	30.85	17.30859	877
EFF_IR	4.658	6.655	25.93441	738
SALES_GROWTH	8.288	13.039	43.21107	864
CASH_ASSETS	0.05915	0.084894	0.089333	877

Industrials				
Variable	Median	Mean	StDev	No. Obs.
ROA	0.06423	0.05444	0.124099	2448
GOP	0.2288	0.2607	0.169513	2446
CCC	65.1	76.75	70.6362	2429
DAYS_AR	53.52	54.15	31.58869	2445
DAYS_AP	39.6375	43.6525	28.85146	2429
DAYS_I	60.547	66	66.94322	2440
TOT_ASSETS	1275.4	5977.4	19280.08	2473
MARKET_CAP	1141.8	7414	19871.92	2456
AGE	27.9137	35.9667	28.77184	2436
EBITDA_MULTP	0.07553	0.07318	0.865175	2383
DEBT_TO_ASSETS	26.19	27.15	19.80361	2450
EFF_IR	4.172	4.861	3.889446	1953
SALES_GROWTH	7.588	11.193	31.99982	2413
CASH_ASSETS	0.07287	0.11037	0.11655	2450

Health Care				
Variable	Median	Mean	StDev	No. Obs.
ROA	0.01058	-0.06541	0.245054	1598
GOP	0.289	0.3307	0.240611	1591
CCC	107.27	121.38	138.8173	1564
DAYS_AR	60	64.85	46.42391	1578
DAYS_AP	55.6674	87.1749	115.5254	1575
DAYS_I	116.78	143.44	141.8333	1580
TOT_ASSETS	598	9512.1	28809.84	1598
MARKET_CAP	1715.7	17399.8	50236.43	1494
AGE	23.348	26.2984	20.16232	1602
EBITDA_MULTP	0.02436	-0.03746	0.808776	1488
DEBT_TO_ASSETS	22.837	26.331	23.93426	1598
EFF_IR	3.965	11.429	68.95696	1242
SALES_GROWTH	11.8	43.907	530.1913	1549
CASH_ASSETS	0.14928	0.22911	0.217956	1598

No. Obs = Number of observations

The data across the Energy, Materials, Industrials, and Health Care sectors reveals distinct patterns in financial performance and operational characteristics.

Starting with Return on Assets, the Materials sector shows the strongest performance with a positive median ROA of 7.3%, indicating that companies in this sector, on average, use their assets efficiently enough to generate profit. In contrast, the Health Care sector struggles with profitability, having a negative mean and a median ROA of around just 1%, coupled with the highest standard deviation (0.245054), signaling a wide disparity in performance across companies. The Energy sector also faces challenges, with a negative mean ROA, suggesting many firms cannot generate a positive EBIT with their assets. The Industrials sector performs better, with a median ROA of 6.4%, reflecting more consistent profitability (around $6.4 of EBIT for every $100 of assets) but still lower than the Materials sector.

When examining Gross Operating Profit, the Health Care sector stands out with the highest median GOP of 28.9%. This indicates strong operational performance, as for every $100 of assets a Health Care company has it generates on median around $29 in gross profits. This contrasts with the low median ROA, which suggests the sector may have high fixed or variable costs not directly tied to production (such as administrative, marketing, research and development, and depreciation) but are necessary for running the business and are eating into profitability. Also, the high standard deviation (0.240611) suggests significant variability, meaning that while some companies are highly profitable, others may not be as successful. The Industrials sector follows with a median GOP of 22.9%, showing strong but more consistent performance across firms. The Materials sector also performs well, with a median GOP of 17.9%, while the Energy sector has the lowest median GOP (11.5%), highlighting its relative struggles in operational efficiency.

The Cash Conversion Cycle provides insights into operational efficiency, with the Health Care sector having the longest median cycle at 107.3 days, along with the highest variability (standard deviation of 138.8). This suggests Health Care companies generally take longer to convert their investments in inventory into cash flows from sales, indicating higher working capital needs and potential liquidity challenges. The Materials sector, with a median cycle of 72.3 days, and the Industrials sector, with 65.1 days, are more efficient in this regard, while the Energy sector shows further efficiency with a low median cycle of 32.5 days. This suggests Energy companies are quicker to sell their inventory and collect payments from clients sooner, while delaying payments to suppliers.

Looking at the DAYS_AR (Days Sales Outstanding), DAYS_AP (Days Payable Outstanding), and DAYS_I (Days Inventory Outstanding), components of the CCC formula, the Health Care and Materials sectors have more extended payment and inventory holding periods compared to Energy and Industrials, reflecting their different operational dynamics. While for receivables and payables the days are relatively similar across all sectors (between 40 and 55 days), for days of inventory there is a sizable difference. The findings suggest Health Care and Materials businesses hold inventory longer, reflecting differences in the nature of goods handled (for instance, pharmaceuticals, chemicals, or raw materials) compared to faster-moving sectors like Energy. Nonetheless, the high standard deviation for these variables across the four sectors indicates different companies may run different working capital management strategies even if they operate in the same sector.

In terms of financial leverage, measured by comparing Total Debt to Total Assets, the Materials sector has the highest median ratio at 30.9%, reflecting a higher reliance on debt financing, which implies higher financial risk. The Energy and the Industrials sectors have slightly lower median leverage ratios, at 27.9% and 26.2% respectively, indicating more conservative financial structures. The Health Care sector has the lowest median ratio at 22.8%, suggesting companies in this sector are less leveraged and have less financial risk. This aligns with the fact Health Care shows the lowest median effective interest rate at around 4%, as the lower the perceived financial risk of a company, the less interest lenders will charge. Coupling this with the fact Health Care has the highest median inventory holding period by far (116.8 days), resulting in a longer Cash Conversion Cycle, and that they have the highest level of cash reserves in proportion to total assets with a median of 14.9%, and there is a strong indication companies in this sector are overall more conservative both in their working capital and debt financing approach.

Lastly, the age of companies across these sectors varies, with the Industrials and Materials sectors housing the oldest firms on median (27.9 and 25.7 years respectively), indicating a well-established market presence. In contrast, the Energy sector, with a median age of 17.9 years, has younger companies.

Overall, the Materials sector emerges as relatively strong in terms of profitability and financial stability, while the Health Care sector, despite its high operational profits, faces greater costs and more cash tied up in inventories. The Industrials sector demonstrates maturity and consistent performance, whereas the Energy sector appears more risky and less profitable, likely due to its higher leverage, mixed profitability, more aggressive working capital policy, and younger businesses.

6.2. Bivariate Analysis

In this section, we perform a bivariate analysis to examine the relationships between the variables in our dataset. We estimate Pearson correlation coefficients to quantify the strength and direction of the linear relationships between all pairs of variables. Any missing values in the data are not considered. Below are the Pearson correlation matrixes for each of the four sectors subject to this study.

Table 6.2: Pearson correlation matrix across all variables, Energy sector, 2017-2022

En	ROA	GOP	CCC	DSO	DPO	DIO	A	MC	AGE	EM	DtA	EIr	SG	CA
ROA	1													
GOP	0.5367	1												
CCC	-0.2654	-0.1315	1											
DSO	-0.175	-0.118	0.5387	1										
DPO	0.0592	-0.0379	-0.3387	0.2053	1									
DIO	-0.1964	-0.1229	0.7458	0.1543	0.1028	1								
A	0.1043	-0.0688	-0.0878	-0.0923	-0.0303	-0.0757	1							
MC	0.1266	-0.0092	-0.0694	-0.0727	-0.0252	-0.0609	0.9423	1						
AGE	-0.0261	-0.1077	-0.0236	0.0129	0.0313	-0.0198	0.3856	0.3874	1					
EM	0.6749	0.3503	-0.1847	-0.1201	0.0425	-0.137	0.0596	0.0605	0.0065	1				
DtA	-0.0322	0.0049	-0.2491	-0.2416	0.0203	-0.1522	-0.0572	-0.0846	-0.1807	-0.012	1			

EIr	0.0497	0.0686	-0.0228	0.0203	0.0448	-0.0143	-0.0407	-0.0368	-0.0216	0.0369	-0.057	1		
SG	-0.0236	-0.0075	-0.0019	0.0125	0.071	0.0397	-0.0152	-0.0124	0.0587	-0.037	-0.0299	0.0137	1	
CA	-0.1328	-0.0851	0.2295	0.1394	0.0133	0.2257	-0.1539	-0.1086	0.0895	-0.0724	-0.3369	0.0071	-0.0196	1

En = Energy Sector, ROA = Return on Assets, GOP = Gross Operating Profit, CCC = Cash Conversion Cycle, DSO = Days Sales Outstanding (or Days Accounts Receivable, DAYS_AR), DPO = Days Payable Outstanding (or Days Accounts Payable, DAYS, AP), DIO = Days Inventory Outstanding (or Days Inventory, DAYS_I), A = Total Assets (TOTAL_ASSETS), MC = Market Capitalization (MARKET_CAP), AGE = Company Age, EM = EBITDA Multiple, DtA = Leverage (DEBT_TO_ASSETS), EIr = Effective Interest Rate (EFF_IR), SG = Revenue Growth (SALES_GROWTH), CA = Cash as % of Total Assets (CASH_ASSETS)

Table 6.3: Pearson correlation matrix across all variables, Materials sector, 2017-2022

Mat	ROA	GOP	CCC	DSO	DPO	DIO	A	MC	AGE	EM	DtA	EIr	SG	CA
ROA	1													
GOP	0.6061	1												
CCC	-0.0858	-0.0007	1											
DSO	-0.0806	0.1203	0.5749	1										
DPO	-0.035	0.1453	-0.1887	0.2997	1									
DIO	-0.0867	0.0293	0.8122	0.3656	0.2673	1								
A	0.085	-0.0179	-0.2018	-0.0725	0.1478	-0.1144	1							
MC	0.126	0.0836	-0.162	-0.0088	0.1364	-0.1076	0.8444	1						
AGE	0.0295	0.124	0.0431	0.1825	0.0535	-0.0121	0.0674	0.1633	1					
EM	0.3782	0.0679	-0.1873	-0.2228	0.0086	-0.1054	0.0369	0.0106	0.002	1				
DtA	0.0621	-0.0383	-0.2286	-0.0422	0.1791	-0.1442	0.0504	0.0397	-0.0813	0.0735	1			
EIr	-0.0192	-0.0128	0.0308	0.0122	-0.03	0.0118	-0.059	-0.0528	-0.0005	-0.0007	-0.1102	1		
SG	0.3416	0.1883	-0.0166	0.0315	0.0615	0.0027	0.0865	0.0607	-0.0273	0.1183	-0.0425	-0.0291	1	
CA	0.0038	-0.0112	0.1144	0.055	-0.121	0.032	-0.0966	-0.0823	-0.0652	-0.0187	-0.2589	0.091	0.0318	1

Mat = Materials Sector

Table 6.4: Pearson correlation matrix across all variables, Industrials sector, 2017-2022

Ind	ROA	GOP	CCC	DSO	DPO	DIO	A	MC	AGE	EM	DtA	EIr	SG	CA
ROA	1													
GOP	0.5085	1												
CCC	-0.0165	0.0456	1											
DSO	-0.0892	0.0087	0.3547	1										
DPO	-0.0766	-0.1083	0.0081	0.3152	1									
DIO	-0.0084	0.0012	0.8881	0.0578	0.2624	1								
A	0.0221	-0.1503	0.0096	-0.0317	0.1721	0.091	1							
MC	0.1549	-0.0678	-0.0026	-0.0693	0.1352	0.0802	0.7396	1						
AGE	0.0829	0.0446	0.2282	0.0738	0.09	0.2402	0.2265	0.1464	1					
EM	0.1497	0.0642	-0.0136	-0.0192	-0.0654	-0.0314	-0.2604	-0.0066	-0.0605	1				
DtA	-0.0267	-0.171	-0.2082	-0.196	-0.0086	-0.1346	0.059	0.0347	-0.1633	0.007	1			
EIr	-0.2539	-0.0682	0.0022	-0.0492	0.0007	0.0239	-0.1032	-0.1565	-0.0978	-0.0051	0.1186	1		
SG	0.1481	0.0227	-0.0329	-0.016	-0.0254	-0.0372	-0.0512	-0.0416	-0.1128	0.0599	0.0352	0.1097	1	
CA	-0.0416	0.0999	0.1035	0.097	0.1164	0.1109	-0.0505	-0.0338	-0.0917	-0.0421	-0.301	-0.0316	0.0321	1

Ind = Industrials Sector

Table 6.5: Pearson correlation matrix across all variables, Health Care sector, 2017-2022

HC	ROA	GOP	CCC	DSO	DPO	DIO	A	MC	AGE	EM	DtA	EIr	SG	CA

ROA	1													
GOP	0.1716	1												
CCC	0.0509	-0.0052	1											
DSO	-0.1233	-0.1147	0.3329	1										
DPO	-0.3	0.038	-0.1866	0.2958	1									
DIO	-0.1281	0.0558	0.7607	0.2482	0.4443	1								
A	0.2156	-0.0973	-0.1121	-0.1026	-0.0355	-0.1065	1							
MC	0.2508	-0.0202	-0.0553	-0.0639	-0.013	-0.0454	0.8511	1						
AGE	0.1889	0.0031	0.006	-0.026	-0.0226	-0.0026	0.3237	0.4606	1					
EM	0.3454	0.0679	0.0577	0.0275	-0.1286	-0.043	0.0765	0.0696	0.066	1				
DtA	-0.068	-0.0358	-0.0512	-0.0701	-0.0685	-0.0793	0.066	0.0469	-0.048	-0.0306	1			
EIr	-0.0205	0.0483	-0.0005	0.0357	0.0255	0.0073	-0.0398	-0.0381	-0.014	-0.0052	-0.092	1		
SG	-0.1542	-0.007	-0.1421	0.2231	0.4399	0.1085	-0.0484	-0.0492	-0.0516	-0.0195	-0.0637	0.0498	1	
CA	-0.388	0.0893	-0.0476	0.057	0.2559	0.1194	-0.2313	-0.1927	-0.1792	-0.1131	-0.1434	0.0584	0.1822	1

HC = Health Care Sector

This table shows the correlations between each parameter. Each cell in the table shows the estimated correlation coefficient between the two corresponding variables. Correlation coefficients range from -1 to 1, where values closer to 1 indicate a strong positive correlation, values closer to -1 indicate a strong negative correlation, and values near 0 indicate no correlation.

As expected, across all sectors, the cash cycle has a strong positive correlation with the days of accounts receivable and days of inventory outstanding, but a negative linear relationship with the days of accounts payable. This is because the days' metrics make up the calculation of the CCC. They also quantify how as companies hold onto their inventory or take longer to collect receivables, their cash cycle increases. When a company takes longer to collect payment from clients, it hinders how quickly it can turn its resources into cash. This again highlights the importance of inventory and receivables management in determining operational efficiency.

Another interesting point across all sectors is the strong positive correlation between total assets and market capitalization, which is not surprising. This reinforces the fact that across sectors larger asset bases often equate to higher market values. Also, there is a negative correlation between GOP and leverage (measured as the ratio of debt to assets), which suggests companies with higher operating profits rely less on debt financing, or those with higher debt levels face operational inefficiencies that impact their gross profits. These inefficiencies may or may not be related to the fact these companies have higher interest payments due to their higher debt, as interest payments do not impact gross profits (subtracted later in the income statement).

In the Energy sector, both ROA and GOP are negatively correlated with CCC (coefficient of -0.2654 and -0.1315 respectively), suggesting the longer a company takes to convert its operations into cash, the less profitable it tends to be. However, Debt to Assets shows a negative correlation with ROA (-0.0322), suggesting companies with higher leverage struggle more with profitability. Unlike in the other sectors, there is also a negative, although weak, correlation between Market Cap and leverage (-0.0846), hinting that companies with higher debt levels might be perceived as riskier and therefore have lower market valuations. This could be because the Energy sector faces uncertainties like fluctuating commodities prices, regulatory changes, and geopolitical risks, making highly leveraged companies more vulnerable to these risks.

For Materials and Industrials, the negative correlation between ROA and CCC is weaker (-0.0858 and -0.0165 respectively) than in the Energy sector, suggesting factors other than a short cash cycle may be more influential in driving profitability for companies in these sectors. Interestingly, in Industrials, there is a notable negative correlation between Debt to Assets and cash as a percentage of assets (-0.301), which implies companies using more leverage tend to hold less cash, potentially due to higher interest payments. This linear negative relationship is strongest in the Energy and Industrials sectors but holds true for all four sectors.

Another interesting finding in the Industrials sector is the positive correlation between days of inventory and companies' age (0.2402). This could indicate that older companies in this sector are more conservative in their approach to working capital management by holding more inventory than necessary to not miss out on spikes in sales. Alternatively, it could also be due to poor sales. We observe something similar in the Materials sector, which has a positive correlation between age and days of receivables (0.1825). This could indicate older firms have more lenient credit terms or face delays in collecting receivables, possibly due to long-standing client relationships or operational inefficiencies that develop over time.

Also in the Materials sector, as expected ROA shows a strong positive correlation with GOP (0.6061), as more profitable companies also generate higher gross operating profits.

In contrast, in Health Care, there is a weaker positive correlation between ROA and GOP (0.1716), much lower than in other sectors, suggesting EBIT is not as closely tied to operating profit margins and vice versa. Another interesting point is the strong negative correlation between ROA and CASH_ASSETS (-0.388), indicating companies holding more cash tend to be less profitable, possibly because they are not investing their resources effectively, perhaps missing out on investment opportunities or being overly conservative. This is one of the strongest negative relationships observed.

Across all sectors there is a negative relationship between CCC and leverage, suggesting a lower cash cycle length fueled by delayed payments to suppliers (which effectively work as debt) reduces the need for external financing. This is in line with the pecking order theory, that is, a business short of funds prefers to generate resources internally before looking to raise debt due to the higher costs of external financing resulting from asymmetric information and conflicts of interest between shareholders and creditors (Myers, 1984).

Additionally, in Health Care there is a noticeable positive correlation between age and both total assets (0.3237) and market capitalization (0.4606), indicating older firms tend to be larger and more valuable, which could reflect their established market positions and reputations. This positive linear relationship between companies' age and valuation is also strong in the Energy sector.

These insights help understand the importance of industry context, and how what drives performance in one sector might not have the same effect in another. However, it is important to remember correlation does not mean causation, and that zero or low correlation between variables only means they do not have a linear relationship, but they can have a perfect non-linear relationship with one another.

6.3. Regression Analysis

In this section, in order to test the hypotheses previously defined, we run a multivariate analysis of the statistics resulting from the multiple linear regression models. For each sector and for both ROA and GOP, we estimate an Ordinary Least Squares model, a Fixed Effects model, and a Random Effects model.

6.3.1. OLS Model

When applied to panel data, the OLS model is often called Pooled OLS because it combines (or "pools") cross-sectional and time-series data into a single dataset, treating all observations as independent and identically distributed (i.i.d.). Unlike Fixed Effects or Random Effects models, pooled OLS ignores the panel data structure. It assumes there are no individual-specific or time-specific effects, implying every company and time period share the same underlying relationship and any variation in the data is random and not due to any consistent differences between companies or over time.

Below we detail the results of this approach for each sector for both regression model equations. As previously detailed, we aim to estimate two regression models. The first one ("ROA model") has CCC as the dependent variable, along with the control variables, explaining the behavior of ROA as the dependent variable, resulting in the following regression equation ROA = CCC + MARKET_CAP + AGE + EBITDA_MULTP + DEBT_TO_ASSETS + EFF_IR + SALES_GROWTH + CASH_ASSETS + FEDFUNDS + RECESSION. Its statistics are as follows.

Table 6.6: ROA model OLS regression results, for all sectors, 2017-2022

	Energy		**Materials**		**Industrials**		**Health Care**	
	Coefficient		Coefficient		Coefficient		Coefficient	
Variable	Estimate	t-test p-value	Estimate	t-test p-value	Estimate	t-test p-value	Estimate	t-test p-value
CCC	-2.92e-04	6.15e-07 ***	9.97e-06	0.834756	-3.50e-05	0.31859	1.17e-05	0.763677
MARKET_CAP	4.02e-07	0.00321 **	5.99e-07	0.002280 **	5.22e-07	2.67e-07 ***	5.94e-07	5.97e-08 ***
AGE	-7.03e-04	0.01088 *	7.01e-05	0.442671	2.47e-04	0.00246 **	3.12e-04	0.261059
EBITDA_MULTP	3.72e-01	< 2e-16 ***	5.86e-02	< 2e-16 ***	2.60e-02	3.52e-11 ***	1.50e-01	< 2e-16 ***
DEBT_TO_ASSETS	-5.35e-04	0.01099 *	3.30e-04	0.095828 .	-5.12e-05	0.70558	-1.22e-03	4.75e-06 ***
EFF_IR	7.86e-05	0.50774	-1.36e-06	0.990497	-7.16e-03	< 2e-16 ***	7.74e-06	0.919736
SALES_GROWTH	-2.20e-07	0.89926	1.17e-03	< 2e-16 ***	5.31e-04	3.52e-14 ***	-1.88e-04	0.000659 ***
CASH_ASSETS	-8.99e-02	0.07091 .	3.84e-02	0.351405	-2.81e-02	0.24115	-3.46e-01	< 2e-16 ***
FEDFUNDS	-4.46e-03	0.57446	-5.96e-03	0.134994	-7.31e-03	0.04139 *	1.60e-02	0.069039 .
RECESSION	-6.34e-02	9.13e-05 ***	-1.54e-02	0.84803	-1.37e-02	0.05727 .	-1.66e-03	0.922187
R-squared	0.5156		0.2491		0.1448		0.2941	
F-statistic p-value	< 2.2e-16		< 2.2e-16		< 2.2e-16		< 2.2e-16	

The second regression model ("GOP model") is based on the equation GOP = DAYS_AR + DAYS_I + DAYS_AP + MARKET_CAP + AGE + EBITDA_MULTP + DEBT_TO_ASSETS + EFF_IR + SALES_GROWTH + CASH_ASSETS + FEDFUNDS + RECESSION, and its statistics are as follows.

Table 6.7: GOP model OLS regression results, for all sectors, 2017-2022

	Energy		**Materials**		**Industrials**		**Health Care**	
	Coefficient		Coefficient		Coefficient		Coefficient	
Variable	Estimate	t-test p-value	Estimate	t-test p-value	Estimate	t-test p-value	Estimate	t-test p-value
DAYS_AR	-1.54e-04	0.09944 .	3.43e-04	0.04130 *	-8.04e-07	0.995484	-7.53e-04	9.41e-07 ***
DAYS_I	-1.13e-04	0.09760 .	-6.37e-05	0.48728	7.40e-06	0.903589	9.78e-05	0.04067 *
DAYS_AP	-8.73e-05	0.34362	3.89e-04	0.00415 **	-7.19e-04	9.35e-06 ***	9.55e-05	0.2056
MARKET_CAP	-7.57e-09	0.94805	3.25e-07	0.24815	-4.30e-07	0.010325 *	-7.34e-08	0.54106

AGE	-6.56e-04	0.00539 **	3.29e-04	0.01394 *	2.69e-04	0.043912 *	1.58e-04	0.60575
EBITDA_MULTP	1.25e-01	3.62e-15 ***	1.42e-02	0.09431 .	1.82e-02	0.004489 **	4.55e-02	0.00164 **
DEBT_TO_ASSETS	-1.70e-04	0.34707	-3.76e-04	0.18964	-1.18e-03	1.47e-07 ***	-1.75e-04	0.55071
EFF_IR	1.45e-04	0.15297	-3.21e-05	0.84468	-2.87e-03	0.004845 **	1.21e-04	0.15199
SALES_GROWTH	4.84e-07	0.7451	8.45e-04	7.89e-06 ***	1.03e-04	0.364029	-4.20e-05	0.53022
CASH_ASSETS	-3.41e-02	0.42367	8.48e-04	0.98857	1.42e-01	0.000342 ***	9.57e-02	0.00232 **
FEDFUNDS	-1.12e-02	0.09902 .	-9.15e-03	0.10871	-1.58e-02	0.007033 **	-1.89e-02	0.05111 .
RECESSION	-1.18e-02	0.39259	-6.83e-02	0.55141	-6.73e-03	0.567877	-1.46e-02	0.43539
R-squared	0.1617		0.08381		0.064		0.04807	
F-statistic p-value	< 2.2e-16		1.23e-08		< 2.2e-16		8.09e-08	

The model summary and coefficients presented tell us the proportion of variance of ROA and GOP explained by the model (R-squared), as well as the t-test p-values of each estimated slope coefficient associated with each independent and control variable to assess their significance as predictors of profitability, and lastly, the F-statistic, which tests whether the model explains a significant amount of variance in the dependent variable.

Using OLS, the ROA model for the Energy sector is the only one where the estimated coefficient for CCC is statistically significant (t-test p-value below 5% significance level), meaning CCC contributes to explaining the variation of ROA. The negative coefficient estimate means CCC length impacts ROA negatively. This suggests a longer CCC (slower conversion of inventory and receivables into cash) leads to lower profitability in the Energy sector. Each additional day in the CCC is associated with a decrease in ROA by approximately 0.0002924 (or 0.02924% for each day) on average and ceteris paribus.

Looking at the overall model fit, the R-squared (or coefficient of determination) value of 0.5156 is also the highest for the ROA model in the Energy sector. It indicates the independent variables explain around 51.6% of the variability of ROA, the dependent variable.

R-squared is lower for the other sectors, meaning the data is further away from the fitted regression line and suggests a lot of factors that explain the behavior of ROA are not included in these models. This indicates in general the GOP model is weak and could mean that gross profit, being closer to the top line, is more heavily influenced by external factors outside the company, such as wider economic conditions, market trends, and sector specificities. These variables are irregular and hard to quantify consistently to include in a linear regression model. In contrast, EBIT is more influenced by internal operational efficiency, which is easier to measure through company-specific data such as the independent variables included in the model. The low R-squared could also indicate there may be non-linear relationships between predictors and the dependent variable, which linear OLS models cannot capture. We will expand on model limitations in the next section.

Across all sectors, when leverage is a statistically significant independent variable it negatively impacts profitability, meaning companies should be cautious about over-leveraging because it hinders their profitability even before accounting for interest expenses (again, ROA is calculated using EBIT instead of net income in this study).

We highlight the negative significant relationship between effective interest rate and profitability in the Industrials sector, meaning, as expected, companies with access to cheaper financing perform better than their peers. For each percentage point increase in the interest rate Industrials' companies pay for the debt in their balance sheet, the ROA decreases approximately by 0.716% on average and if all else remains constant. The Industrials sector is also the only one where the federal funds rate (as a means to gauge the state of the economy) has a statistically significant impact on both ROA and GOP.

Across all sectors, when the market capitalization of companies (as a proxy of firm size) is a statistically significant variable, its estimated coefficient is positive. This is expected as bigger companies tend to have better corporate performance. The same applies to the EBITDA multiple, for which the estimated coefficient is always positive and always statistically significant in explaining the variation of both ROA and GOP across all four sectors. This suggests better corporate performance is accompanied by better perception in the market, which translates into higher market valuation and leads to a higher enterprise value (the numerator in the EBITDA multiple formula).

In the GOP model, the days' variables are not consistent in explaining the behavior of gross profit. In the Health Care sector, Days Sales Outstanding and GOP have a negative statistically significant linear relationship, suggesting a decrease in trade credit given to clients leads to an increase in gross profits. In the Industrials sector, only one of the CCC components shows a statistically significant relationship with gross profit. There is a negative relationship between gross profit and Days Accounts Payable, meaning the quicker a company pays its suppliers (thus increasing its Cash Conversion Cycle) the higher its gross operating profit, which is not in line with most previous literature. However, the opposite happens in the Materials sector, where there is a positive statistically significant relationship between GOP and Days Accounts Payable, indicating more profitable companies take longer to pay their bills to suppliers.

We can also conclude the recession in 2020 impacted Energy firms' EBIT but not the gross profit because there is a statistically significant relationship (p-value associated with the t-test is below 5%) between the RECESSION dummy variable in the ROA model and not in the GOP model. This could be because while revenue goes down during a recession, the accompanying costs of selling subtracted in the gross profit calculation also tend to decrease, keeping gross profit relatively stable. However, fixed costs stay the same which means EBIT may be more significantly impacted in an economic downturn.

As expected, given the pooled OLS model ignores the panel data structure the overall model fit—measured through R-squared—is low. Nonetheless, the widely different statistics across the different sectors highlight the importance of separating the companies by their sector instead of aggregating them all in one go. It is also worth noting that for all sectors and across both models, the F-statistic is statistically significant (p-value below 5%) and suggests at least one of the predictors in the model has a non-zero coefficient and contributes to explaining the variance in the dependent variable. However, pooled OLS does not account for unobserved individual effects.

6.3.2. Fixed Effects Model

A Fixed Effects regression controls for time-invariant characteristics in panel data (data collected over multiple periods for the same companies). It allows us to estimate the impact of variables that change over time within a company.

While the OLS regression estimates the average effect of the independent variables on the dependent variable across all observations and assumes unobserved characteristics are randomly distributed, a Fixed Effects regression estimates the effect of the independent variables on the dependent variable within each company over time, controlling for all time-invariant characteristics of each by looking at how changes in the independent variables for the same company over time affect the dependent variable. This removes any bias from fixed, unobserved characteristics and focuses on the true effect of the independent variables within each company.

In our study this means the Fixed Effects model looks at how changes in the CCC for the same company over time affect its profitability. The pooled OLS model estimated the coefficients of the linear relationship between the CCC and profitability across all companies, assuming differences between companies (including unobserved, time-invariant factors) are random and do not need to be controlled for.

This means pooled OLS does not account for company-specific characteristics that do not change over time such as the company's age, the dummy variable RECESSION, and the FEDFUNDS control variable, potentially leading to biased estimates if such characteristics are correlated with the CCC or profitability.

We used the Hausman test to determine whether a Fixed Effects model or a Random Effects model is more appropriate for our panel data analysis. As detailed in the next section, the p-value of the test is near zero for all sectors and models, thus we reject the null hypothesis. This rejected hypothesis states the preferred model is the Random Effects model and assumes the unobserved entity-specific effects are unique to each entity and uncorrelated with the independent variables. Under the null hypothesis, these entity-specific effects are considered part of the error term and assumed not to affect the relationship between the independent variables and the dependent variable. Since we reject this hypothesis, it suggests there is a correlation between the unobservable factors and the independent variables, and thus the Fixed Effects model is more appropriate.

Below are the statistics of the Fixed Effects for each sector with ROA as the dependent variable.

Table 6.8: ROA model FE regression results, for all sectors, 2017-2022

	Energy		**Materials**		**Industrials**		**Health Care**	
	Coefficient		Coefficient		Coefficient		Coefficient	
Variable	Estimate	t-test p-value	Estimate	t-test p-value	Estimate	t-test p-value	Estimate	t-test p-value
CCC	-2.04e-04	0.02729 *	3.88e-04	4.840e-05 ***	-8.48e-05	0.1830459	1.69e-04	0.001586 **
MARKET_CAP	1.02e-06	0.00148 **	1.83e-06	0.0001017 ***	-1.74e-08	0.9414325	2.93e-07	0.152906
EBITDA_MULTP	4.47e-01	< 2.2e-16 ***	3.90e-02	9.016e-15 ***	1.12e-02	4.92e-05 ***	7.59e-02	3.29e-16 ***
DEBT_TO_ASSETS	-2.01e-03	7.82e-10 ***	-2.94e-03	1.96e-14 ***	-1.15e-03	8.72e-11 ***	-1.33e-03	3.54e-05 ***
EFF_IR	1.82e-04	0.1241	-9.16e-05	0.2777061	-1.91e-03	0.0011069 **	2.63e-06	0.958924
SALES_GROWTH	2.57e-04	2.29e-05 ***	1.11e-03	< 2.2e-16 ***	7.55e-04	< 2.2e-16 ***	-7.76e-05	0.048383 *
CASH_ASSETS	9.80e-02	0.08953 .	1.76e-01	1.6e-05 ***	9.40e-02	0.0005307 ***	6.96e-02	0.043129 *
FEDFUNDS	-5.70e-03	0.32847	-8.27e-03	0.0026256 **	-4.73e-03	0.0389362 *	8.94e-03	0.090929 .
RECESSION	-3.17e-02	0.01002 *	2.19e-02	0.7043347	-1.05e-02	0.0212118 *	-3.17e-03	0.753051
R-squared	0.68753		0.41691		0.19922		0.11995	
F-statistic p-value	< 2.2e-16		< 2.2e-16		< 2.2e-16		< 2.2e-16	

For the GOP model with the Cash Conversion Cycle components (DAYS_AR, DAYS_I, DAYS_AP) as independent variables instead of CCC itself, the statistics for each sector are as follows.

Table 6.9: GOP model FE regression results, for all sectors, 2017-2022

	Energy		**Materials**		**Industrials**		**Health Care**	
	Coefficient		Coefficient		Coefficient		Coefficient	
Variable	Estimate	t-test p-value	Estimate	t-test p-value	Estimate	t-test p-value	Estimate	t-test p-value
DAYS_AR	-3.88e-04	0.0002901 ***	-6.51e-04	0.0005848 ***	-8.52e-04	2.045e-08 ***	-7.02e-04	1.49e-05 ***
DAYS_I	-1.18e-04	0.2345166	2.98e-04	0.0072470 **	-3.52e-04	2.203e-06 ***	-8.56e-05	0.1948013
DAYS_AP	2.83e-05	0.8100981	-6.81e-04	0.0012552 **	-3.51e-04	0.036419 *	-9.87e-05	0.1744339
MARKET_CAP	1.16e-06	2.730e-06 ***	1.47e-06	0.0007756 ***	-6.65e-08	0.782586	2.58e-08	0.9015192
EBITDA_MULTP	1.36e-01	< 2.2e-16 ***	1.06e-02	0.0216996 *	6.40e-03	0.022167 *	1.80e-02	0.0532711 .
DEBT_TO_ASSETS	-1.87e-04	0.4496582	-2.96e-03	3.136e-16 ***	-1.15e-03	1.990e-10 ***	1.24e-03	0.0001535 ***
EFF_IR	1.14e-04	0.208167	-5.12e-05	0.5153255	1.94e-03	0.001192 **	8.18e-05	0.1159448
SALES_GROWTH	2.34e-04	5.636e-07 ***	1.01e-03	< 2.2e-16 ***	4.06e-04	4.106e-15 ***	1.53e-04	0.0013351 **
CASH_ASSETS	-6.21e-02	0.1601176	4.34e-02	0.2527122	-5.64e-02	0.040774 *	-7.72e-02	0.0277851 *
FEDFUNDS	-1.24e-02	0.0061740 **	-6.80e-03	0.0086960 **	-9.31e-03	7.519e-05 ***	-1.02e-02	0.0569531 .
RECESSION	5.73e-03	0.5513826	-3.03e-02	0.5740564	-5.94e-03	0.201602	-1.56e-02	0.1269974
R-squared	0.34734		0.35491		0.1652		0.075801	
F-statistic p-value	< 2.2e-16		< 2.2e-16		< 2.2e-16		3.84e-11	

In the OLS regression, the estimated coefficient for the independent variable was not statistically significant most time. This may be because pooled OLS ignores the panel structure, treating each observation as an independent data point.

With Fixed Effects, we see the R-squared is higher across both models, especially in the Energy sector where the independent variables explain 68.8% of the variance of ROA. However, for Health Care and similar to the OLS regression, the R-squared is low, meaning the independent variables we selected are less predictive of profitability in this sector.

CCC has a significant negative effect on ROA for the Energy sector (t-test p-value = 0.02729), while a significant and positive effect for the Materials and Health Care sectors. This contrasts with the findings of the OLS model, where CCC was not a statistically significant predictor of ROA for all sectors except Energy. It also suggests that how efficiently a company manages its cash cycle impacts profitability very differently across sectors.

In line with the pooled OLS model and the *H2* alternative hypothesis set earlier in this study, companies in the Energy sector benefit from higher profitability when they reduce the length of their Cash Conversion Cycle by collecting payments from clients faster, decreasing the inventory they hold at a time, and delaying their payments to suppliers.

Looking at the GOP model in the Materials and the Industrials sectors, all three working capital management components—Days of Accounts Receivable, Days of Accounts Payable, and Days of Inventory—are statistically significant in explaining the variance of gross profit. This indicates the efficiency with which businesses in these sectors manage their receivables, payables, and inventory levels has a meaningful impact on their profitability. While in the Materials sector the negative estimated coefficient for days of receivables indicates higher profitability when clients pay quicker, at the same time the positive estimated coefficient for inventory days suggests conservative companies that keep higher inventory levels see higher gross profit as well. Additionally, the negative estimated coefficient for days of payables could indicate firms with higher profitability are in a better financial situation and thus can pay their suppliers quickly. In the Industrials sector, the estimated coefficient for days of receivables is negative (-8.52e-04, t-test p-value = 2.045e-08), suggesting faster collections from clients contribute to higher profitability by improving cash flow. However, the negative significant relationship between days of inventory and gross profit suggests that, unlike in Materials, companies benefit from keeping inventory levels low.

It is also worth highlighting the DEBT_TO_ASSETS variable is significant and negatively linearly related to ROA across all sectors, suggesting higher leverage is generally detrimental to profitability regardless of the sector. The EBITDA Multiple is another significant predictor of the behavior of the dependent variable across sectors, similar to the OLS regression. As the estimated coefficient is always a positive number, it suggests companies with higher valuations have higher profitability across the different sectors.

Across all four sectors and in line with the OLS regression, we find the R-squared is higher when ROA is the dependent variable instead of gross profit. This could indicate the Cash Conversion Cycle and its components, along with the control variables, have a stronger impact on the elements of an income statement that are subtracted after gross profit but before EBIT, such as selling, general, and administrative expenses (SG&A), depreciation, and other operating expenses. Although inventory and accounts payable are part of the cash cycle and directly related to the cost of goods sold, given the R-squared is higher when the ratio of EBIT divided by total assets is the dependent variable, this portrays the broader influence of the Cash Conversion Cycle on overall profitability, not just on gross profit.

For the sake of completeness and to leave no stone unturned, we also estimated the pooled OLS and Fixed Effects models with GOP as the dependent variable and CCC as the main independent variable, as well as ROA as the dependent variable and DAYS_AR, DAYS_I, and DAYS_AP as the main independent variables. The results are in the appendix, and as expected, are similar to the above, meaning the variables explain the variation of ROA better.

6.3.3. Model Robustness Tests

When estimating a multiple regression model, it is important to confirm the model fits the data well and meets the assumptions of linear regression.

Under the Gauss-Markov theorem, the ordinary least squares estimators are the Best Linear Unbiased Estimator (BLUE) of the coefficients. This means these estimators are efficient because they have the smallest variance among all possible linear and unbiased estimators. If any of the assumptions are violated, OLS estimators may no longer be BLUE, and other methods or adjustments may be required. Additionally, for hypothesis testing and constructing confidence intervals, it is typically assumed the errors are normally distributed.

Below we present the key model evaluation and diagnostic tests to test the assumptions of multicollinearity, normality, linearity, homoscedasticity, and independence of residuals.

Table 6.10: Model robustness tests

			Overall Model Fit		**Multi-collinearity**	**Autocorrelation**		**Hetero-scedasticity**	**Functional Form**	
Sector	Method	Model	R-squared	Adjusted R-squared	VIF Ratio	DW Test Statistic	Wooldridge's Test p-value	Breusch-Pagan Test p-value	RESET Test p-value	Hausman Test p-value
Energy	OLS	ROA	0.5156	0.508	All <10	1.2535	-	<2.2e-16	<2.2e-16	-
	FE	ROA	0.68753	0.60896	-	-	2.724e-06	<2.2e-16	-	<2.2e-16
	OLS	GOP	0.1617	0.1459	All <10	0.9925	-	0.7579	2.842e-11	-
	FE	GOP	0.34734	0.18006	-	-	0.000188	0.7579	-	6.507e-08
Materials	OLS	ROA	0.2491	0.2383	All <10	1.0227	-	<2.2e-16	<2.2e-16	-
	FE	ROA	0.41691	0.27978	-	-	8.796e-10	<2.2e-16	-	3.317e-15
	OLS	GOP	0.08381	0.06804	All <10	0.58547	-	0.0001632	0.000293	-
	FE	GOP	0.35491	0.20041	-	-	<2.2e-16	0.0001632	-	2.008e-06
Industrials	OLS	ROA	0.1448	0.1403	All <10	0.96883	-	<2.2e-16	<2.2e-16	-
	FE	ROA	0.19922	0.011999	-	-	8.48e-09	< 2.2e-16	-	<2.2e-16
	OLS	GOP	0.06402	0.05802	All <10	0.5343	-	1.845e-06	<2.2e-16	-
	FE	GOP	0.1652	-0.031317	-	-	<2.2e-16	1.845e-06	-	0.1629
Health Care	OLS	ROA	0.2941	0.288	All <10	1.0802	-	1.79e-11	<2.2e-16	-
	FE	ROA	0.11995	-0.11371	-	-	0.0001185	1.79e-11	-	< 2.2e-16
	OLS	GOP	0.04807	0.03814	All <10	0.83783	-	0.04184	1.58e-06	-
	FE	GOP	0.075801	-0.17213	-	-	3.33e-14	0.04184	-	0.002112

We include both the OLS and Fixed Effects regression models for each of the four sectors in this study.

Starting with the overall model fit, R-squared and Adjusted R-squared measure the proportion of the variance in the dependent variable predictable from the independent variables. As noticed before, the R-squared values for some OLS models are relatively low (for example, OLS GOP for Industrials: 0.06402, OLS GOP for Health Care: 0.04807). This low R-squared indicates the independent variables in these models explain only a small portion of the variability in gross profits, meaning key variables might be missing from the model, making it difficult to predict individual outcomes of the dependent variable with much accuracy.

For Fixed Effects regressions, the difference between R-squared and Adjusted R-squared is bigger compared to OLS models, and in some cases the Adjusted R-squared is even negative. The Adjusted R-squared adjusts for the number of predictors in the model, providing a more accurate measure of model fit by penalizing for adding variables that do not improve the model. In contrast, R-squared increases with every new explanatory variable added, which can tempt us to continue adding variables even if they have no relevance to the study. As such, this sizable difference between the two could indicate overfitting due to many entity-specific effects that add little explanatory power. Nonetheless, OLS and FE models are not directly comparable since OLS captures both within- and between-group variation, while FE focuses only on within-group variation.

To test for multicollinearity we use the Variance Inflation Factor (VIF) ratio. Multicollinearity is when several independent variables are correlated with each other, resulting in less reliable statistical conclusions because it inflates the variance of the coefficient estimates, making them unstable and sensitive to minor changes in the model. This can lead to difficulties in assessing the individual effect of each variable, distorted significance levels, and potentially misleading interpretations of the model's results. The VIF ratio measures how much the variance of an estimated regression coefficient increases when the predictors are correlated. It is calculated for each predictor. The higher the value, the higher the suggested level of multicollinearity, with common thresholds set at 5 or 10.

After initially running the test, the VIF ratio was high for both Total Assets and Market Capitalization. This is expected as both variables indicate the size of a company, so they ought to be correlated. This was also confirmed in the correlation matrix we analyzed before. As such, we removed the Total Assets variable to avoid multicollinearity and improve the model's reliability. The model results presented before and the robustness table above already include this change. We chose to remove Total Assets and not Market Capitalization as it had higher t-test p-values across most models and because it is a figure that is already indirectly present in the ROA formula. Additionally, removing Total Assets had little effect on the R-squared across the regression models.

After removing Total Assets, the VIF ratio is between 1 and 1.7 for all variables across all models, which is well below the threshold of 10 which indicates a problem of multicollinearity and poorly estimated coefficients. The VIF ratio does not apply to Fixed Effects models since they subtract the individual mean of each variable, which alters the data structure and can make the concept of multicollinearity less straightforward. As such, we also looked at the pairwise correlation matrix presented in the Bivariate Analysis section to confirm there are no extremely high correlations between variables.

Next, we look for autocorrelation among residuals by running the Durbin-Watson (DW) test. Autocorrelation is when residuals (errors) from one time period are correlated with residuals from another period. In other words, it measures whether the error terms in a time series are correlated with their lagged versions. Autocorrelation is common and often expected in both panel data and time series data due to the nature of these data structures. It is only normal for the behavior of the same entity at a point in time to be related to its behavior at previous points. Nonetheless, it violates the OLS assumption of independence of observations. The Durbin-Watson test tests if the errors from one observation are correlated with errors from another observation. Durbin, J. and Watson, G.S. invented this test in 1950, and since then, it has become a standard tool in econometrics. A value close to 2 suggests no autocorrelation, while values approaching 0 or 4 suggest positive or negative autocorrelation, respectively.

The results above suggest there is more autocorrelation in the GOP model across the four sectors, as the statistic is further away from 2. Overall, the results are quite far below 2, suggesting an issue with positive autocorrelation, which might violate the assumptions of the linear regression model and potentially affect the reliability of the results. Although not shown in the table above, the test statistic was statistically significant (p-value below 5%) for all tests.

The Durbin-Watson statistic in the context of Fixed Effects models can be more complex due to the presence of individual-specific effects and the way these models handle time-invariant variables. As such, we use the Wooldridge test for autocorrelation for Fixed Effects regressions, in which the null hypothesis is of no autocorrelation. Proposed in 2002 by Jeff

Wooldridge, this test specifically checks for first-order autocorrelation in the residuals of a panel data regression. As the p-value is always below the 5% significance level, we reject the null hypothesis of no autocorrelation. This means there is significant evidence of autocorrelation in the residuals and our Fixed Effects models may not fully account for the time-related dependencies in the data.

Another assumption of the Gauss-Markov theorem is homoskedasticity, meaning the error terms (the random disturbances in the linear relationship between the independent variables and the dependent variables, in this case ROA and GOP) have constant variance across all levels of the independent variables. Heteroskedasticity, on the other hand, occurs when the variance of the error terms varies with the values of an independent variable. An OLS regression aims to minimize residuals and produce the smallest possible standard errors. By design, OLS gives equal weight to all observations. However, when heteroskedasticity is present, observations with larger error terms disproportionately influence the regression results (they have more "pull" than other observations), leading to biased standard errors and unreliable statistical inferences.

To assess the presence of heteroskedasticity in the model we use the Breusch-Pagan test. The p-value is below the 5% significance level for most models, meaning we reject the null hypothesis of homoskedasticity. This suggests there is evidence of heteroskedasticity in the model, suggesting that the variance of the residuals is not constant. This violation of the homoscedasticity assumption can lead to inefficient estimates and incorrect standard errors, which can affect hypothesis tests and confidence intervals.

Lastly, we test for model specification errors to confirm the functional form of the models is appropriate. For the OLS model, we use the Ramsey RESET test, introduced in a 1969 paper by J.B. Ramsey. It works by adding non-linear auxiliary combinations of the independent variables to the model. If the relationship between the dependent variable and the independent variables is indeed linear as is assumed in the OLS model, the estimated coefficients of those additional terms should not be statistically different from zero.

From the results above, the p-value for the added terms is below the significance level, which indicates the original model might be mis-specified in terms of linear functional form. Therefore, this suggests there may exist some non-linearities in the relationship between the dependent and independent variables that the linear model could not capture.

To address this, a common approach is to transform either the dependent variable or the independent variables into their logarithmic forms. However, as there are many negative ROA and GOP values in our sample, this transformation is not feasible without compromising the data set on top of the sizable adjustments we already made due to missing data. Additionally, taking the log of the non-negative independent variables did not correct the functional form issue.

Following Wooldridge, 2013 p. 496, we also ran the Hausman test to compare Fixed Effects with Random Effects models. It essentially compares the coefficients of both models to see if there is a systematic difference, specifically testing whether the individual-specific effects (i.e., unique errors) in the data are correlated with the regressors. The null hypothesis of the Hausman test is that the Random Effects model is preferred, implying the random effects are uncorrelated with the explanatory variables. As we reject the null hypothesis across all sectors whether ROA or GOP is the dependent variable, the Fixed Effects model is appropriate. The one exception to this is the Industrials sector GOP model, for which Random Effects is more appropriate (Hausman test p-value = 0.1629, which provides evidence in favor of the null hypotheses). Consequently, we have presented only the Fixed Effects regression results in the previous sections, while the Random Effects results are provided in the appendix.

7. Conclusion

This study set out to extend the current literature on the impact of working capital management on profitability by analyzing six years of panel data of NYSE-listed companies in the Energy, Materials, Industrials, and Health Care sectors. We used the Cash Conversion Cycle as a measure of working capital management and ROA (calculated as EBIT over total assets) and Gross Operating Profit as proxies for profitability. Descriptive statistics, along with correlation and regression analysis allow us to conclude the cash cycle varies significantly across different sectors.

Across all sectors for both OLS and FE, the R-squared value is higher when ROA is the dependent variable, compared to GOP. This suggests CCC and its components, along with the control variables, have a more significant effect on income statement items subtracted after gross profit but before EBIT, such as selling, general, and administrative expenses, depreciation, and other operating costs. While inventory and accounts payable are integral to the cash cycle and directly tied to COGS, the higher R-squared when the ratio of EBIT over Total Assets is the dependent variable highlights the broader impact of the Cash Conversion Cycle on overall profitability, beyond just gross profit (which is calculated as revenues minus COGS).

Based on the results of the estimation of both Pooled OLS and Fixed Effects linear regressions, there is strong evidence suggesting companies in the Energy sector may improve their ROA by reducing the length of their CCC. This indicates a longer cash cycle length may be associated with inefficiencies, reducing profitability.

For Materials and Health Care, CCC was a statistically significant explanatory variable when estimating an FE regression. For both sectors profitability has a positive linear relationship with CCC length, which is not in line with a lot of the previous literature and the *H2* hypothesis set earlier in this study. In contrast with Energy, for Materials and Health Care, a longer cash cycle may be associated with better corporate performance, suggesting businesses in these sectors do better than their peers when they have a more conservative WCM approach, such as maintaining high inventory levels.

Regarding Industrials, in both Pooled OLS and Fixed Effects regressions, the t-test p-value associated with the estimated coefficient for CCC is below the significance level, suggesting it does not contribute to explaining the variation of ROA. Looking at the GOP model with the days' variables however, there is a negative linear relationship between all three variables and gross profit, in line with the findings of Deloof (2003) and as we saw in the bivariate analysis. This means Industrials' businesses may benefit from speeding up collections from clients (shortening DSO) and reducing inventory levels (decreasing DIO). However, the negative relationship between DPO and gross profit suggests more profitable businesses pay suppliers earlier, which increases cash cycle length.

Another relevant predictor of the variance in profitability is leverage, for which the results suggest across most sectors leverage is associated with poorer performance. Additionally, and as expected, market capitalization and EBITDA multiple are statistically significant (t-test p-value below 5%) regressors of profitability in general, with an associated estimated coefficient that is always positive across all four sectors. This suggests bigger companies with higher valuations have higher profitability.

Overall, the results vary meaningfully across sectors and different models, with the exception of the Energy sector. In Energy, there is strong evidence suggesting managers should strive for a low cash cycle length to improve profitability, in line with the initial research hypotheses and existing literature. The regression models for this sector also show a higher R-squared. In contrast, the other three sectors show lower R-squared values, indicating the models struggle to predict individual outcomes of the dependent variable with much accuracy.

The key conclusion is that working capital management practices vary considerably between industries. Managers should carefully consider the specific characteristics and financial realities of their sector before attempting to adjust their CCC. This includes analyzing whether to shorten or lengthen the cash cycle, by financing operations through bank debt or by delaying payments to suppliers for example. A one-size-fits-all approach is not appropriate. Instead, businesses should tailor their decisions to the unique dynamics of the industry in which they operate to boost corporate performance.

7.1. Limitations and Suggestions for Future Research

Similar to previous research, this study has its limitations, which can be considered suggestions for future research.

Starting with the dataset, the data from Bloomberg had significant missing information, effectively cutting the original sample in half. This introduces survivorship bias, as the analysis only includes a subset of the target population (NYSE-listed companies), excluding those with missing data. Although these excluded companies are real and their data would enhance the analysis, it is simply not readily available. This limitation restricts the study's ability to truly analyze the target population, potentially skewing the results and reducing the generalizability of the findings.

We set out to focus on sectors where it is more common for businesses to sell to other businesses (B2B), as we assume the importance of working capital management is higher because when selling directly to individual consumers, it is uncommon for trade credit to exist. However, not all companies in the Energy, Materials, Industrials, and Health Care sectors focus on selling to other companies. Additionally, other sectors left out of the analysis include a lot of businesses whose main clients are other businesses. Hence it would have been interesting to study how working capital management impacts their performance. Future research may benefit from finding a better way to isolate B2B businesses in the same sector with similar operations, as this would allow to extend the study to more sectors and a more uniform comparison between companies.

The AGE variable does not account for mergers, acquisitions, or other corporate restructuring actions. For instance, if a century-old company separates itself into two independent, publicly traded companies, the data set we used counts as if the company was founded in the year of this event. Similarly, when a company undergoes a merger or acquisition, it inherits the existing synergies, relationships with suppliers, brand reputation, and operational efficiencies from the merged or acquired entity, which may impact the Cash Conversion Cycle. However, the data treats the reorganized company as if it were established at the time of the most recent restructuring event, while the goal of this variable was to confirm if older companies have a quicker cash cycle. It is difficult to account for these nuances and it can be misleading. Future studies can hopefully have a better way to account for historical experience, market presence, and accumulated knowledge of merged or acquired businesses.

Since this study focuses on sector-specific dynamics, we used fiscal year data, as companies within a sector often align their fiscal years with their business cycles. However, calendar year data provides a more consistent time frame. Future studies could look for differences between the two types of data. Another limitation is our analysis uses year-end data, which means short-term changes in working capital policies are not assessed. To address this, it would be beneficial to analyze fluctuations throughout the year.

Initially, we wanted to introduce another dummy variable to account for family businesses. Anderson and Reeb (2003) suggest family-owned companies have better longer-standing relationships with suppliers. They found family ownership is associated with better corporate performance, and that family ownership in public companies reduces agency problems. One consequence of families maintaining a long-term presence is the company will enjoy a lower cost of debt financing compared to nonfamily firms. This impacts how it manages working capital. However, we were not able to include this dummy variable mainly because there is no universally agreed-upon definition for what constitutes a family business, leading to inconsistencies in categorization and comparison across studies. It was also difficult to find the level of family ownership or quantify the involvement in management for the large sample used in this study. It would have to be done one by one for every one of the 987 companies in the final sample. We consulted with Bloomberg's customer support team to inquire whether they currently offer a variable that identifies family businesses. They informed us this feature is under development and not yet available. Future studies could take advantage and include this dummy variable once it is available to potentially increase the explanatory power of the model.

Lastly, all the regression models showed statistical significance (F-statistic p-value below 5%), implying there is at least one explanatory variable whose variation contributes to explaining the variation on the dependent variable. However, the robustness tests suggest the models may not fully capture the relationships between variables or may be sensitive to specification errors. Additionally, the models assume a linear relationship between dependent and independent variables, but this relationship may not be a simple straight line. Future research could address these limitations by using more advanced regression techniques, such as the Generalized Method of Moments (GMM) for example, to improve model accuracy. Exploring potential non-linear relationships could further improve the reliability of the results.

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Annexes

Annex A: Sample derivation

Step	Description	Companies	Observations
Initial sample	All companies listed in "NYSE Arca", "NYSE Chicago", "NYSE American", "NYSE National", and "New York" exchanges in the "Energy", "Materials", "Industrials", and "Health Care" sectors (GICS).	2,124	12,744
First adjustment	Removal of all companies for which Bloomberg database does not provide consistent data points for the key variables for at least three years of the study period (2017-2022).	-982	-5892
Second adjustment	Removal of all outlier data points in key variables for regression	-155	-930
Final sample	Data points used for statistical analysis in this study	987	5922

Annex B: Random Effects regressions

ROA Model

	Energy		Materials		Industrials		Health Care	
	Coefficient		Coefficient		Coefficient		Coefficient	
Variable	Estimate	t-test p-value	Estimate	t-test p-value	Estimate	t-test p-value	Estimate	t-test p-value
CCC	-3.32e-04	3.522e-06 ***	8.93e-05	0.1909815	-8.82e-05	0.063281 .	8.55e-05	0.0630763 .
MARKET_CAP	6.11e-07	0.002270 **	1.04e-06	0.000458 ***	4.25e-07	0.007139 **	5.47e-07	0.0005023 ***
AGE	-9.76e-04	0.032175 *	1.22e-05	0.9440653	4.26e-04	0.004782 **	9.61e-04	0.0608506 .
EBITDA_MULTP	4.18e-01	< 2.2e-16 ***	4.59e-02	< 2.2e-16 ***	1.33e-02	1.540e-06 ***	8.64e-02	< 2.2e-16 ***
DEBT_TO_ASSETS	-1.20e-03	3.714e-06 ***	-9.29e-04	0.000734 ***	-6.76e-04	1.248e-05 ***	-1.26e-03	1.242e-05 ***
EFF_IR	1.53e-04	0.166516	-5.66e-05	0.5154383	-3.15e-03	2.270e-08 ***	8.85e-07	0.9866951
SALES_GROWTH	1.58e-07	0.92837	1.17e-03	< 2.2e-16 ***	6.94e-04	< 2.2e-16 ***	-9.29e-05	0.0195369 *
CASH_ASSETS	4.87e-02	0.35394	1.14e-01	0.0035089 **	2.92e-02	0.22814	-1.02e-01	0.0006545 ***
FEDFUNDS	-3.61e-03	0.557347	-7.09e-03	0.0120019 *	-5.27e-03	0.025039 *	1.08e-02	0.0506770 .
RECESSION	-0.0557	8.052e-06 ***	8.72e-04	0.9884008	-1.09e-02	0.020790 *	-2.07e-04	0.9843731
R-squared	0.60231		0.31997		0.15236		0.13348	
Adjusted R-squared	0.59607		0.31024		0.14783		0.12596	
F-statistic p-value	< 2.2e-16		< 2.2e-16		< 2.2e-16		< 2.2e-16	

GOP Model

	Energy		Materials		Industrials		Health Care	
	Coefficient		Coefficient		Coefficient		Coefficient	
Variable	Estimate	t-test p-value	Estimate	t-test p-value	Estimate	t-test p-value	Estimate	t-test p-value
DAYS_AR	-3.51e-04	0.0003228 ***	-5.28e-04	0.002303 **	-6.73e-04	5.588e-07 ***	-6.90e-04	2.386e-06 ***
DAYS_I	-1.26e-04	0.1172201	1.93e-04	0.056595 .	-2.65e-04	4.819e-05 ***	2.69e-06	0.961578
DAYS_AP	4.61e-08	0.9996481	-2.13e-04	0.22753	-4.57e-04	0.002615 **	-4.53e-05	0.495971

MARKET_CAP	4.76e-07	0.0062628 **	1.10e-06	0.002557 **	-1.61e-07	0.433326	-5.78e-08	0.726565
AGE	-8.94e-04	0.0406565 *	3.48e-04	0.231959	4.91e-04	0.076061 .	2.60e-04	0.656836
EBITDA_MULTP	1.37e-01	< 2.2e-16 ***	1.04e-02	0.026098 *	7.07e-03	0.011094 *	2.00e-02	0.029435 *
DEBT_TO_ASSETS	-2.38e-04	0.2592784	-2.19e-03	3.09e-12 ***	-1.22e-03	8.875e-13 ***	9.05e-04	0.002081 **
EFF_IR	1.71e-04	0.0462569 *	-5.19e-05	0.52	1.66e-03	0.004742 **	9.02e-05	0.083217 .
SALES_GROWTH	7.78e-07	0.6116917	1.01e-03	< 2.2e-16 ***	3.89e-04	3.171e-14 ***	1.05e-04	0.022623 *
CASH_ASSETS	-2.99e-02	0.4671927	4.19e-02	0.270392	-3.55e-02	1.79e-01	-2.79e-02	0.362359
FEDFUNDS	-1.02e-02	0.0260085 *	-7.41e-03	0.004784 **	-1.00e-02	1.988e-05 ***	-1.15e-02	0.033930 *
RECESSION	-0.01184	0.2088363	-3.80e-02	0.492337	-5.30e-03	0.256431	-1.66e-02	0.109064
R-squared	0.2571		0.27839		0.13866		0.057096	
Adjusted R-squared	0.24306		0.26597		0.13313		0.047266	
F-statistic p-value	< 2.2e-16		< 2.2e-16		< 2.2e-16		6.32e-09	

Annex C: Additional regressions

Below are the results for the following regression equation: GOP = CCC + MARKET_CAP + AGE + EBITDA_MULTP + DEBT_TO_ASSETS + EFF_IR + SALES_GROWTH + CASH_ASSETS + FEDFUNDS + RECESSION, using both OLS and Fixed Effects.

OLS

	Energy		**Materials**		**Industrials**		**Health Care**	
	Coefficient		Coefficient		Coefficient		Coefficient	
Variable	Estimate	t-test p-value	Estimate	t-test p-value	Estimate	t-test p-value	Estimate	t-test p-value
CCC	-8.45e-05	0.08937 .	1.59e-05	0.81774	1.24e-05	0.82989	-1.12e-05	0.79597
MARKET_CAP	9.40e-09	0.93552	4.29e-07	0.12933	-5.30e-07	0.00141 **	-4.65e-08	0.70121
AGE	-6.73e-04	0.00442 **	4.06e-04	0.00218 **	2.12e-04	0.11194	1.78e-04	0.56435
EBITDA_MULTP	1.26e-01	1.79e-15 ***	1.04e-02	0.2183	1.98e-02	0.00205 **	3.97e-02	0.00622 **
DEBT_TO_ASSETS	-1.46e-04	0.41749	-1.89e-04	0.50755	-1.22e-03	5.06e-08 ***	-1.54e-04	0.60439
EFF_IR	1.37e-04	0.17811	-2.71e-05	0.86983	-3.03e-03	0.00304 **	1.11e-04	0.19606
SALES_GROWTH	2.69e-07	0.8566	9.12e-04	1.73e-06 ***	1.17e-04	0.30657	-6.05e-05	0.32328
CASH_ASSETS	-4.02e-02	0.34466	-4.66e-03	0.93758	1.16e-01	0.00328 **	1.10e-01	0.00045 ***
FEDFUNDS	-1.22e-02	0.07242 .	-8.49e-03	0.14096	-1.66e-02	0.00494 **	-1.86e-02	0.05772 .
RECESSION	-8.16e-03	0.55358	-6.49e-02	0.57509	-4.03e-03	0.73379	-1.57e-02	0.40658
R-squared	0.1547		0.06126		0.05246		0.02527	
Adjusted R-squared	0.1414		0.04783		0.0474		0.01682	
F-statistic p-value	< 2.2e-16		2.74e-06		< 2.2e-16		0.0009901	

Fixed Effects

	Energy		**Materials**		**Industrials**		**Health Care**	
	Coefficient		Coefficient		Coefficient		Coefficient	
Variable	Estimate	t-test p-value	Estimate	t-test p-value	Estimate	t-test p-value	Estimate	t-test p-value
CCC	-1.94e-04	0.006429 **	5.15e-05	0.569502	-4.16e-04	3.422e-10 ***	-9.63e-05	0.07915 .
MARKET_CAP	1.17e-06	2.568e-06 ***	1.44e-06	0.001304 **	-1.54e-07	0.52884	4.26e-08	0.84018
EBITDA_MULTP	1.39e-01	< 2.2e-16 ***	7.79e-03	0.096243 .	6.93e-03	0.01459 *	1.93e-02	0.04085 *
DEBT_TO_ASSETS	-1.38e-04	0.57551	-3.10e-03	< 2.2e-16 ***	-1.18e-03	1.307e-10 ***	1.21e-03	0.00026 ***
EFF_IR	1.02e-04	0.265146	-7.14e-05	0.374785	2.36e-03	9.468e-05 ***	8.91e-05	0.09093 .
SALES_GROWTH	2.39e-04	3.397e-07 ***	9.63e-04	< 2.2e-16 ***	4.22e-04	9.152e-16 ***	2.86e-05	0.4794
CASH_ASSETS	-5.84e-02	0.188472	6.10e-02	0.113618	-5.48e-02	0.05006 .	-6.23e-02	0.07839 .
FEDFUNDS	-1.41e-02	0.001734 **	-8.41e-03	0.001352 **	-1.00e-02	2.285e-05 ***	-9.97e-03	0.06729 .
RECESSION	1.12e-02	0.234911	-2.73e-02	0.621290	-2.56e-03	0.58636	-1.76e-02	0.09018 .
R-squared	0.33727		0.32175		0.13812		0.047225	
Adjusted R-squared	0.17063		0.16223		-0.06338		-0.20574	
F-statistic p-value	< 2.2e-16		< 2.2e-16		< 2.2e-16		1.08e-06	

Below are the results for regression equation ROA = DAYS_AR + DAYS_I + DAYS_AP + MARKET_CAP + AGE + EBITDA_MULTP + DEBT_TO_ASSETS + EFF_IR + SALES_GROWTH + CASH_ASSETS + FEDFUNDS + RECESSION, using OLS and FE.

OLS

	Energy		**Materials**		**Industrials**		**Health Care**	
	Coefficient		Coefficient		Coefficient		Coefficient	
Variable	Estimate	t-test p-value	Estimate	t-test p-value	Estimate	t-test p-value	Estimate	t-test p-value
DAYS_AR	-4.01e-04	0.000266 ***	3.67e-05	0.75418	-2.94e-04	0.000685 ***	-3.16e-04	0.01994 *
DAYS_I	-2.64e-04	0.000939 ***	-2.29e-05	0.72024	4.10e-06	0.912234	1.67e-05	0.69307
DAYS_AP	2.21e-04	0.041479 *	-2.07e-04	0.02841 *	-2.49e-04	0.011558 *	-3.89e-04	8.39e-09 ***
MARKET_CAP	3.88e-07	0.004527 **	6.38e-07	0.00117 **	5.31e-07	2.19e-07 ***	6.10e-07	1.35e-08 ***
AGE	-6.90e-04	0.012535 *	7.49e-05	0.42066	2.62e-04	0.001265 **	3.43e-04	0.2068
EBITDA_MULTP	3.71e-01	< 2e-16 ***	5.84e-02	< 2e-16 ***	2.53e-02	1.02e-10 ***	1.42e-01	< 2e-16 ***
DEBT_TO_ASSETS	-5.70e-04	0.007289 **	3.85e-04	0.05438 .	-8.91e-05	0.512493	-1.29e-03	7.77e-07 ***
EFF_IR	8.39e-05	0.479824	-1.59e-06	0.98885	-7.21e-03	< 2e-16 ***	7.61e-06	0.91942
SALES_GROWTH	-1.67e-07	0.923862	1.19e-03	< 2e-16 ***	5.25e-04	4.96e-14 ***	-4.64e-06	0.93775
CASH_ASSETS	-9.04e-02	0.070916 .	3.06e-02	0.45879	-1.70e-02	0.479136	-3.12e-01	< 2e-16 ***
FEDFUNDS	-3.53e-03	0.657846	-5.58e-03	0.16081	-6.97e-03	0.050389 .	1.44e-02	0.09393 .
RECESSION	-6.59e-02	5.38e-05 ***	-1.09e-02	0.89113	-1.55e-02	0.031325 *	-1.81e-04	0.99132
R-squared	0.517		0.2554		0.1565		0.3252	
Adjusted R-squared	0.5079		0.2426		0.1511		0.3182	

F-statistic p-value	< 2.2e-16	< 2.2e-16	< 2.2e-16	< 2.2e-16

Fixed Effects

	Energy		**Materials**		**Industrials**		**Health Care**	
	Coefficient		Coefficient		Coefficient		Coefficient	
Variable	Estimate	t-test p-value	Estimate	t-test p-value	Estimate	t-test p-value	Estimate	t-test p-value
DAYS_AR	-1.19e-05	0.931033	3.33e-04	0.100359	-8.72e-05	0.557138	-1.65e-04	0.29315
DAYS_I	-2.08e-04	0.107539	4.15e-04	0.000524 ***	-9.47e-05	0.193263	9.74e-05	0.12842
DAYS_AP	5.25e-04	0.000639 ***	-2.99e-04	0.184912	-1.15e-04	0.484528	-4.13e-04	6.22e-09 ***
MARKET_CAP	1.03e-06	0.0012648 **	1.82e-06	0.0001158 ***	-4.43e-09	0.985095	2.63e-07	0.19307
EBITDA_MULTP	4.49e-01	< 2.2e-16 ***	3.91e-02	1.31e-14 ***	1.10e-02	6.182e-05 ***	7.35e-02	1.19e-15 ***
DEBT_TO_ASSETS	-1.97e-03	1.42e-09 ***	-2.92e-03	4.57e-14 ***	-1.15e-03	9.542e-11 ***	-1.35e-03	2.31e-05 ***
EFF_IR	1.64e-04	0.165738	-9.18e-05	0.277748	-1.96e-03	0.0008785 ***	-9.00e-06	0.85845
SALES_GROWTH	2.65e-04	1.19e-05 ***	1.11e-03	< 2.2e-16 ***	7.51e-04	< 2.2e-16 ***	5.85e-05	0.20406
CASH_ASSETS	1.03e-01	0.0716533 .	1.78e-01	1.53e-05 ***	9.33e-02	0.000586 ***	5.25e-02	0.12308
FEDFUNDS	-8.13e-03	0.165336	-8.42e-03	0.002509 **	-4.44e-03	0.0541897 .	8.88e-03	0.08855 .
RECESSION	-2.37e-02	0.0577111 .	2.20e-02	0.704287	-1.12e-02	0.0146103 *	-6.50e-04	0.94778
R-squared	0.69297		0.4172		0.20023		0.14746	
Adjusted R-squared	0.61427		0.27761		0.011959		-0.081253	
F-statistic p-value	< 2.2e-16		< 2.2e-16		< 2.2e-16		< 2.2e-16	