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How Does Inventory Management Affect the Financial Health of Manufacturing Companies in Europe during the Wake of COVID-19

Bachelor Thesis

International Bachelor of Economics and Business Economics

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Abstract

Inventory management is crucial for supply chain efficiency, especially during economic disruptions like the COVID-19 pandemic. This study investigates the impact of the Inventory Conversion Period of the inventory subcategories and the overall inventory on profitability, measured by EBIT margin. The motivation stems from the volatility and supply chain disruptions caused by the pandemic, highlighting the need for effective inventory strategies. Existing literature suggests a negative relationship between conversion periods and profitability, indicating that longer ICPs typically reduce profitability. This thesis aims to examine how different management practices influence company profitability during economic shocks, focusing on inventory changes induced by COVID-19. A fixed effects model, comprising five separate models, was utilized to analyze secondary data from the LSEG database, focusing on European manufacturing companies from 2019 to 2023. Additionally, a paired t-test was conducted to compare inventory levels before and after the onset of COVID-19. The findings reveal that the conversion periods of finished goods and inventories negatively affect EBIT margins, with these being the only statistically significant results. Other models were inconclusive. The paired t-test shows that inventory levels increased after COVID-19, which contradicts existing literature.

Keywords: Inventory management, profitability, COVID-19, economic disruption, supply chain, Inventory Conversion Period, manufacturing sector, Europe.

Chapter 1. Introduction

1.1 Research Problem and Motivation

People in society typically operate within a predictable status quo, where routines and systems are optimized for efficiency in day-to-day tasks. However, when disruptions occur, uncertainty quickly emerges. The goal of this study is to explore optimal strategies during times of crisis, particularly focusing on the significant impact of inventory management within the manufacturing sector.

The European Union, like many developed regions, experienced profound disruptions during the COVID-19 pandemic, significantly affecting international trade and supply chains. Temporary border closures and logistical challenges disrupted supply chains and impacted export figures. These disruptions underscore the critical role of efficient inventory management, especially in mitigating the adverse effects of such crises. Inventory represents a substantial asset for many organizations, often comprising a significant portion of their expenses and total capital investment. Understanding how companies manage this critical asset during crises is essential for management decision-making and investor confidence.

The manufacturing industry, heavily reliant on efficient inventory practices, faces unique challenges during crises. Supply chain disruptions, as highlighted by recent studies, underscore the importance of responsive inventory management strategies in maintaining operational continuity and financial stability. Historical research has shown correlations between inventory levels and long-term stock performance. Companies with excessively high inventories tend to experience poorer stock returns compared to those with leaner inventory management practices. This observation raises crucial questions about the optimal balance in inventory management to enhance long-term financial health and resilience during crises. That led to the formation of the research question of this study:

"How does inventory management affect the financial health of manufacturing companies in Europe in the period 2019-2023?"

1.2 Research Objective and Relevance

Contemporary systems are finely tuned for efficiency under normal conditions but often falter under stress. This research aims to understand the impact the end of the supply chain - inventories has on profitability during volatility and uncertainty. Inventory management plays a pivotal role in the operations of manufacturing companies, influencing their ability to function and thrive. By examining the inventory conversion periods effects on company performance, this thesis aims to offer valuable insights for market participants and regulatory bodies, enhancing their understanding of critical issues in crisis management.

1.3 Research Outline

This thesis is structured to first review existing literature on inventory management and crisis responses, followed by an analysis of data from European manufacturing firms using a fixed effects model and paired t-tests to examine the impact of inventory management practices. The results are discussed in relation to crisis management strategies, concluding with recommendations for future research.

Chapter 2. Literature Review

2.1 Inventory Management and Manufacturing

One of the most used indicators of short-term health for a company is working capital (WC), which explains the presence of academic literature on this topic and why it is still discussed since the concept's first introduction in the 1970s. The formula to calculate WC is: Working Capital = Current Assets - Current Liabilities, (Fernando, 2023)

By maintaining liquidity, working capital management seeks to both boost profitability and allow companies to pay back their maturing debt (Pass & Pike, 1987). (Deloof, 2003; Nastiti et al., 2019; Prša, 2020; Shaik, 2020) further establish a significant connection between WC and some variation of financial performance. Similarly, to other studies on the topic these employ a common approach to investigating working capital management (WCM) they take the different aspects of WC – Cash, Inventory, Accounts Receivable and Accounts Payable and through statistical analysis, they find a correlation. However, different papers find different variables significant – the one that is always significant is inventory.

Inventory to WC ratio is measurement to see the percentage of stock within the working capital. According to *Working Capital Ratios* (n.d.) that ratio for the US market is almost 10 percent, while some specific industries go up to 20-30%, one example of this is the Metals & Mining sector, where the number is above 20%. Meaning that inventories are a significant part of the balance sheet and current assets. However, we cannot just compare inventories of big and small companies, that would be like comparing apples and oranges, hence a comparable variable such as inventory to WC ratio is more appropriate.

The easiest way to measure profitability is to take the EBIT, however that is an absolute value which will not represent the relative profitability of companies. Hence EBIT Margin is introduced (EBITP = EBIT/Revenue*100). This is a variable established in the financial sector for profitability evaluation that represents a comparable indicator for evaluation. An alternative to EBITP is return on equity (ROE) and return on assets (ROA). However, ROE does not consider how leveraged a company is or how much debt it carries. A limitation of ROA is it cannot be used across industries. In this study, companies in different manufacturing sub-sectors are within the dataset, hence this can be a problem. Thus, leading to the formulation of hypothesis number one of this study:

H1: There is a correlation between inventory to WC ratio and EBIT Margin

2.2 Inventory management and financial health

The development of inventory management is an interesting topic that is covered in many papers. While in the past excess inventory was perceived as a sign of wealth, nowadays everyone tries to optimize their inventory using different systems such as Just-in-Time (JIT), Activity Based Costing (ABC) or others Ajayi et al. (2021). Moreover, this study emphasizes in the findings the importance of effective inventory management, which leads to improved financial performance. According to Munyaka & Yadavalli (2022, p. 1) “Inventory is the most important asset held by many organizations, representing as much as half of the company’s expenses, or even half of the total capital investment.” So, an insight into the dealings for the biggest expense account is material to people from management to investors. However, inventory is a broad term, which is why bellow is a breakdown of the main categories of inventories:

1. Raw materials
2. Work-in-progress (WIP)
3. Finished goods
4. Commodities

Etale et al. (2016) concludes that Nigerian listed companies would benefit from effective inventory cost management and would improve their profitability by lowering their cost. One way that is suggested is reducing the inventory conversion period (ICP) Panigrahi (2013), the study done in India finds a negative correlation between ICP and firm's profitability. Howard (1974) theorizes that there are two main reasons:

1)Holding Cost – which relates to the cost of storing and preserving the different materials and products a company uses and offers to clients, and

2) Out-of-Stock costs – this relates to the money, but not only, that a firm loses when they are unable to meet demand. The paper elaborates more that usually these costs are large but rare.

Furthermore, (Ahire & Dreyfus, 2000; Camacho-Minano et al., 2013; Flynn et al., 1995; Kuruppuarachchi & Perera, 2010; Shah & Ward, 2003; Shin et al., 2000; Vanichchinchai & Igel, 2011 as cited in Shin et al.,2016) states that these papers have contributed to the literature that confirms the introduction of JIT, Total quality management (TQM), and Supply Chain Management (SCM) plays a crucial role in improving inventory management, which in turn improves financial health.

The majority of the papers listed in the previous paragraph focus on the relationship between inventory management and financial performance (in this paper financial performance and financial health are interchangeable). Most find that more lean systems, such as JIT, lead to more profitable outcomes. In other words, the less time products and materials are in stock the more money a company earns. Hong et al. (2005) did a study on the change in inventories of American companies from 1981 to 2000, that was during a time where Japanese car manufacturers were leading the market because of their just-in-time (JIT) system. The study found that firms with abnormally high inventories have abnormally poor long term stock returns and ones with lower inventories perform better. Another study done in Belgium suggest similar results - Boute et al. (2007) reported a negative correlation between every type of inventory and return on investment in different sectors of the Belgium manufacturing industry. Both present the same logic – lower inventories, lower expense accounts, which lead to higher profitability. Another example is Gołaś, (2020), where the Polish manufacturing sector was studied and presented again negative relationship. In these papers lower inventory is a relative term, which refers to the time that products are held, Amahalu (2018) uses Inventory Conversion Time (ICT, same as ICP) (365 days * Average inventory) / Cost of goods sold). Hashed (2022) also utilizes this approach and both find a negative relationship between ICP and return on assets (ROA) in Nigeria and Saudi Arabia respectably. Gołaś, Z. (2020) takes a more in-depth approach and makes a sub-category for every type of inventory and how much time they stay in storage on average.

All of this leads to the formulation of the following hypotheses:

H2: Inventory Conversion Period affects EBIT margin negatively

H3: Inventory time in storage for each specific sub-category affects EBIT margin negatively

2.3 Inventory management and Covid-19

The entire world changed under the pandemic that was Covid-19, supply chains were distorted, demand was unpredictable, and that is not mentioning the health impact it had on humankind. What does that mean for industries? The economy was under stress, and when under distress companies act differently. Distress can originate from factors that are either internal or external to the firm; management mistakes, excessive leverage, rising costs, uncontrolled growth and sluggish demand are typical causes of distress. External economic factors can include unfavorable industrial structures, governmental deregulation activities, rising interest rates, increasing competition and industry overcapacity (Altman and Hotchkiss, 2006 cited in Steinker et al., 2016). Steinker et al. (2016) continues to explain that previous research, despite being theoretical, suggests that firms usually sell inventory and lower days in stock to generate cash and avoid illiquidity. Beaver et al. (2010) elaborates more on this – one of the key things companies do when under financial pressure is to transform assets into cash. Molina and Preve (2009) also propose that firms are expected to generate cash by utilizing internal assets such as inventory, assets, accounts payable, and accounts receivable. Moreover, the Pecking order theory by Myers (1984) would suggest that internal resources would be preferred by a company over external financing. There are multiple macroeconomic research papers on the topic, one of which is Guariglia and Mateut (2010), however they have not explored the firm-level impact of inventory under distress.

Steinker et al. (2016) Explores the intricacies of inventory and the role it plays in companies during financial uncertainty. The main finding of this paper that concerns this study is that companies lower their absolute and relative inventory while facing economic pressure. Thus, formulating the next hypothesis:

H4: Companies will have lower inventory levels after 2019

Chapter 3. Data and Methodology

3.1 Research Design

All manufacturing companies in Europe are included in the data for this study, which is based on the North American Industry Classification System (NAICS). The study period is between 2019-2023, additionally the information for years 2016-2019 is available for two reasons. The first one is for the testing of the 4^{th} hypothesis and secondly, in order to have a lag for the calculation of some variables. The panel data is collected from the LSEG database. The initial sample has 24,000 observations; however, after removing companies that did not have critical data for the analysis and other explanatory variables needed for the research, the final sample consists of 455 firm-year observations. Based on previous research on the topic a regression analysis using Ordinary Least Squares (OLS) is utilized.

3.2 Variables

3.2.1 Key variables

The dependent variable in this paper is EBIT margin – how profitable a company is compared to their sales. This variable is available in the LSEG database within the "Company Fundamentals", which includes the financial statement and the balance sheet of companies (Refinitiv, 2024). According to the company that provides the database Refinitiv (2024) " The data provides the user with a company's current financial health and when combined historically, the financial 'life-story' of the company". The formula for EBIT margin is simple:

$$EBIT\ M\arg i\, n = \frac{EBIT}{SALES}$$

In this study the independent variable is inventory conversion period (ICP). ICP is also available in the Refinitiv database because it is calculated by variables available in the balance sheet. The formula is presented below:

$$ICP = \frac{Invenoty}{COGS} \times 365$$

Where:

COGS - Cost of Goods Sold

INV - Inventory

3.2.2 Control variables

Studies on inventory done in previous years usually employ an array of control variables that account for company size, key financial ratios or key financial indicators (KPI's), liquidity, and income growth. In other words, short-term and long-term metrics. Eroglu and Hofer (2010) uses the natural logarithm of total assets as an indication of size and growth of sales for an indicator of income growth. Golas (2020) has a similar approach with the addition of liquidity metric.

In this paper the control variables utilized are:

$$Liq = \frac{CA-INV}{SLiab}; \Delta SALES = \frac{(S_t - S_{t-1})}{S_{t-1}} \times 100; Ln(Total\ Assets); LnEBITP\ L1.$$

Where:

Liq – Liquidity

CA – Current Assets

SLiab – Short-term Liability

$\Delta SALES$ - Growth in sales

St – Sales in period t (t-1)

L1. = Lag

3.2.3 Measurement for the COVID-19 pandemic

According to *EU-Monitor COVID19: Economic Consequences of the Pandemic - German Federal Statistical Office* (2023) the economic impact of Covid19 started in 2020, hence this is going to be the first year in the dataset considered as pandemic start. In order to reflect that a dummy variable is created, having a value of 1 for years – 2020 to 2023, and 0 from 2016 to 2019.

3.3 Data Analysis Method

The established method used in the studies researched is regression analysis, but first the type of regression model must be chosen. For that, a Hausman test is performed to determine whether a fixed effects model or random effects model should be used. This test, also known as the exogeneity assumption test, determines if the unobserved individual effect is correlated with the conditioning regressors in the model Hahn et al. (2011).

Table 3.1 Hausman test

	(b)	(B)	(b-B)	sqrt(diag(V_b-V_B))
	Re	Fe	Difference	Std. err.
ICP_Ln	0.032	-0.053	0.085	.
EBITP_Ln L1.	0.035	0.015	0.020	0.001
Sales_growth	0.002	0.005	-0.003	0.001
Liquidity	-0.006	-0.022	-0.016	.
TotalAssets_Ln	0.002	0.004	-0.016	.
Hausman Test	Chi2(5) = 205.87		df = 5	p-value = 0.0000

3.3.1 Fixed effects model

Borenstein et al. (2010) elaborates more on this form of meta-analysis, explaining the differences of the two models (random and fixed effects). After performing the required tests, the fixed effects model was chosen. This is a statistical method used in regression analysis to control unobserved variables that may vary across entities but are constant over time. This approach helps isolate the impact of the independent variables on the dependent variable by accounting for individual-specific characteristics, thereby reducing potential bias in the estimated coefficients. deHaan (2020) further explains how the model works – the pitfalls and upsides that accompany using fixed effects. One major point to be considered is whether to use it or utilize OLS, however, since there are variables such as operational efficiency and management quality that can affect both the independent and dependent variable. That is why in this study a fixed model is employed. Below the models for each hypothesis are presented:

H2:

$$EBITP_{it} = \beta_0 + \beta_1 LnICP_{it} + \beta_1 LnEBITP\ L1 + \beta_2 LnSalesGrowth_{it} + \beta_4 Liq_{it} + \beta_5 LnTotalAssets_{it} + \varepsilon_{it}$$

H3:

$$EBITP_{it} = \beta_0 + \beta_1 LnRawMat_{it} + \beta_1 LnEBITP\ L1 + \beta_2 LnSalesGrowth_{it} + \beta_4 Liq_{it} + \beta_5 LnTotalAssets_{it} + \varepsilon_{it}$$

$$EBITP_{it} = \beta_0 + \beta_1 LnWIP_{it} + \beta_1 LnEBITP\ L1 + \beta_2 LnSalesGrowth_{it} + \beta_4 Liq_{it} + \beta_5 LnTotalAssets_{it} + \varepsilon_{it}$$

$$EBITP_{it} = \beta_0 + \beta_1 LnFG_{it} + \beta_1 LnEBITP\ L1 + \beta_2 LnSalesGrowth_{it} + \beta_4 Liq_{it} + \beta_5 LnTotalAssets_{it} + \varepsilon_{it}$$

$$EBITP_{it} = \beta_0 + \beta_1 LnINV\ O_{it} + \beta_1 LnEBITP\ L1 + \beta_2 LnSalesGrowth_{it} + \beta_4 Liq_{it} + \beta_5 LnTotalAssets_{it} + \varepsilon_{it}$$

3.3.2 T test

For the last hypothesis a T test is performed, this method is commonly used when comparing differences in means (Coman et al, 2013; Hedberg & Ayers, 2015). Here this statistical is performed for the years before and after COVID19 (2016-2019;2020-2023) Hence we formulate the null and the alternative hypothesis:

Ho: $\mu_b - \mu_a = 0$

Ha: $\mu_b - \mu_a \neq 0$

Where:

μ_b - mean of inventory level before covid

μ_a - mean of inventory level after covid

3.4 Robustness Checks

One requirement of statistical test of any nature is normality, hence all variables are screened for a normal distribution. This is done using histograms, if necessary, a modification is made by utilizing the natural logarithm of the absolute value. Next a Wooldridge test is performed for autocorrelation between variables used in the fixed effects models. According to O'brien (2007) The Variance Inflation Factor (VIF) and tolerance are both widely used measures of the degree of multi-collinearity of the i^{th} independent variable with the other independent variables in a regression model. And it is a good indicator for multicollinearity, thus this paper will perform the test. Moreover, a Breusch–Pagan/Cook–Weisberg test is utilized to check for heteroskedasticity. Furthermore, for the last hypothesis a different approach is employed to ensure concrete results – that is Wilcoxon Signed-Rank Test.

Chapter 4. Results

This section presents the findings of our study on inventory management in the manufacturing sector across Europe from 2019 to 2023. The results are organized into four distinct parts. First, we provide descriptive statistics to offer an overview of the key variables and trends observed during the study period. Second, we analyze the relationship between inventory levels and profitability, shedding light on how effective inventory management practices impact financial performance. Third, we explore the influence of the COVID-19 pandemic on inventory practices, assessing how firms adapted their strategies in response to unprecedented disruptions. Finally, we conduct robustness tests to verify the reliability and validity of our findings, ensuring that our conclusions are well-supported and generalizable.

4.1 Descriptive statistics

Table 4.1.1

Variable	Mean	Std. Dev.	Min	Max
Total Assets	25700	77600	275	663000
COGS	10400	32200	53.33	287000
Net WC	1950	9630	-10500	132000
EBITP	0.119	0.087	-0.467	0.451
Current Assets	10600	31200.00	98.30	264000
Current Liab	8800	26900	34.10	227000
Revenue	15000	41400	101	356000
ROA	0.855	0.340	0.081	1.989
Liquidity	1.192	0.708	0.271	6.360
Sales Growth	7.455	21.815	-62.250	264.042

Notes: Total Assets = Total Assets; COGS = Cost of Goods Sold; Net WC = Net Working Capital; EBITP = Earnings Before Interest and Taxes as a Percentage of Total Assets; Current Assets = Current Assets; Current Liab = Current Liabilities; Revenue = Revenue; ROA = Return on Assets; Liq = Liquidity Ratio; Sales Growth = Sales Growth. Values are in millions of US dollars except for Earnings Before Interest and Taxes as a Percentage of Total Assets (EBITP), Return on Assets (ROA), Liquidity Ratio (Liq), and Sales Growth, which are in ratios or percentages. The number of observations for each variable is 455

Table 4.1.1 presents the descriptive statistics for variables related to or used in this study. These numbers relate to the dataset of manufacturing companies in Europe during the period 2019-2023. The mean Total Assets of these companies is 25,700 million USD, with a substantial standard deviation indicating a broad range of company sizes. This diversity in company sizes suggests a highly heterogeneous market structure where both small and large firms coexist. The

COGS (Cost of Goods Sold) also show considerable variation, underscoring the differences in operational scales. The mean Earnings Before Interest and Taxes Percentage (EBITP) at 11.94% with a wide range highlights the varying profitability levels across firms. The presence of negative values suggests that some companies are experiencing losses, which may be due to competitive pressures, inefficient operations, or economic downturns, such as the volatility in the market as a result of Covid19.

The descriptive statistics reveal a highly diverse and dynamic manufacturing sector in the EU. The substantial variability in financial and operational metrics suggests that firms adopt different strategies and face varying market conditions. High variability in inventory management practices, profitability, and liquidity positions indicates that while some firms are thriving, others may be struggling to optimize their operations and financial performance.

Table 4.1.2 presents descriptive statistics for key inventory management variables in the European manufacturing sector from 2019 to 2023. Inventory (INV) averages 2,840 units with a substantial standard deviation of 7,350, indicating significant variability among firms. Inventory Cycle Period (ICP) and Work-In-Progress days (WIP_days) show mean values of 143.90 and 39.23 days, respectively, highlighting differences in inventory turnover and processing times. Additionally, Finished Goods days (FG_days) and Raw Material days (Raw Mat_days) display considerable variation, reflecting diverse inventory management practices across the sector.

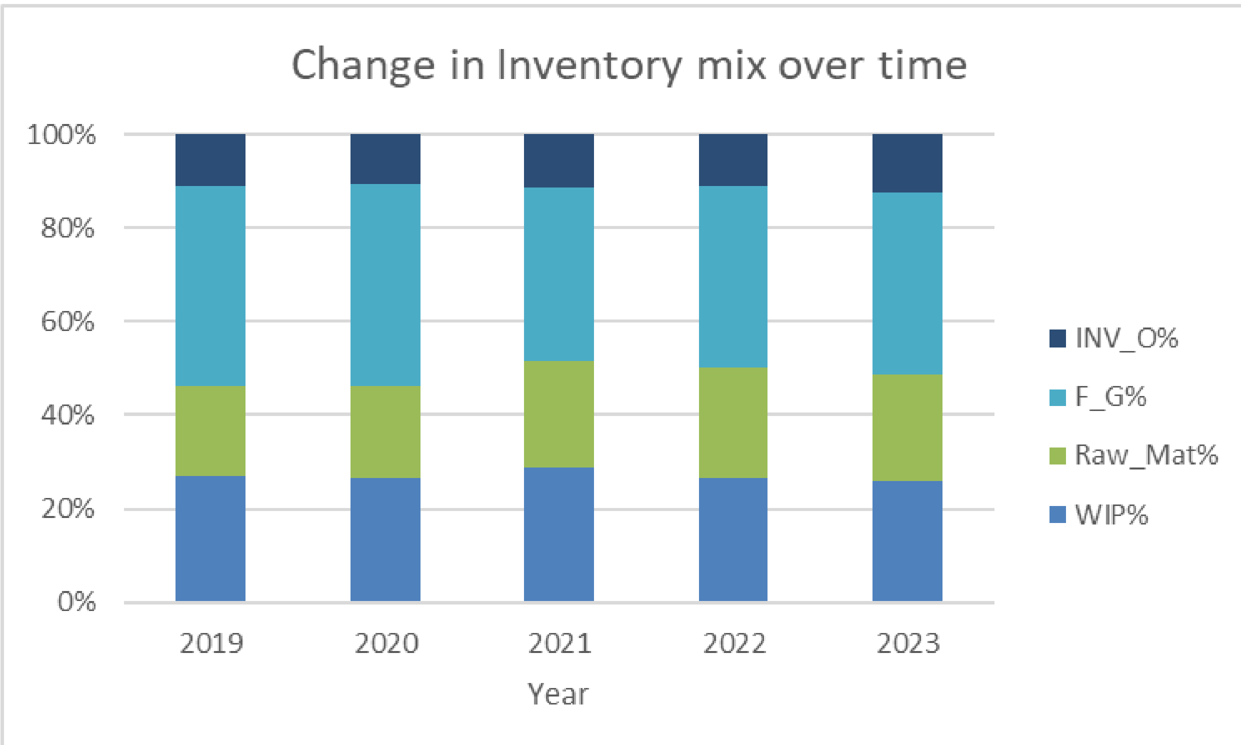
Table 4.1.2

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
Inventory	2840	7350	14.60	58700
ICP	143.90	152.41	29.42	1656
WIP_CP	39.23	79.09	0.00	624.71
Raw Mat_CP	44.46	31.90	0.19	253.04
FG_CP	60.47	81.98	1.70	830.39
INV_O_CP	5.28	36.53	-191.58	185.28

Notes: INV = Total Inventory; ICP = Inventory Conversion Period; WIP = Work in Process; Raw Mat = Raw Materials; FG = Finished Goods; INV_O = Other Inventory; CP = Conversion Period. Values are in days. The number of observations for each variable is 455.

Figure 4.1.1 provides the percentage composition of inventory types for EU manufacturing companies over the period 2019-2023. This table sheds light on the structural dynamics within inventory management, reflecting the relative importance of different inventory categories: Work-in-Progress, Raw Materials, and Finished Goods. In 2019, Finished Goods constituted the largest share of total inventory at 45%, indicating a significant focus on maintaining high levels of completed products, likely to meet immediate demand fluctuations and ensure quick delivery. However, by 2023, the share of Finished Goods declined to 40%. This reduction suggests a shift towards leaner inventory strategies or improved demand forecasting, which could reduce the need for holding large amounts of finished products.

Figure 4.1.1



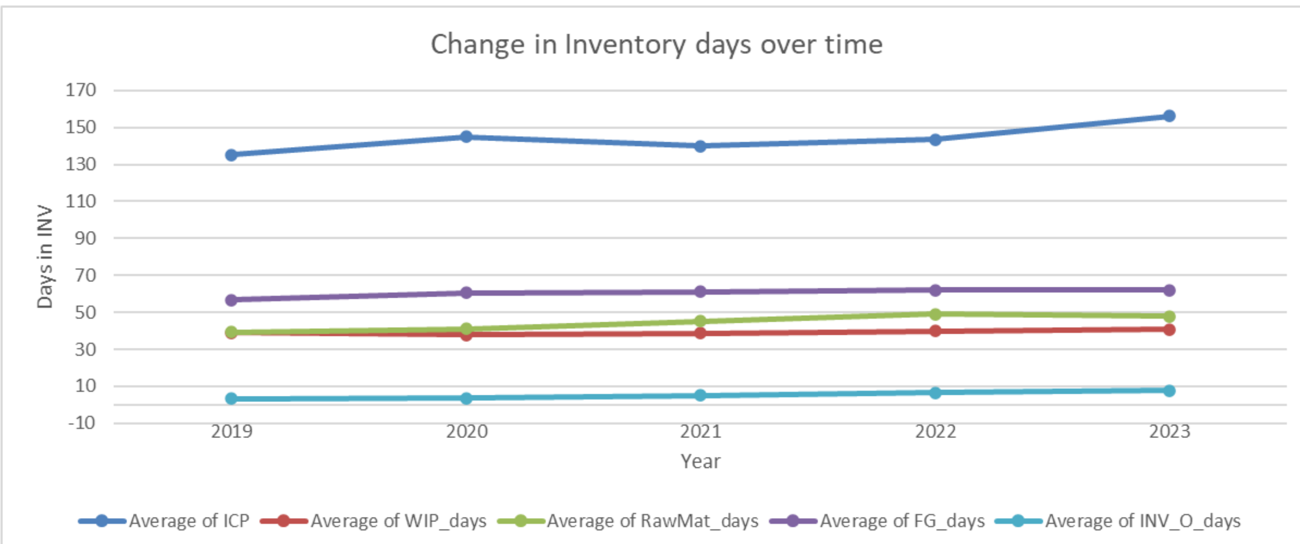
Notes: INV = Total Inventory; WIP = Work in Process; Raw Mat = Raw Materials; FG = Finished Goods; INV_O = Other Inventory. Values are in percentages. The number of observations for each variable is 455.

Figure 4.1.1 delineates the composition of inventory components as a percentage of total inventory from 2019 to 2023. The Work-in-Progress inventory percentage exhibits minor fluctuations, ranging between 27% and 29% throughout the years, indicating a relatively stable processing stage. The proportion of Raw Materials increases gradually from 20% in 2019 and 2020 to 25% in 2022, followed by a slight decline to 23% in 2023. This trend suggests an intermittent augmentation in raw material stockpiling over the period. The Finished Goods component demonstrates a significant decline from 45% in 2019 to a range of 38% to 42% in the subsequent years, potentially reflecting an accelerated turnover or a reduction in finished goods inventory.

Conversely, Other Inventory maintains relative stability but shows a modest increase from 11% in 2019 to 13% in 2023, indicating a slight rise in the proportion of other inventory types.

Overall, the changes in inventory mix over the period highlight the dynamic nature of inventory management in response to both internal efficiencies and external market conditions. The decline in Finished Goods inventory, coupled with fluctuations in Raw Materials and WIP, suggests a strategic shift towards optimizing inventory levels and reducing holding costs.

Figure 4.1.2



Notes: INV = Total Inventory; WIP = Work in Process; Raw Mat = Raw Materials; FG = Finished Goods; INV_O = Other Inventory. Values are in days. The number of observations for each variable is 455.

Figure 4.1.2 presents the average duration for which various inventory components are held over the period from 2019 to 2023. The Inventory Conversion Period shows a steady increase from 135.21 days in 2019 to 156.21 days in 2023, indicating an elongating period required to convert inventory into sales. The average days Work-in-Progress inventory is held remains relatively stable, oscillating around 38 to 41 days, suggesting consistent processing times. Raw Materials display a noticeable increase from 39.20 days in 2019 to a peak of 48.94 days in 2022, before slightly decreasing to 47.77 days in 2023, reflecting alterations in raw material turnover times. The Finished Goods component increases from 56.67 days in 2019 to approximately 62 days in the later years, indicating a longer period required to sell finished products.

The data highlights trends in inventory management for manufacturing companies in Europe from 2019 to 2023. The increase in the average Inventory Conversion Period (ICP) and the days different inventory components are held suggests potential challenges in inventory turnover and management efficiency. Moreover, the shifts in the inventory mix percentages underline changes in inventory strategies, possibly driven by market dynamics, production processes, or strategic decisions made by the companies.

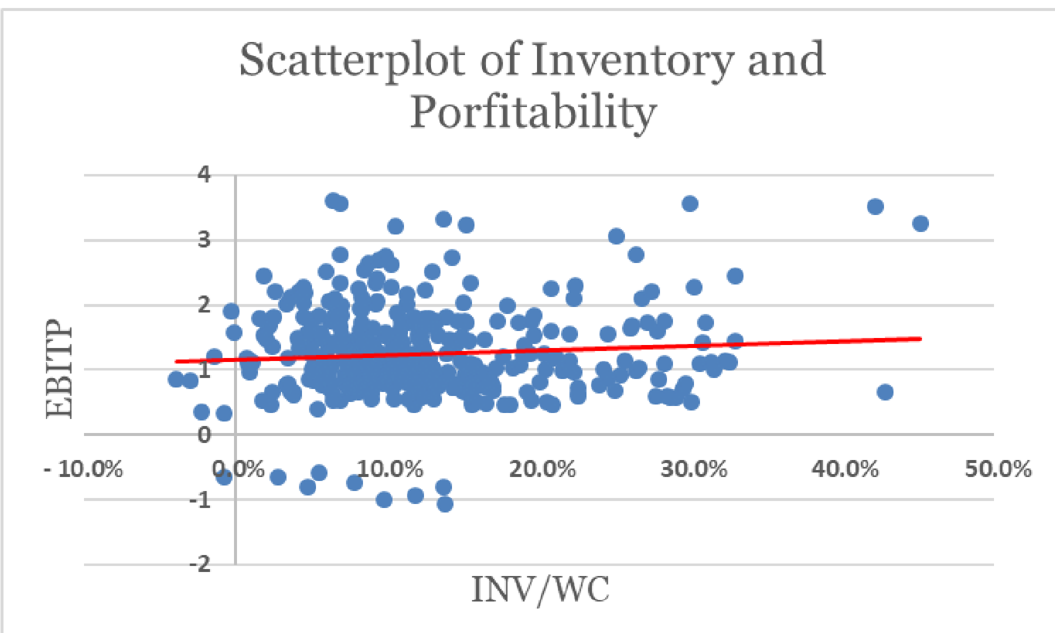
4.2 Inventory and Profitability

In this section, first the relationship between inventory levels and profitability is explored by establishing a trend between inventory levels and working capital. Furthermore, the study investigates the dynamic between conversion periods and profitability using Pearson's correlation analysis and five fixed-effects models. This comprehensive approach allows to understand the strength and direction of the correlation, while accounting for potential confounding variables and firm-specific effects

4.2.1 Inventory Levels and EBIT Margin

Figure 4.2.1 visualizes the relationship between the Inventory to Working Capital (INV/WC) ratio and Earnings Before Interest and Taxes (EBIT) margin (EBITP). Each blue dot represents an individual observation, indicating how different levels of inventory relative to working capital are associated with corresponding EBIT margins.

Figure 4.2.1 Scatterplot of Inventory and Profitability



Notes: The scatterplot illustrates the relationship between the Inventory to Working Capital (INV/WC) ratio and Earnings Before Interest and Taxes (EBIT) margin (EBITP). In red a trendline is presented.

The red trendline, which has been added to the scatterplot, indicates a slight positive correlation between INV/WC and EBITP. This suggests that as the inventory to working capital ratio increases, there is a marginal increase in EBIT margin. However, the wide dispersion of points around the trendline implies that this relationship is weak and not highly predictive. This is not definitive evidence supporting the first hypothesis, but it indicates there might be merit to it.

4.2.2 Inventory turnover and Profitability

The Pearson's correlation, presented in *Table 4.2.1*, highlights the relationships between key inventory variables and profitability (EBITP) in the manufacturing sector. Notably, Finished Goods days (FG_day_Ln) shows the strongest positive correlation with EBITP (0.34), suggesting that higher levels of finished goods are associated with increased profitability. Other Inventories (INV_O_days_Ln) and Raw Material days (RawMat_day_Ln) also display positive correlations with EBITP (0.26 and 0.25, respectively), indicating that efficient management of these inventory categories is beneficial to profitability. Additionally, Inventory Cycle Period (ICP) and Work-In-Progress days (WIP_days_Ln) are positively correlated with EBITP (0.21 and 0.13, respectively), although to a lesser extent, emphasizing the complex interplay between various stages of inventory and overall financial performance. However, that is the opposite of what the literature on the topic suggested and the hypothesis made based on them.

Table 4.2.1: Pearson's correlation

	EBITP	ICP	RawMat_CP_Ln	FG_CP_Ln	WIP_days_Ln	INV_O_days_Ln	EBITP_Ln L1	Sales_growth	Liq	TotalAsset_Ln
EBITP	1.00	0.21	0.25	0.34	0.13	0.26	0.65	-0.08	0.03	-0.09
ICP	0.21	1.00	0.32	0.53	0.54	0.42	0.12	-0.05	0.26	0.11
RawMat_CP_Ln	0.25	0.32	1.00	0.00	0.39	0.28	0.18	-0.05	-0.06	-0.27
FG_CP_Ln	0.34	0.53	0.00	1.00	0.11	-0.01	0.22	-0.07	0.06	0.12
WIP_CP_Ln	0.13	0.54	0.39	0.11	1.00	0.35	0.07	-0.03	0.28	0.05
INV_O_CP_Ln	0.26	0.42	0.28	-0.01	0.35	1.00	0.30	-0.05	0.07	0.08
EBITP_Ln L1.	0.65	0.12	0.18	0.22	0.07	0.30	1.00	-0.06	0.01	-0.05
Sales_growth	-0.08	-0.05	-0.05	-0.07	-0.03	-0.05	-0.06	1.00	0.01	0.02
Liq	0.03	0.26	-0.06	0.06	0.28	0.07	0.01	0.01	1.00	-0.06

TotalAsset_Ln	-0.09	0.11	-0.27	0.12	0.05	0.08	-0.05	0.02	-0.06	1.00

Notes: The table presents Pearson's correlation coefficients among various financial and inventory management variables in the manufacturing sector from 2019 to 2023. EBITP refers to Earnings Before Interest and Taxes as a percentage of Sales. ICP represents Inventory Cycle Period. RawMat_day_Ln, FG_day_Ln, WIP_days_Ln, and INV_O_Ln refer to the natural logarithms of Raw Material days, Finished Goods days, Work-In-Progress days, and Other Inventory days, respectively. EBITP_Ln L1 indicates the natural logarithm of lagged EBITP. Sales_growth denotes the growth rate of sales. Liq represents liquidity, and TotalAsset_Ln indicates the natural logarithm of total assets.

Other interesting numbers to highlight are the strong positive correlation between profitability (EBITP) and lagged profitability (EBITP_Ln L1) (0.65), pointing out the persistence of financial performance over time. Additionally, Total Assets (TotalAsset_Ln) shows a negative correlation with Raw Material days (RawMat_day_Ln) (-0.27), suggesting that larger firms may manage raw materials more efficiently. Finally, Liquidity (Liq) is positively correlated with Work-In-Progress days (WIP_days_Ln) (0.28), indicating that firms with higher liquidity tend to have more work-in-progress inventory.

Table 4.2.2: Fixed effects models

	FE Model – ICP (1)	**FE Model – Raw Mat (2)**	**FE Model – WIP (3)**	**FE Model – FG (4)**	**FE Model – INV_O (5)**
IV	-0.054**	0.018	-0.003	0.019**	-0.002
	(0.02)	(0.016)	(0.009)	(0.009)	(0.006)
EBITP_Ln L1.	0.015***	0.013**	0.014***	0.014***	0.015***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Sales_growth	0.005**	0.004*	0.004*	0.004**	0.006*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Liq	-0.022**	-0.016*	-0.019**	-0.018**	-0.019*
	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)
TotalAssets_Ln	-0.004	-0.004	-0.002	-0.008	-0.023
	(0.017)	(0.017)	(0.019)	(0.018)	(0.031)
constant	0.520	0.204	0.219	0.267	0.688
	(0.422)	(0.407)	(0.419)	(0.403)	(.0.735)

Number of observations	242	242	239	242	169
R^2	0	0.20	0.19	0.23	0.09
F	6.78	6.84	6.66	6.83	5.71

Notes: The regression model used is Fixed effects model and the dependant variable is EBITP – EBIT margin, the five columns are different models with different variables, in brackets the standard deviation is presented, * p<0.10 ** p<0.05 *** p<0.01. ICP represents Inventory Cycle Period. RawMat_day_Ln, FG_day_Ln, WIP_days_Ln, and INV_O_Ln refer to the natural logarithms of Raw Material days, Finished Goods days, Work-In-Progress days, and Other Inventory conversion period, respectively.

Fixed-effects regressions were conducted to investigate the factors influencing EBIT margin (EBITP) within the manufacturing sector in Europe during the COVID-19 pandemic. The analysis revealed several significant findings across different operational metrics. Firstly, in examining the Inventory Conversion Period (Model 1), the regression model demonstrated a significant relationship ($F(83, 153) = 6.78$, $p < 0.0000$). The equation predicting EBIT margin is:

$$EBITP = 0.52 - 0.054(ICP\ Ln) + 0.015(EBITP\ Ln\ L1) + 0.022(Liq) + 0.005(Sales\ growth) - 0.004(TotalAssetsLn)$$

The negative coefficient for ICP_Ln suggests that for each 1% increase in the Inventory Conversion Period (measured in days), EBIT margin decreases by approximately 5.35%, furthermore this relationship approached statistical significance ($p = 0.05$). This finding supports hypothesis 2 of this study, suggesting that reducing the inventory conversion cycle could potentially enhance a company's profitability. A longer inventory conversion period implies that capital is tied up in inventory for a longer duration before generating sales revenue, which can negatively impact profitability due to increased holding costs and potential obsolescence risks. Moreover, the positive coefficient (0.005) for Sales growth and EBITP across every model suggests that an increase in sales growth is associated with a slight improvement in EBIT margin, implying that higher sales volumes contribute positively to profitability, which aligns with expectations of increased revenue translating into higher earnings before interest and taxes (EBIT).

Secondly, focusing on Raw Material Days (Model 2), the regression model yielded a significant result ($F(83, 153) = 6.84$, $p < 0.000$). The equation predicting EBIT margin is:

$$EBITP = 0.204 + 0.018(Raw\ Mat\ Ln) + 0.015(EBITP\ Ln\ L1) - 0.022(Liq) + 0.004(Sales\ growth\ Ln) - 0.004(TotalAssetsLn)$$

The positive coefficient (0.018) associated with raw materials turnover indicates that for each 1% increase in raw material days, there is an expected increase of approximately 0.018 percentage points in EBIT margin. Although this relationship did not reach conventional levels of statistical significance ($p = 0.254$). Moreover, the negative coefficient (-0.022) for Liquidity (Liq) implies that higher liquidity levels correlate with a slight reduction in EBIT margin. This suggests that excessive liquidity might lead to underutilization of assets. Such underutilization can hinder profitability by missing opportunities for higher returns through investments in growth initiatives like research and development, or operational expansions. Additionally, holding excess liquidity may incur opportunity costs, where funds could have been more effectively deployed to enhance EBIT margin through strategic investments or debt reduction.

Furthermore, examining work-in-progress (Model 3) revealed a significant relationship ($F(82, 151) = 6.66$, $p < 0.000$). The equation predicting EBIT margin is:

$$EBITP = 0.219 - 0.003(WIP\ Ln) + 0.014(EBITP\ Ln\ L1) - 0.019(Liq) + 0.004(Sales\ growth\ Ln) - 0.002(TotalAssetsLn)$$

Here, the negative coefficient for WIP_days_Ln indicates that for each 1% increase in raw material days (measured in days), EBIT margin decreases by approximately 2.87% ($p = 0.766$), however this is not statistically significant relationship, hence no decisive conclusions can be made. Additionally, examining Finished Goods Days (Model 4) revealed a significant relationship ($F(83, 153) = 6.83$, $p < 0.000$). The equation predicting EBIT margin is:

$$EBITP = 0.267 + 0.019(FG\ Ln) + 0.014(EBITP\ Ln\ L1) - 0.018(Liq) + 0.004(Sales\ growth\ Ln) - 0.008(TotalAssetsLn)$$

The positive coefficient for FG_days_Ln suggests that for each 1% increase in finished goods days (measured in days), EBIT margin increases by approximately 1.85% ($p = 0.038$). The reasoning behind this may be that during the COVID-19 pandemic, businesses that effectively controlled their finished goods inventory coped better with fluctuating demand and supply chain disruptions. This adaptability helped maintain product availability, meet customer expectations, and sustain profitability amid challenging conditions.

Finally, the analysis of Inventory Outstanding Days (Model 5) showed a significant relationship ($F(59, 104) = 8.71$, $p < 0.000$). The equation predicting EBIT margin is:

$$EBITP = 0.688 - 0.002(INV\ O\ Ln) + 0.015(EBITP\ Ln\ L1) - 0.019(Liq) + 0.006(Sales\ growth\ Ln) - 0.0023(TotalAssetsLn)$$

The non-significant coefficient for INV_O_days_Ln (-0.002) suggests that changes in inventory outstanding days do not significantly impact EBIT margin. Therefore, similar to work-in-progress, conclusions regarding the influence of inventory outstanding days on profitability cannot be drawn based on the current analysis. Furthermore, model 1 supports Hypothesis 2, demonstrating that lower inventory turnover is associated with higher EBIT margins, indicating that efficient inventory management positively impacts profitability. However, the findings from Models 2, 3, 4, and 5 do not fully support Hypothesis 3, as the explanatory power of these models is limited, reflected in their relatively low R-squared values. This suggests that while there may be some relationship between the variables under consideration and profitability, it is not strong or consistent enough to draw definitive conclusions. Consequently, more research is required to explore these relationships further, potentially incorporating additional variables or different methodological approaches to better understand the factors influencing EBIT margins.

4.3 Inventory and Covid19

Table 4.3.1 Paired T test

Group	Obs	Mean	Std. err.	Std. dev.	95% interval		t	df	P(2-tailed)	Pr(T > t)
Before Covid	364	20.32	0.079	1.503	20.17	20.48				
After Covid	364	20.62	0.073	1.396	20.47	20.76				
Combined	728	20.47	0.054	1.456	20.36	20.58				
diff		-0.29	0.107		-0.50	-0.07	-2.70	726	0.0071	0.0000

Notes: This table presents the results of a paired samples t-test comparing the natural logarithm of inventory values (Ln(inventory)) of European companies before and after the COVID-19 pandemic. df – degree of freedom

The results of the paired samples t-test, presented in *Table 4.3.1* lead us to reject the null hypothesis, which posited that there would be no difference in the logarithm of inventory values of European companies before and after the COVID-19 pandemic started. The statistically significant p-value (p = 0.0071) indicates that there is indeed a significant change in inventory levels after 2019.

To interpret the magnitude of this change, we examine the mean difference in values, which is -0.290. Since we are working with logarithmic values, this difference can be converted to a percentage change. The formula to convert the difference in logarithms to a percentage change is given by $\left(e^{diff}-1\right)\times 100$. This calculation suggests that there was approximately a 25.2% increase in inventory levels after the onset of COVID-19, relative to the inventory levels before the pandemic. Interestingly, this result contradicts Hypothesis 4 of this study, which anticipated that inventory levels would decline post-pandemic. This contradiction highlights a notable departure from patterns observed in previous financial crises, where companies often reduced inventories to preserve cash flow and minimize holding costs.

However, the COVID-19 pandemic introduced unprecedented disruptions and volatility in global supply chains, prompting companies to adapt their inventory strategies. The observed increase in inventory levels can be attributed to a combination of rising demand and the need to maintain customer satisfaction. Companies likely held higher inventory buffers to avoid stockouts and lost sales opportunities in a highly uncertain environment. The pandemic's impact on supply chains further exacerbated this need, as companies faced delays and shortages that necessitated larger inventories to ensure continuous operations.

4.4. Robustness

The Wooldridge test for autocorrelation in panel data was conducted to examine the presence of first-order autocorrelation in the regression model. Autocorrelation occurs when error terms in a time series or panel data model are correlated across observations, potentially biasing the coefficient estimates.

Table 4.4.1 presents the result, which indicates strong evidence against the null hypothesis (H0: no first-order autocorrelation), suggesting that first-order autocorrelation is present in the model. (Add how a counter measure is the lag you included)

Table 4.4.1 Wooldridge test for autocorrelation

MODEL	**1**	**2**	**3**	**4**	**5**
F (1, 49)	15.977	13.902	14.785	12.971	22.802
Prob > F	0.0002	0.0005	0.0003	0.0007	0.0000

Notes: INV = Total Inventory; WIP = Work in Process; Raw Mat = Raw Materials; FG = Finished Goods; INV_O = Other Inventory. Values are in days. The number of observations for each variable is 455.

The Variance Inflation Factor (VIF) test was conducted to detect multicollinearity among the independent variables in the regression model. Multicollinearity occurs when independent variables are highly correlated, leading to inflated variance of the coefficient estimates and potential instability in the model.

Table 4.4.2.

The Variance Inflation Factor (VIF)

Variable	VIF	1/VIF
ICP_Ln	1.12	0.87
EBITP_Ln L1.	1.06	0.94
Liq	1.11	0.90
Sales_growth	1.03	0.97
TotalAssets_Ln	1.01	0.99
Mean VIF	1.07	

Notes: INV = Total Inventory; WIP = Work in Process; Raw Mat = Raw Materials; FG = Finished Goods; INV_O = Other Inventory. Values are in days. The number of observations for each variable is 455.

The results presented in *Table 4.4.1* for all the independent variables were found to be well below the threshold of 10, with the highest VIF being 1.12 for ICP_Ln. The mean VIF was 1.07. These results indicate that multicollinearity is not a concern in this model, suggesting that the estimates of the regression coefficients are stable and reliable.

Table 4.4.3. Breusch and Pagan/Cook-Weisberg test for heteroskedasticity

H0: Constant variance	
chi2 (1) =	3.61
Prob > chi2 =	0.0575

Notes: INV = Total Inventory; WIP = Work in Process; Raw Mat = Raw Materials; FG = Finished Goods; INV_O = Other Inventory. Values are in days. The number of observations for each variable is 455.

The Breusch-Pagan/Cook–Weisberg test assesses the assumption of constant variance (homoscedasticity) of error terms in a regression model. This test is crucial as it determines whether the variability of the error terms changes significantly with the values of the independent variables. The test statistic (chi2) presented in *Table 4.4.3* is 3.61 with a p-value of 0.0575, This suggests that there is no strong evidence of heteroskedasticity in the residuals, meaning the assumption of constant variance holds.

Table 4.4.4 Wilcoxon Signed-Rank Test

Sign	Obs	Sum ranks	Expected
Positive	317	59013	33215
Negative	47	7417	33215
Zero	0	0	0
All	364	66430	
H0: INV_after = INV_before		Z= 12.842	Prob > |z| = 0.000

Notes: The Wilcoxon signed-rank test examined differences in inventory levels before and after the COVID-19 pandemic. The table presents counts of observations, sum ranks, and expected values categorized by positive and negative changes in inventory levels.

The results of *Table 4.4.4* indicate significant evidence (z = 12.842, p < 0.0001) supporting the hypothesis that there is a difference between pre- and post-intervention inventory levels. Specifically, the test yielded a z-score of 12.842, suggesting a substantial deviation from the null hypothesis that inventory levels remain unchanged. This finding aligns with the conclusions drawn from the t-test and reinforces the robustness of the observed effect across different statistical methods. The use of non-parametric testing further strengthens confidence in the results, as it provides a robust alternative that does not rely on assumptions of normality in data distribution.

Chapter 5. Conclusion and Discussion

In this study, we explore the critical role of inventory conversion periods in shaping the profitability of European manufacturing firms, especially in the context of crises such as the COVID-19 pandemic. The findings underscore a clear relationship: companies that maintain shorter inventory conversion periods tend to exhibit enhanced profitability. In other words, lower conversion periods for overall inventory levels and finished goods leads to a higher EBIT margin. This operational advantage might come from efficiencies gained through reduced holding costs and improved cash flow, facilitated by faster turnover of inventory. Whether achieved through optimized production schedules, efficient logistics, or accelerated sales cycles, the ability to swiftly convert raw materials into finished goods aligns closely with financial resilience and sustainable growth.

During periods of economic upheaval like the COVID-19 pandemic, firms faced heightened uncertainty and supply chain disruptions. Many responded by adopting more cautious inventory management strategies, including increasing inventory levels as a buffer against potential disruptions, shown by the results in this study. This defensive approach of increasing inventory levels by more than 25 percent on average could have aimed to safeguard against supply shortages and ensure uninterrupted service to customers. Despite the temporary increase in inventory levels, our study highlights that the fundamental principle of efficient inventory management remains crucial. Companies adept at balancing lean inventory practices with strategic reserves are better positioned to navigate market volatility and maintain operational continuity.

These insights carry significant implications for industry practitioners and policymakers alike. For managers and supply chain professionals, optimizing inventory conversion periods emerges as a strategic imperative for enhancing profitability and resilience in turbulent economic environments. By refining inventory management practices to align with both stability and crisis scenarios, firms can mitigate risks, capitalize on market opportunities, and sustain long-term competitiveness.

Chapter 6. Limitations and Future Research

While this study provides valuable insights into the relationship between inventory conversion periods and profitability in European manufacturing firms, several limitations should be considered.

This study primarily relies on secondary data sources, such as financial reports and industry databases. While these sources provide robust insights into financial performance metrics and inventory management practices, they may lack granularity in capturing the nuanced operational details and strategic decisions that influence inventory dynamics during crises. Furthermore, the study does not account for the potential influence of external financial support measures, such as government subsidies and stimulus packages, which could have artificially bolstered the profitability of firms during the crisis. These interventions might confound the observed relationship between inventory management practices and profitability, making it challenging to isolate the true impact of inventory conversion periods.

The results identify a relationship between shorter inventory conversion periods and improved profitability, but it does not establish causality. Factors beyond inventory management, such as market demand fluctuations, competitive pressures, and macroeconomic trends, could also influence financial performance outcomes. Moreover, a limitation of these study is the assumption of linear correlation, Eroglu and Hofer (2010) explore that limitation and find compelling evidence in the US manufacturing industry of a non-linear relationship between lean inventory management and company's performance. Meaning there is an optimal level of inventory level, beyond which there is little to none or even negative effect on the financial performance.

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