

The Impact of Inventory Management Strategies on Financial Performance Metrics in the Pharmaceutical Industry

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Abstract

This study investigates the relationship between inventory management strategies and financial performance in the global pharmaceutical industry. Given the sector's high service requirements, demand uncertainty, and product perishability, maintaining an effective balance between inventory availability and holding costs is critical for profitability. The study adopts an integrated analytical framework combining macro-level firm analysis and micro-level product analysis. At the macro level, Fixed Effects panel regression is used to examine the impact of inventory turnover on profitability, while K-means clustering is employed to classify firms according to their financial and operational characteristics. At the micro level, correlation and scenario analyses are conducted to assess the effect of supplier-imposed Minimum Order Quantity (MOQ) constraints on product margins. The findings indicate that inventory turnover has a statistically significant positive effect on return on assets, and that high profitability is associated not only with inventory efficiency but also with conservative leverage structures. In addition, the results reveal a strong negative relationship between MOQ coverage and profit margin, suggesting that procurement constraints can be a major source of inventory-related inefficiency. By integrating firm-level financial analysis with product-level supply chain diagnostics, the study shows that financial performance in pharmaceutical supply chains is shaped not only by managerial decisions but also by external procurement restrictions.

Keywords

Pharmaceutical industry; Inventory management; Financial performance; Fixed Effects panel regression; K-means clustering; Minimum Order Quantity

1. Introduction

All contemporary industries depend on the effective management of material flows from suppliers to final customers. The pharmaceutical industry is particularly challenging due to high service requirements, erratic demand, and product perishability. Therefore, firms must balance product availability with inventory costs to maintain both operational efficiency and financial performance.

As a major global industry, pharmaceuticals are highly affected by inventory management decisions. This study investigates the following research question: How do procurement restrictions and inventory management practices influence the profitability and financial performance of multinational pharmaceutical companies? Understanding this

relationship is critical for improving both strategic and operational performance. To address this question, the study employs a Fixed Effects Model to control for time-invariant firm-specific characteristics, such as management quality, corporate culture, and brand reputation, and to assess the impact of inventory efficiency on profitability. In addition, K-Means Clustering is used to classify firms according to their financial and operational characteristics, enabling the identification of distinct performance patterns.

The analysis examines the relationship between inventory management efficiency and financial performance at both firm and product levels. It explores how inventory holding behaviour differs across product categories and evaluates the role of supplier-imposed Minimum Order Quantity (MOQ) constraints in shaping inventory decisions and profitability. Furthermore, alternative procurement scenarios are assessed to identify potential improvement opportunities and support more effective decision-making. By integrating firm-level financial performance with product-level supply chain dynamics, this study provides a comprehensive perspective on the financial implications of inventory management in the pharmaceutical industry.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature. Section 3 presents the methodology. Section 4 reports the empirical findings. Section 5 discusses conclusions and future research directions, while Section 6 summarizes the main findings and their managerial and academic implications.

2. Literature Review

2.1. Supply Chain Structure and Inventory Management Dynamics in The Pharmaceutical Industry

Controlling material flows from raw material suppliers to final consumers is a critical issue, and supply chain management has become strategically important across industries (Axsäter, 2015). Inventory management is central to procurement, storage, and utilization processes (Nallusamy, 2021). Pharmaceutical supply chains are characterized by high service requirements, uncertain demand, and perishable, complex product portfolios (Uthayakumar and Priyan, 2013).

The pharmaceutical industry is distinct due to its impact on human health, strict regulations, and short product shelf lives. Therefore, inventory management is crucial for cost control and ensuring continuous medicine availability (Sinha and Singh, 2025). Since products may degrade over time, inventory systems must consider deterioration to protect patient health, while balancing demand responsiveness and holding costs (Sahoo and Panda, 2024; Sinha and Singh, 2025). Supply chains may be single-stage or multi-stage; however, pharmaceutical systems are inherently multi-layered, requiring coordination across all nodes from suppliers to end users (Sbai and Berrado, 2023). Performance is further affected by reliance on imported Active Pharmaceutical Ingredients (API), increasing vulnerability to global disruptions. Supplier reliability and lead times are key determinants of inventory levels (Basu and Chaudhuri, 2022; Hansen et al., 2023).

Pharmaceutical demand is influenced by therapeutic class, seasonality, geography, and price changes, making forecasting highly complex (İmece, 2019). Therefore, forecasting models must incorporate not only historical data but also seasonal and promotional effects that may distort sales patterns (İmece, 2022). In such a complex system, focusing optimization on a single stage may create inefficiencies elsewhere (Sbai and Berrado, 2023). Finally, combining ABC and VED analysis is important for balancing cost and criticality in inventory classification (Sinha and Singh, 2025).

2.2. Global Crises and The Impact of The Covid-19 Pandemic on Inventory Management

The COVID-19 pandemic severely disrupted global supply chains and highlighted the importance of inventory management in the pharmaceutical industry (Basu and Chaudhuri, 2022). Restrictions and raw material shortages reduced production capacity and negatively affected inventory levels, with India's pharmaceutical sector experiencing a 20–30% increase in raw material costs and a decline in production capacity (Basu and Chaudhuri, 2022). During crises, demand structures also shift due to price changes and new competing products (Sahoo and Panda, 2024), with panic buying of chronic disease medicines increasing demand by 8.9% by March 2020 (Basu and Chaudhuri, 2022). These uncertainties also raised stockout costs at the retail level (Sahoo and Panda, 2024).

Despite these disruptions, firms with efficient inventory management and high turnover maintained or improved performance through cost reductions, and non-uniform replenishment cycle systems proved more cost-effective than traditional models during crisis periods.

2.3. The Relationship Between Inventory Management and Financial Performance: Empirical Findings

Effective inventory management is closely linked to profit maximization, as inventory levels directly affect revenues and profitability. A study of manufacturing firms listed on the Saudi stock exchange found a positive and statistically significant relationship between inventory turnover and profitability, as higher turnover reduced holding costs and improved EPS, ROA, and GPM, while enhancing liquidity and efficiency (Alnaim and Kouaib, 2023).

In contrast, research on the Greek industrial sector found a negative relationship between profitability and inventory holding periods, suggesting that lean inventory increases returns, whereas excess inventory raises costs. Evidence from Pakistan shows mixed results: inventory turnover has a positive but statistically insignificant effect on ROE in the pharmaceutical sector (Zaheer et al., 2023), and no significant effect on ROA in non-financial industries, implying that inventory management may function more as an operational requirement than a direct profitability driver. Financial performance measures such as ROA, ROE, and GPM are widely used to assess risk-return profiles (Boloş et al., 2025). Clustering analyses show that firms grouped by these indicators achieve higher risk-adjusted returns than the market average (Boloş et al., 2025). Similarly, EBITDA is an effective indicator for evaluating financial health and predicting future performance (Chiriac, 2020).

2.4. Analytical Methods Used in Financial Performance and Inventory Management Analysis

In the literature, a wide methodological spectrum, extending from traditional econometric models to machine learning algorithms, is employed to analyze the complex relationships between inventory management efficiency and financial performance indicators (Tutcu et al., 2024). Researchers select among different analytical techniques based on the structural characteristics of the dataset, the presence or absence of non-linear relationships, and the level of uncertainty within the decision-making process.

2.4.1. Regression-Based Models

Regression analyses are widely used to identify causal relationships and effect coefficients between financial ratios (Tutcu et al., 2024), with model selection depending on dataset structure and econometric issues (Boloş et al., 2025). The Fixed Effects Model was applied in the Saudi manufacturing sector to control for unobserved firm-specific heterogeneity such as management quality, corporate culture, technological infrastructure, and brand value, and it confirmed a positive and statistically significant relationship between inventory turnover and profitability (Alnaim and Kouaib, 2023).

In contrast, the Generalized Method of Moments (GMM) used in Pakistani non-financial firms addressed endogeneity and found no significant effect of inventory management on profitability, with firm size and sales growth being more influential (Farooq, 2019). Similarly, an OLS-based study of Greek manufacturing firms found that excessive inventory negatively affects performance, supporting lean production benefits (Koumanakos, 2008). Consistently, a multiple regression study on Pakistani pharmaceutical firms showed that inventory turnover and Capital Work in Progress were not statistically significant for ROE, while long-term debt had a negative impact on profitability (Zaheer et al., 2023). Finally, Multiple Linear Regression (MLR) performs well in predicting financial performance with lower RMSE than decision trees, but has lower explanatory power compared to artificial neural networks (Tutcu et al., 2024).

2.4.2. Unsupervised Learning and Clustering Algorithms

Unsupervised learning algorithms are widely used in financial data classification as they can identify hidden patterns and structures without predefined labels (Chiriac, 2020). In a study by Chiriac (2020), firms with similar financial characteristics were successfully grouped using K-Means clustering based on EBITDA and revenue data. In a more comprehensive study of S&P 500 firms, K-Means clustering was applied using profitability, liquidity, and solvency indicators (Boloş et al., 2025). The results showed that one cluster exhibited lower risk and balanced performance, while another delivered higher returns but greater volatility. It was also found that clusters formed using profitability measures such as ROA and gross profit margin achieved higher risk-adjusted returns compared to the market index.

2.4.3 Other Machine Learning Techniques

In financial analysis and inventory management literature, traditional statistical methods may be insufficient when data contains imprecision or non-linear relationships (Chiriac, 2020). Computational intelligence methods provide an alternative, focusing on cost-efficient and optimal solutions rather than strict accuracy (Chiriac, 2020). Regression and clustering methods may also be limited under uncertainty and non-linear structures (Chiriac, 2020). In such cases,

computational intelligence offers strong alternatives: fuzzy logic models reduce inventory and shortage costs during crises such as COVID-19 (Sahoo and Panda, 2024), while methods like Multiple Linear Regression (MLR) and artificial neural networks better capture complex relationships when traditional models fail (Tutcu et al., 2024). These approaches handle uncertainty by using variable ranges instead of fixed values, improving decision-making and operational efficiency (Chiriac, 2020; Sahoo and Panda, 2024).

Overall, inventory management is critical in the pharmaceutical industry due to complexity, demand uncertainty, and perishability. While effective inventory practices generally improve financial performance, the strength of this relationship varies across contexts. The literature also highlights the importance of firm-level and product-level factors such as lead times, supplier reliability, and Minimum Order Quantity (MOQ). Advanced analytical methods further emphasize the need to capture both causal and hidden patterns in financial data. Based on this, the next section presents the methodology combining firm-level and product-level analysis.

3. Proposed Methodology

The primary objective of this study is to empirically examine the impact of inventory management policies of leading global pharmaceutical firms on financial performance (profitability). A quantitative research design is used based on annual financial statement data, and the study follows a two-stage analytical framework.

In the first stage, Panel Data Regression Analysis is applied to test the relationship between inventory turnover and profitability, using both cross-sectional (firms) and time-series (years) dimensions. K-Means Clustering is then used to group firms according to financial and operational characteristics. In the second stage, a product-level case study using ABC analysis is conducted for one firm in the sample to validate the findings at the micro level and examine the inventory–profitability relationship. The overall framework is presented in Figure 1.

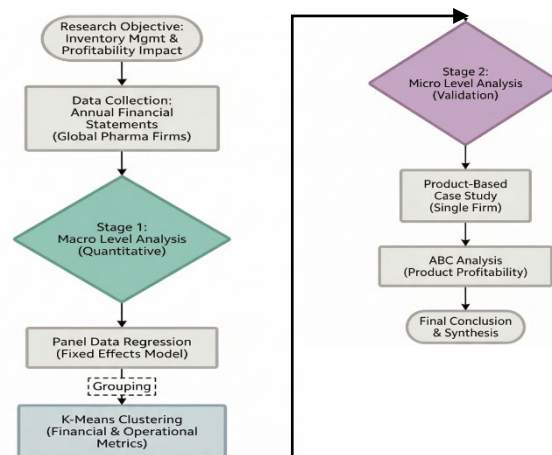


Figure 1. Flowchart of the proposed methodology

3.1 Dataset

The empirical analysis of this study was conducted using a homogeneous sample group possessing high representational capability regarding the financial dynamics of the global pharmaceutical industry. The scope of the study comprises firms within the "Big Pharma" group, which are publicly traded in international markets and regarded as industry leaders in terms of market share. The temporal dimension of the study encompasses a 4-year period covering the 2021–2024 fiscal years. This period is significant for observing the financial outcomes of inventory management strategies, as it incorporates the post-pandemic recovery process, supply chain shocks, and the subsequent stabilization of the global market.

Table 1 presents the hierarchical structure of the research model to evaluate the impact of inventory management strategies on the financial performance of 10 global pharmaceutical companies.

Table 1. Research framework proposal.

	Hierarchy	Description		
	Objective	Evaluation of the Impact of Inventory Management on Financial Performance in the Global Pharmaceutical Industry		
	Variables	Return on Assets (ROA) Inventory Turnover Ratio (ITR) Firm Size (SIZE)	Financial Leverage (LEV) Current Ratio (CR)	
	Sample Firms	Johnson&Johnson Pfizer Eli Lilly AbbVie GSK	AstraZeneca PLC Novartis Roche Sanofi Novo Nordisk	

3.2 Data Analysis Techniques and Model Design

3.2.1 Regression Analysis: Fixed Effects Model

Alnaim and Kouaib (2023) applied a Fixed Effects Model in the Saudi manufacturing sector to capture unobservable firm-specific factors such as corporate culture, managerial quality, and technological infrastructure. This approach enables a more accurate estimation of the relationship between inventory turnover and profitability. Similarly, Tutcu et al. (2024) highlight that regression-based models remain reliable for analyzing linear relationships among financial ratios, particularly in small to medium-sized datasets. Alternative approaches in the literature include OLS, used by Koumanakos (2008) for cross-sectional analysis of Greek manufacturing firms, and GMM, applied by Farooq (2019) to address endogeneity issues in Pakistani firms.

In this study, the Fixed Effects Model is adopted following Alnaim and Kouaib (2023), due to the presence of unobserved, time-invariant firm characteristics in the pharmaceutical industry, such as management quality, corporate culture, and brand value. The model isolates these effects, allowing a more precise estimation of the impact of inventory turnover on profitability. The Hausman Test is used to validate the choice between Fixed and Random Effects Models. The econometric model established to test the research hypotheses is presented in Equation 1.

$$ROA_{it} = \beta_0 + \beta_1(ITR_{it}) + \beta_2(SIZE_{it}) + \beta_3(LEV_{it}) + \beta_4(CR_{it}) + \mu_i + \varepsilon_{it} \quad (1)$$

where

i denotes the firm ($i = 1, \dots, 10$) and t denotes the year ($t = 2021, \dots, 2024$).

ROA_{it} represents the Return on Assets (Dependent Variable).

ITR_{it} is the Inventory Turnover Ratio (Independent Variable of Interest).

$SIZE_{it}$, LEV_{it} , and CR_{it} are the control variables for firm size, leverage, and liquidity, respectively.

μ_i represents the unobserved firm-specific fixed effects.

ε_{it} is the idiosyncratic error term.

β_1 (Coefficient of Interest) measures the effect of ITR on ROA and is expected to be positive and significant ($\beta_1 > 0$, $p < 0,05$), consistent with Alnaim and Kouaib (2023).

$\beta_2, \beta_3, \beta_4$ control for firm size, leverage, and liquidity, included to isolate the effect of inventory management on profitability (Zaheer et al., 2023).

To mitigate distortion from outliers in financial data, extreme values are capped at the 1st and 99th percentiles, following Alnaim and Kouaib (2023), to improve robustness. The Hausman Test is used to choose between Fixed and Random Effects. If $p < 0,05$, H_0 is rejected and the Fixed Effects model is adopted, consistent with Alnaim and Kouaib (2023).

H_0 : The Random Effects model is appropriate (coefficients are consistent and efficient).

H_1 : The Fixed Effects model is appropriate (Random Effects coefficients are inconsistent).

3.2.2 Clustering Analysis: K-Means Algorithm

In the literature, computational intelligence and fuzzy logic methods are used to handle uncertainty in inventory systems, where Sahoo and Panda (2024) apply fuzzy models to reduce costs during crises and Chiriac (2020) highlights their effectiveness in complex and non-linear environments. In this study, K-Means Clustering is used as an unsupervised learning method to classify pharmaceutical firms based on financial performance, complementing the regression analysis by grouping firms with similar financial behavior patterns.

K-Means is preferred over fuzzy and hierarchical methods because it provides clear and distinct categories (e.g., high vs low performance) instead of partial membership, while also identifying hidden structures in financial data (Chiriac, 2020) and offering more interpretable risk-return classification than more complex algorithms (Boloş et al., 2025). The clustering is based on variables from the regression model: ROA (profitability), ITR (efficiency), and LEV (risk). Since these variables have different scales, all data are standardized using the Z-score method to prevent dominance of high-magnitude variables (Boloş et al., 2025). The number of clusters is set to $k=2$, following financial portfolio management literature (Boloş et al., 2025).

3.3 Inventory Management and Profitability of Product Groups

In this phase of the study, a case study is conducted to test the inventory–profitability relationship at the micro (product) level, complementing the firm-level analysis. A leading pharmaceutical firm with the highest data accessibility is selected, and its product portfolio is classified using ABC Analysis. The relationship between inventory holding periods and product profitability is then examined using correlation analysis.

ABC analysis is widely used in inventory management and is based on the Pareto Principle (80/20 rule). Sinha and Singh (2025) emphasize that classifying pharmaceutical inventories by cost and usage value is essential for minimizing inventory costs while ensuring the availability of critical medicines. In this study, products are categorized based on annual sales (revenue contribution) as follows:

- **Group A Products:** High-value items generating approximately 80% of revenue with 10–20% of SKUs
- **Group B Products:** Medium-Value items that account for 15% of total revenue.
- **Group C Products:** Low-Value items that represent 5% of total revenue, forming the largest share of SKUs

Following the classification, the Months of Coverage (MoC) metric will be utilized to evaluate the efficiency of inventory management for each product group. Basu and Chaudhuri (2022) show that pandemic-related supply chain disruptions increased MoC values and production costs. Accordingly, the correlation between MoC values of Group A, B, and C products and their Profit Margins (PM) will be analyzed to test whether a low MoC (fast turnover) strategy for Group A leads to higher profitability. Pearson Correlation Analysis is used to measure the direction and strength of the relationship between MoC and PM. The correlation coefficient (r) indicates whether profitability increases or decreases as inventory holding duration rises.

4. Application

4.1 Dataset and Descriptive Statistics

The study is based on a balanced panel dataset of ten leading global pharmaceutical companies (“Big Pharma”) over 2021–2024, consisting of 40 firm-year observations ($N=10$, $T=4$). Financial data were extracted from audited statements, including Net Income, Total Assets, Inventory, COGS, Total Liabilities, and Current Assets/Liabilities, and converted into US dollars for comparability. The dataset was checked for errors and outliers, and extreme values were winsorized at the 1% and 99% levels. Descriptive statistics are reported for ROA (dependent), ITR (independent), and control variables (SIZE, LEV, CR). Firm Size (SIZE) is defined as the natural logarithm of Total Assets to avoid scaling issues arising from the large size of pharmaceutical firms and to ensure comparability with ratio-based variables such as ROA and leverage, resulting in values between 24–26.

Table 2 presents the descriptive statistics (mean, standard deviation, minimum, maximum) to summarize central tendency and dispersion before regression analysis.

Table 2. Descriptive Statistics of the Variables

	Ratio	Mean	Std. Dev.	Min	Max	
	ROA	0,107	0,069	0,004	0,259	
	ITR	2,157	1,087	1,097	5,345	
	SIZE	25,525	0,487	24,617	26,714	
	LEV	0,653	0,143	0,409	0,955	
	CR	1,075	0,236	0,691	1,501	

4.2 Data Analysis Applications

4.2.1 Regression Analysis: Fixed Effects Model

The study examines the effect of inventory management efficiency on financial performance using a Fixed Effects (FE) panel regression model. The FE specification is chosen to control for unobserved time-invariant heterogeneity across firms, such as management quality, brand reputation, and corporate culture. The Poolability F-test ($p < 0,01$) confirms the presence of significant firm-specific effects, showing that FE provides more consistent estimates than pooled OLS. The regression is defined in Equation (1). To address heteroskedasticity, clustered standard errors at the firm level are used, ensuring robust t-statistics and p-values. Table 3 reports the FE regression results, examining the relationship between ROA and ITR while controlling for SIZE, LEV, and CR.

Table 3. Fixed Effects Panel Regression Results

	Variable	Coefficient	Std. Error	t- Statistic	Prob. (p- value)	
	Constant	0,02	0,93	0,02	0,983	
	ITR	0,055	0,02	3,49	0,002	
	SIZE	-0,01	0,03	-0,38	0,704	
	LEV	0,27	0,49	0,54	0,592	
	CR	0,09	0,07	1,21	0,237	

Table 4 refers to the model diagnostics.

Table 4. Model Diagnostics

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	Observations	40		R-squared (Within)	0,286	
	F-statistic (Robust)	8,103		Prob (F-statistic)	0,0002	
	F-test for Poolability	5,583		Prob (Poolability)	0,0003	

The statistical validity of the model is confirmed through multiple tests. First, the Poolability F-test yields a p-value of 0,0003 ($p < 0,01$), indicating that the Fixed Effects Model is preferred over pooled OLS and strongly rejecting the null hypothesis of homogeneity, confirming the need to control for unobserved firm-specific heterogeneity such as brand equity and managerial quality. Second, the Robust F-statistic of 8,103 with a p-value of 0,0002 confirms overall model significance, showing that the explanatory variables jointly affect profitability. The Within R-squared value is 0,286, indicating that the model explains approximately 28,6% of the variation in ROA within firms over time, which is acceptable given macroeconomic influences.

The regression results (Table 3) support the main hypothesis, showing that structural financial factors and operational efficiency affect profitability differently. The key finding is a positive and statistically significant relationship between Inventory Turnover Ratio (ITR) and Return on Assets (ROA). The coefficient of ITR is 0,05 ($p < 0,01$), implying that a one-unit increase in ITR increases ROA by approximately 0,055 (5,5 percentage points), ceteris paribus. This indicates that higher inventory turnover improves profitability by reducing holding costs, lowering obsolescence risk,

and releasing working capital. Overall, efficient inventory management is a key driver of profitability in the pharmaceutical industry.

In contrast, control variables (SIZE, LEV, CR) are not statistically significant ($p > 0,05$). Firm Size (SIZE) is not significant, suggesting that within large “Big Pharma” firms, small differences in asset size do not meaningfully affect profitability between 2021 and 2024. Liquidity (CR) is also insignificant, indicating that short-term liquidity conditions do not explain ROA variations in this sample. Similarly, Leverage (LEV) is not significant, implying that debt levels do not materially affect profitability, likely due to strong cash flows and high creditworthiness allowing borrowing at favorable conditions. Overall, the results show that operational efficiency (ITR) is a more important determinant of profitability than financial structure variables (SIZE, LEV, CR) during the analyzed period.

4.2.2 Clustering Analysis: K-Means Algorithm

After the regression analysis, pharmaceutical firms are classified using K-Means Clustering, an unsupervised learning method, to group companies based on operational and financial characteristics and provide a complementary perspective on the inventory–profitability relationship. The dataset is first aggregated by calculating 2021–2024 firm-level mean values to reduce short-term volatility and capture structural performance. Variables are then standardized using Z-score normalization to avoid scale dominance (e.g., Total Assets vs. ROA), ensuring equal contribution to distance calculations. K-Means is selected for its ability to form clear non-overlapping groups, and $k=2$ is used given the sample size ($N=10$) and the aim of separating high- and low-performing firms. This allows a clear comparison between high-efficiency/high-profitability firms and lower-performing firms. Table 5 reports the cluster assignments, while Table 6 presents the cluster centroids and internal dispersion of the financial indicators.

Table 5. Company Cluster Assignments

	Cluster 0			Cluster 1		
	Novo Nordisk Sanofi	Johnson & Johnson Novartis	Pfizer Roche	AbbVie AstraZeneca	Eli Lilly GSK	

Table 6. Cluster Characteristics (Mean Values)

	Variable	Cluster 0 (Mean ± Std)	Cluster 1 (Mean ± Std)	Interpretation	
	ROA	12,44% ± 6,35%	8,03% ± 3,62%	Cluster 0 is significantly more profitable.	
	ITR	1,98 ± 0,63	2,43 ± 1,60	Cluster 1 manages inventory faster.	
	SIZE	25,76 ± 0,41	25,17 ± 0,40	Cluster 0 firms are larger in asset size.	
	LEV	0,57 ± 0,09	0,78 ± 0,12	Cluster 1 is highly leveraged (more debt).	
	CR	1,17 ± 0,19	0,93 ± 0,12	Cluster 0 has better liquidity.	

Figure 2 shows the scatter plot distribution of the pharmaceutical firms based on their ROA and ITR, visually distinguishing between Cluster 0 and Cluster 1.

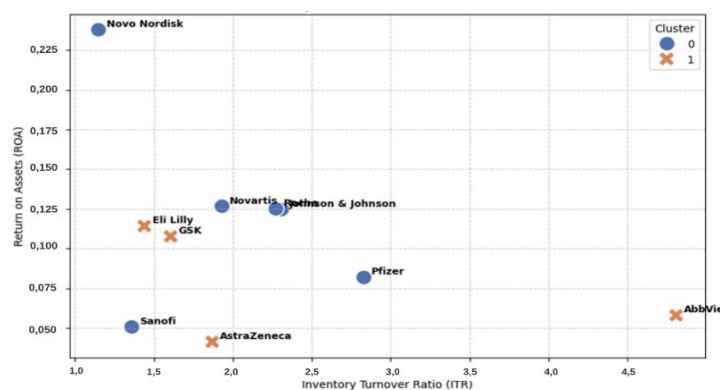


Figure 2. Cluster Analysis: ROA vs. ITR

The clustering analysis reveals a clear strategic split in the “Big Pharma” industry between financial stability and operational speed. Cluster 0 (Pfizer, Novo Nordisk, Johnson & Johnson, etc.) shows higher profitability with an average ROA of 12,44% ($\pm 6,35\%$), despite a lower ITR of 1,98 ($\pm 0,63$). These firms rely on strong financial structures, including high liquidity and low leverage of 0,57 ($\pm 0,09$). Cluster 1 (AbbVie, AstraZeneca, Eli Lilly, GSK) exhibits higher operational efficiency with an ITR of 2,43 ($\pm 1,60$), but lower profitability with an ROA of 8,03% ($\pm 3,62\%$). This is mainly due to higher leverage of 0,78 ($\pm 0,12$), which offsets the net income gains from faster inventory turnover. To empirically validate this distinction and resolve the interpretational tension between the regression and clustering findings, a cross-sectional between-firm ordinary least squares (OLS) regression was conducted using the 4-year averages of each firm. The comparative robustness results are presented in Table 7.

Table 7. Robustness Check: Comparison of Within-Firm and Between-Firm Regressions

	Variable	FE (Within-Firm)	OLS Firm Averages (Between-Firm)
	ITR	0,055 (p = 0,002)	-0,055 (p = 0,024)
	SIZE	-0,01 (p = 0,704)	+0,111 (p = 0,034)
	LEV	0,27 (p = 0,592)	+0,458 (p = 0,083)
	CR	0,09 (p = 0,237)	+0,128 (p = 0,345)

The findings indicate that operational efficiency alone is insufficient to explain profitability differences across firms. Although inventory turnover positively affects profitability within firms, cross-sectional variation in financial structure appears to influence firm performance. Nevertheless, because leverage is not statistically significant in the Fixed Effects model and only marginally significant in the between-firm analysis, the role of financial structure remains inconclusive. Overall, inventory turnover constitutes a more robust and consistent determinant of profitability than financial structure variables.

4.3 Inventory Management and Profitability of Product Groups: Correlation Analysis

In this section, a correlation analysis is conducted to examine the relationship between inventory holding behavior and financial performance across product categories. The model evaluates the relationship between Average Months of Coverage (MoC), MOQ Coverage, and Profit Margin. Table 8 reports the average MoC, MOQ Coverage, and Profit Margin values for Groups A, B, and C for the selected company.

Table 8. The average MoC, MOQ coverage and profit margin by groups

	Grup	Avg MoC	MOQ Coverage	Profit Margin	
	A	2,57	1,84	0,64	
	B	1,98	2,78	0,47	
	C	4,340	5,51	0,2138	

The correlation technique is used to measure the direction and strength of the relationship between Average MoC, MOQ Coverage, and Profit Margin. The analysis utilizes this technique to identify monotonic rank-ordering patterns between variables. The resulting coefficients characterize descriptive macro-trends across the categorized product groups, serving as a visualization of operational trade-offs rather than a measure of micro-level SKU variance. MOQ Coverage captures how well suppliers’ minimum order quantities align with monthly demand and is analyzed together with MoC to assess whether procurement-driven high inventory levels are associated with lower profitability.

Table 9 presents the correlation matrix for Product Groups A, B, and C, summarizing the relationships between the three key variables.

Table 9. Correlation Matrix for Product Groups

	Variable	Avg MoC	MOQ Coverage	Profit Margin	
	Avg MoC	1,00	0,88	-0,80	
	MOQ Coverage	0,88	1,00	-0,99	
	Profit Margin	-0,800	-0,99	1	

MOQ Coverage and Profit Margin show an almost perfect negative correlation of -0,99, indicating that low-margin products face higher MOQ requirements relative to demand, creating a dual burden of higher inventory investment for lower returns. Average MoC and Profit Margin also show a strong negative correlation of -0,80, suggesting that low margins are linked to higher inventory holding and inefficient turnover driven mainly by external constraints. In addition, the strong positive correlation of 0,88 between Avg MoC and MOQ Coverage confirms that supplier-imposed MOQs directly increase inventory levels, forcing firms to maintain high coverage despite limited profitability. Overall, the results show that procurement constraints significantly increase inventory intensity and reduce working capital efficiency, especially for low-margin products.

4.3.1 Scenario Analysis: Impact of Procurement Negotiation on Profitability

A “What-If” scenario is constructed to assess the financial impact of optimizing procurement terms. The focus is on Group C, the least efficient category, with a Profit Margin of 21,38% and a high MOQ Coverage of 5,51 months. The scenario estimates profitability if MOQ Coverage is reduced to Group B’s level (2,78 months), using a linear regression model based on observed data. Figure 3 shows this relationship, highlighting Group C’s highest operational burden.

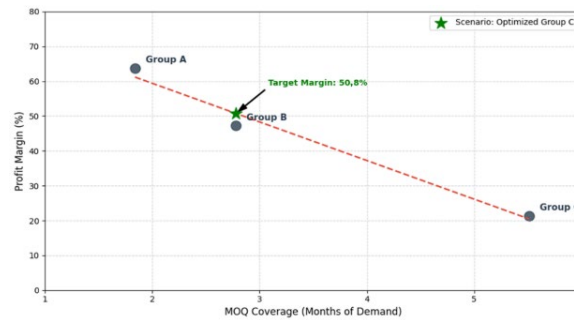


Figure 3. Scenario Analysis: Profit Margin Improvement via MOQ Reduction

The results suggest that low profitability is largely driven by supply chain constraints rather than pricing alone, providing quantitative support for renegotiating procurement terms. Reducing MOQ toward more efficient levels could release tied-up capital and improve overall financial performance.

5. Results and Discussion

This research provides an empirical analysis of how inventory management affects financial performance in the international pharmaceutical sector. The Fixed Effects model confirms that the Inventory Turnover Ratio (ITR) is a statistically significant driver of profitability (within-firm), where a one-unit increase in turnover is associated with an approximate 5,5 percentage point increase in ROA. This indicates that faster inventory-to-revenue conversion reduces holding costs, limits obsolescence risk, and improves working capital efficiency, which is critical due to strict expiration constraints.

Conversely, the K-Means clustering and the between-firm OLS robustness check reveal structural differences across firms. While improvements in inventory turnover are associated with higher profitability within firms, cross-sectional variation in firm characteristics may also contribute to performance differences. The clustering results indicate that firms with lower leverage and higher liquidity tend to exhibit higher average profitability. However, because leverage is not statistically significant in the Fixed Effects model and only marginally significant in the between-firm analysis,

the role of financial structure should be interpreted with caution. Overall, inventory turnover emerges as a more robust determinant of profitability than financial structure variables during the analyzed period.

At the product level, there is a strong inverse rank-relationship between MOQ Coverage and Profit Margin ($r = -0,99$), showing that higher minimum order requirements are associated with lower profitability. Group C products, with high inventory coverage and low margins, create inefficiency by tying up working capital in low-return items. This extends the findings of Basu and Chaudhuri (2022), indicating that high inventory levels driven by external constraints reduce efficiency. Additionally, the positive correlation between Average MoC and MOQ Coverage ($r = 0,88$) shows that supplier-imposed constraints drive inventory accumulation, highlighting the role of external factors in inventory management, in line with Sinha and Singh (2025). Finally, the scenario analysis demonstrates that reducing MOQ to benchmark levels could increase profit margins to approximately 50,8%, emphasizing procurement optimization as a key lever for performance improvement in complex pharmaceutical supply chains (Sbai and Berrado, 2023).

6. Conclusion

This study addressed four interrelated objectives through a multi-stage empirical analysis. First, the Fixed Effects panel regression confirmed a statistically significant positive relationship between internal inventory turnover and profitability across ten global pharmaceutical firms between 2021 and 2024. Second, K-Means clustering and a between-firm robustness check demonstrated that while operational efficiency drives profitability internally, industry-wide performance appears to be influenced by structural factors, including financial structure. Third, the correlation analysis identified a near-perfect inverse rank-relationship between MOQ Coverage and Profit Margin. Fourth, the scenario analysis indicated that optimizing Group C MOQ levels could increase profit margins from 21,4% to approximately 50,8%.

The main contribution of this study is the integration of firm-level econometric analysis, distinguishing between within-firm and between-firm variation, with micro-level supply chain diagnostics. Unlike prior studies focusing separately on financial performance or inventory systems, this research demonstrates that inventory inefficiencies are often driven by external MOQ constraints rather than internal managerial factors. This reframes the inventory–profitability relationship and highlights strategic procurement negotiation as a key lever for performance improvement.

Future research should expand the model by incorporating external macroeconomic factors such as inflation and regulatory changes. Additionally, applying advanced computational intelligence methods could further capture non-linear dynamics within pharmaceutical supply chains, deepening our understanding of the complex interaction between operational efficiency and long-term financial health.

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