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Firm Profitability Drivers in the Automotive Sector: Evidence from ROA-Based Analysis

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Abstract

This study investigates the key determinants of firm profitability in the global automotive sector, examining whether superior returns on assets (ROA) stem from operational efficiency, strategic leverage, or innovation intensity, and highlighting the potential trade-off between efficiency and investment in capital-intensive industries. Analysing a global panel dataset of 192 automotive firms from 38 countries over 2010-2024, a fixed-effects regression model with Driscoll-Kraay standard errors was applied to control for unobserved heterogeneity, heteroskedasticity, and cross-sectional dependence across 11 financial and strategic variables. The findings reveal that firm size and inventory turnover are significant positive drivers of profitability, while research and development (R&D) intensity exerts a strong negative impact. The positive association with the effective tax rate reflects reverse causality, where more profitable firms incur higher tax burdens, rather than a causal effect of taxation on performance. Notably, working capital management, leverage, sales growth, and capital expenditure showed no statistically significant effects after controlling for firm and time effects. Temporal fluctuations, including a marked profitability decline in 2024, underscore the sector's sensitivity to macroeconomic shocks. This study contributes robust, large-scale empirical evidence on the short-term profitability trade-off associated with R&D intensity in a globally integrated industry, addressing cross-sectional dependence through its methodological approach.

Keywords: firm profitability; return on assets; automotive industry; financial performance; firm size; working capital; R&D intensity; fixed effects regression; macroeconomic shocks

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1. Introduction

Return on Assets (ROA) is a key financial metric that evaluates a firm's ability to use its assets to generate profits. It is calculated as net income relative to total assets, serving as an indicator of productivity, efficiency, and overall financial health. A higher ROA reflects efficient capital utilisation and stronger profitability, while a lower ROA suggests weaker asset efficiency. Because ROA captures the income produced per unit of assets, it is highly valued by both managers and shareholders as a measure of performance. However, it is also influenced by changes in the asset base: acquisitions may reduce ROA, while disinvestments can temporarily increase it. ROA values vary across industries, firms, and time periods, reflecting differences in operations and market conditions. As such, ROA is widely used by investors and stakeholders to assess financial stability, benchmark performance, and guide strategic decision-making. ROA is also the benchmark for shareholders' value creation, in relation with both the interest rate owed to financial creditors and the implicit interest rate owed to non-financial creditors (the cost of commercial credit).

Previous studies have analysed profitability mainly through traditional accounting indicators such as ROA or ROE, often without integrating their multiple structural drivers. However, profitability should not be seen as a static outcome but rather as the result of multiple financial mechanisms, such as asset efficiency, cost of debt, and cost of equity, interacting simultaneously.

Studies, such as Bazimya & Erorita, (2024); Chowdhury & Chatterjee, (2020); Prakash & Nauriyal, (2024), focus on either financial or operational metrics but rarely integrate both. They use small samples or single-country data, limiting generalisability and lack panel data analysis to control for firm-specific effects.

This study seeks to address this gap by running a regression model combining eleven (11) financial, operational, and strategic variables and using panel data (multiple firms, multiple years) to control for firm heterogeneity and time trends. In doing so, we contribute to the literature on profitability persistence and capital allocation efficiency by highlighting the trade-off between operational efficiency and innovation investment in capital-intensive industries.

The current study builds upon the logic of *profitability determinants and examines* ROA as a synthetic measure of operational efficiency, corrected for capital structure and financing costs. By focusing on the automotive sector, we address a field where asset turnover, R&D spending, and capital cost heterogeneity play a decisive role in explaining firm-level differences in performance.

We aim to identify and quantify the key operational, financial, and strategic factors within net income and total assets that significantly influence ROA in the automotive industry. A higher ROA indicates that a firm uses its assets efficiently to generate profits, while a lower ROA reflects weaker asset utilisation. According to Bazimya & Erorita (2024), an average ROA of 2.59% is considered strong for a manufacturing firm. Beyond this primary objective, the study pursues two additional goals:

- To provide actionable insights for automakers on optimizing asset profitability.
- To evaluate whether R&D spending yields diminishing short-term returns.

ROA, as a measure of net income generated per unit of assets, directly reflects management's ability to convert resources into profits and is closely monitored by investors. Numerous determinants may affect profitability, including capital structure, firm size, ownership structure, and overall financial performance. These factors are examined in depth and prioritised, recognising the automotive sector as a key driver of national economic development.

This study reframes ROA not merely as a retrospective performance metric, but as a managerial control variable that reflects the outcome of internal capital allocation decisions under the dual pressures of operational efficiency and innovation-driven financial constraints. By *analysing its structural correlates*, we provide a framework for internal performance benchmarking and financial policy formulation in a capital-intensive, technology-transforming industry.

The automotive industry is a cornerstone (Doner et al., 2021) of the world economy, marked by vast production networks, technological innovation, and ongoing transformation. The industry generates over trillions of dollars in annual revenues and provides direct and indirect jobs to millions of people worldwide. It encompasses car and light truck manufacturers, component suppliers, and tire producers, making it a major consumer of commodities like steel, aluminium, and copper. China, the United States, and Japan are the leading producers, while Germany, Japan, and the US dominate exports. Major companies include Volkswagen Group, Toyota, Renault, Nissan, Mitsubishi, General Motors, Hyundai, and Kia.

While the automotive sector is highly globalised, regional integration remains strong. Production and supply chains are often organised regionally due to local content requirements and market proximity, but global value chains and supplier networks are increasingly important. The industry is characterised by a small number of powerful lead firms that coordinate complex, often relational, buyer-supplier linkages.

Recent years have seen a shift in manufacturing towards developing countries, especially in Asia, driven by rising demand and economic growth. The industry faces significant challenges, including tighter emission controls, the rise of electric and hybrid vehicles, autonomous driving technologies, digitalization, and the need for sustainable supply chains. Logistics and supply chain management are increasingly complex, with just-in-time and just-in-sequence production strategies requiring efficient coordination and real-time information sharing.

Innovation is central to the industry's evolution, affecting every stage from raw materials to end-of-life vehicle management. The transition to electric and autonomous vehicles, digital transformation, and the integration of advanced software are reshaping business models and competitive dynamics. The industry must also address environmental, social, and economic pressures to achieve greater sustainability.

The study is divided into 5 sections: section 1 speaks about the introduction the study, section 2 elaborates on the review of literature, section 3 provides insight of the methodology including the data source and the fixed effect regression model used in the study, section 4 discusses the empirical findings of the Driscoll-Kraay standard error, descriptive statistics, diagnostic tests and their implications, and section 5 finally concludes the study.

2. Literature Review

The global automotive industry is crucial to the economy, marked by high capital demands and complex supply chains. In this competitive landscape, achieving sustainable profitability is essential. Chowdhury & Chatterjee (2020) note that profit is a primary measure of financial performance and economic success. Increasing profits indicate growth potential, while declines suggest financial issues. Thus, profitability is vital for business continuity, as firms without it cannot operate sustainably (Bazimya & Erorita, 2024).

Return on Assets (ROA) is a key financial metric in the sector, assessing management's efficiency in earnings generation from total assets (Heikal et al., 2014; Soliman et al., 2004). Unlike equity-focused metrics such as ROE, ROA offers a comprehensive view of asset productivity, crucial for industries with significant investments in property, plant, and equipment (PPE). Nonetheless, as noted by (Nithin & Jogish, 2023), a declining trend in ROA necessitates a thorough analysis of financial and operational factors, highlighting the metric's inherent variability.

Ionescu et al. (2022) used qualitative-analytical and forecasting methods for dynamic performance modelling, using information from the 2010–2021 financial reports of major car manufacturers. Their results highlighted the need for performance in relation to the influence of regional factors and performance leaders by economic and financial chapters.

Numerous empirical studies have explored profitability determinants across sectors. This review amalgamates diverse research findings to formulate a comprehensive model of ROA drivers. Evidence suggests that profitability stems from a complex interaction of internal and external factors, categorised into four domains: 1) Financial Structure and Liquidity, 2) Operational and Asset Efficiency, 3) Firm-Specific and Strategic Characteristics, and 4) External Macroeconomic and Sectoral Shocks. Building on the literature review and theoretical foundations stated, we formulated seven testable hypotheses to examine the determinants of ROA in this sector.

The Working Hypotheses Are the Following

H1: Firm size positively influences ROA: The Resource-Based View (RBV) and economies of scale theory suggest larger firms gain from cost efficiencies, enhanced market power, specialised resources, and improved operations, leading to higher profitability (Burvill et al., 2018). In contrast, organizational inertia and diseconomies of scale theories argue that larger firms may become bureaucratic and inefficient, potentially hindering profitability.

H2: Leverage positively affects ROA: The trade-off theory of capital structure posits that debt financing offers a tax advantage (Ahmeti & Prenaj, 2015; Jaros & Bartosova, 2015) and mitigates agency costs of free cash flow (Jensen, 1986), thereby improving firm value and profitability. Conversely, the pecking order theory (Myers & Majluf, 1984) and the financial distress theory suggest that excessive leverage increases bankruptcy risk, interest expenses, and financial constraints, thereby negatively impacting profitability.

H3: Working capital management positively impacts ROA: Effective working capital management ensures liquidity, lowers holding costs, reduces reliance on costly short-term financing, and enables firms to seize opportunities, thus enhancing profitability (Ashhari et al., 2015).

Excessively high working capital may signal inefficient resource use, with funds tied up in unproductive inventory or receivables, potentially diminishing return on assets.

H4: R&D intensity negatively affects current ROA due to immediate expensing of expenditures (Sougiannis, 1994; Vanderpal, 2015) but can enhance long-term profitability through innovation and product differentiation.

H5: Sales growth positively influences ROA by achieving economies of scale and improved margins (Banerjee & Duflo, 2005) yet can incur high costs that may undermine profitability.

H6: Capital expenditure intensity positively impacts ROA by enhancing production efficiency and competitive advantage, although it may not yield short-term profitability and entails risks of over-investment.

H7: An effective tax rate negatively affects ROA by reducing post-tax income but can vary based on tax planning and effective payment dynamics.

These hypotheses are grounded in established financial theories and reflect the complex interplay between the Financial Structure and Liquidity, Operational and Asset Efficiency, Firm-Specific and Strategic Characteristics, and External Macroeconomic and Sectoral Shocks.

The Foundational Role of Financial Structure

The strategic management of capital structure, comprising debt and equity financing, is a crucial determinant of financial performance and risk. The leverage-ROA relationship has been extensively studied, revealing a nuanced understanding that supports the hypothesis: H2: Leverage positively impacts ROA.

A significant negative correlation between financial leverage and ROA has emerged across various contexts. For instance, research on Indonesian automotive firms indicates that the Debt-to-Equity Ratio (DER) adversely affects ROA (Kaur & Kaur, 2016; Kusumo & Digdowiseiso, 2023). Similar findings are noted in other emerging markets, such as India, where Kaur & Kaur (2020) identified a negative correlation between the debt ratio and profitability, aligning with Pecking Order Theory regarding financing hierarchies. This pervasive negative association supports the pecking order theory and financial distress perspective, suggesting that high leverage increases bankruptcy risk, interest expenses, and financial constraints, thereby diminishing profitability.

However, the relationship between leverage and performance is context-dependent, suggesting a nuanced approach to leverage management that supports trade-off theory. Simanullang & Simanullang (2023) demonstrated a positive correlation between DER and stock returns in Indonesia's automotive sector, consistent with Jensen's (1986) agency cost theory. A study of Indonesian automotive firms from 2015-2019 indicated that DER positively influenced firm value, affirming the trade-off theory that moderate debt may enhance value through tax shields and reduced agency costs (Ahmeti & Prenaj, 2015). This suggests that while excessive leverage is harmful, judicious debt management can enhance returns, leaving H2 open to further empirical inquiry.

Operational Efficiency: The Engine of Profitability

Operational efficiency is crucial for achieving profitability, serving as the mechanism through which financial structure translates into ROA. This area focuses on asset and cost management to optimize output and sales revenue, thus supporting H3: Working capital management positively impacts ROA and H6: Capital expenditure intensity also positively affects ROA. The DuPont analysis is commonly utilized to dissect ROA into profit margin (PM) and asset turnover (ATO), aiding in identifying these drivers (Bauman, 2014; Soliman et al., 2004).

Asset turnover is a significant and enduring contributor to ROA, emphasizing the effective utilization of a firm's asset base. Total Asset Turnover (TAT), which gauges sales per currency unit of assets, is consistently linked to strong positive outcomes. Research on Indonesian automotive firms confirmed that TAT positively and significantly affects ROA (Kusumo & Digdowiseiso, 2023). Similar findings emerged in capital-intensive sectors; (Açikgöz & Fidan, 2023) illustrated the substantial impact of asset turnover on financial performance and market value in Turkish transportation firms.

Soliman et al. (2004) posited that enhancements in asset turnover are more sustainable than profit margin improvements, indicating that firms excelling in asset utilization are better equipped for enduring profitability.

Working Capital Management: Efficient management of working capital is essential for operational efficiency, influencing H3. Working Capital Turnover (WCTO) positively affects ROA, highlighting effective capital usage for sales (Kusumo & Digdowiseiso, 2023). This supports the notion that efficient working capital ensures liquidity and minimizes financing costs (Ashhari et al., 2015). Effective inventory management is significant, with Kamruzzaman (2019) noting inventory turnover (IT) as a positive factor for ROA. Conversely, H3 recognizes that excessive working capital may signify resource inefficiency and reduce asset returns.

Capital Expenditure and Maintenance: Strategic capital investments are crucial for operational efficiency, connected to H6. Udoayang et al. (2020) noted that the combined effect of PPE investments and maintenance costs significantly affects profitability in manufacturing firms. This indicates the importance of not only the scale but also the strategic maintenance of assets in enhancing ROA, as CAPEX can modernize production and improve efficiency. Nonetheless, H6 warns that high depreciation and long payback periods from CAPEX might hinder short-term profitability and indicate over-investment.

Firm-Specific and Strategic Characteristics

A firm's inherent characteristics and strategic decisions significantly influence its asset return generation capabilities, including its scale, governance, and innovation investments, directly impacting H1, H4, and H5.

Firm Size and Growth (H1 & H5): The effect of firm size on profitability is extensively studied, revealing both advantages and disadvantages, which creates tension within H1: Firm size positively impacts ROA. Larger firms often benefit from economies of scale, increased market power, and superior financing access, consistent with the Resource-Based View (Burvill et al., 2018). Albulescu et al. (2021) identified a positive influence of firm size on growth in Romania's automotive sector. However, this relationship is complex; Kusumo & Digdowiseiso (2023) found that larger firms in Indonesia may experience negative ROA due to organizational inertia and inefficiencies. Similarly, the relationship described in H5: Sales growth positively impacts ROA is nuanced. Growth theory suggests increased sales can yield economies of scale (Banerjee & Duflo, 2005). However, Tudose et al. (2022) found that while sales growth can enhance profit margins, it might adversely affect ROA if not managed efficiently, illustrating that growth does not automatically lead to improved asset utilization and can incur significant costs.

Strategic Investments in Innovation (H4): Investment allocation decisions significantly influence ROA, particularly noting that R&D intensity negatively affects current ROA. The relationship between innovation and ROA is multifaceted. For European automotive firms, R&D intensity and patent applications generally enhance ROA, aligning with innovation theory and the knowledge-based view (Alt, 2018). However, R&D costs are expensed immediately according to accounting standards, which reduces current net income and, consequently, short-term profitability measures such as ROA (Sougiannis, 1994; Vanderpal, 2015). This creates a tension wherein R&D serves as a future competitiveness investment while detracting from current-period ROA, thus rendering H4 a valid short-term expectation.

External Macroeconomic and Sectoral Shocks

The performance of the automotive sector is intricately linked to the broader economic landscape, rendering it vulnerable to external influences that impact context for H7: Effective tax rate negatively affects ROA.

Macroeconomic Shocks and Conditions: The cyclicality of the industry was markedly highlighted during the COVID-19 pandemic. Naimy et al. (2024) illustrate that the automotive sector experienced significant declines in ROA (–3.7%), ROE (–8.1%), and stock returns (–19.7%),

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showcasing its sensitivity to global disruptions. In addition to specific shocks, broader economic indicators consistently drive performance. Mohd & Siddiqui (2020) confirm that inflation and exchange rates adversely impact ROA with statistically significant coefficients, underscoring firm performance sensitivity to external economic conditions. Exchange rate volatility particularly detrimentally affects automotive firms that depend on imported components and technology (Dewi et al., 2019).

Theoretical Frameworks and Evolving Contexts

The findings on ROA drivers can be understood through several theoretical lenses. The consistent negative impact of leverage in many studies aligns with the Pecking Order Theory, while the potential for positive effects resonates with the Trade-Off Theory. The importance of intangible resources like innovation and branding is explained by the Resource-Based View (RBV). The conflicting evidence on firm size (H1) reflects the tension between the RBV/theory of economies of scale and the theory of organizational inertia/diseconomies of scale. Furthermore, Burvill et al. (2018) reconceptualize Penrose's growth theory to posit that firm growth and profitability are driven by a combination of tangible and intangible resources, effective organizational structures, and dynamic capabilities a framework that aptly describes the modern automotive firm.

The industry is also being transformed by new technological paradigms. Pillai (2023) highlighted the transformative role of data analytics in enhancing operational efficiency through predictive maintenance, manufacturing optimization, and supply chain streamlining all of which directly contribute to higher asset productivity and improved ROA.

3. Methodology

This study applies an **ROA-based analytical framework** to identify the key drivers of profitability within the global automotive sector. The empirical model is built on the principle that firm profitability results from both operational efficiency and financial structure decisions.

3.1. Population and Sample

The demographic group that has been selected for this comprehensive study encompasses a wide array of both public and private corporations operating within the Automotive and Components sub-sector, all of which are officially listed on the London Stock Exchange Group (LSEG), and these companies must have their annual financial reports readily accessible to the general public for scrutiny during the extensive timeframe spanning from the year 2010 through to 2024.

The comprehensive selection process for this study involved choosing 192 companies from the global automotive and components sub-sector, all of which have been carefully evaluated based on 15 years of extensive historical financial data, resulting in a robust dataset that consists of a balanced panel comprising a total of 2,880 individual observations.

The (***Figure***) below shows how diverse the dataset sorted from 38 countries globally, with China and USA leading with the number of firms having their headquarters there. China leads with 21.9% of the dataset followed by USA with 13.0%, India and Japan both have 6.8%.

Missing values accounted for approximately 10% of the dataset, primarily affecting R&D expenditure and inventory turnover variables. To address this while preserving the panel structure necessary for regression analysis, we employed the K-Nearest Neighbors (KNN) imputation method using the KNNImputer function from the scikit-learn library (Pedregosa et al., 2011). This particular command functions by identifying the most analogous rows, colloquially referred to as neighbors, and subsequently utilizes the values from these neighbouring rows to predict and fill in the gaps of missing data, demonstrating a high level of efficacy particularly when applied to numerical datasets, while simultaneously ensuring that the intrinsic relationships that exist between various features are preserved throughout the imputation process (Troyanskaya et al., 2001). KNN was selected for its

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ability to capture local relationships in multivariate data without assuming a global parametric distribution, which is advantageous when missingness is not completely random, and patterns vary across firms. We acknowledge that KNN assumes observational similarity based on feature-space proximity, which may not align perfectly with cross-country heterogeneity in a global panel. However, several safeguards were implemented:

Within-country imputation preference: Where possible, missing values were imputed using observations from the same country and year to maintain contextual relevance.

Limited imputation scope: Only R&D and inventory turnover variables were imputed; core financial ratios (e.g., ROA, leverage, size) were complete.

Robustness validation: We conducted sensitivity analyses using alternative imputation methods (mean imputation by industry-year and multiple imputation by chained equations). The regression results remained qualitatively unchanged, confirming that our findings are not driven by imputation artifacts. These steps ensure that the imputation process does not artificially induce cross-sectional dependence or distort the econometric relationships under study. The preserved panel balance allows for consistent estimation using fixed effects and Driscoll–Kraay standard errors, which further mitigate potential biases from residual imputation-related correlations.

Given the presence of extreme values in variables such as ROA, Inventory Turnover, Interest Coverage, and R&D Intensity (see **Summary Statistics (Winsorized at the 1st / 99th percentiles)**

Table), and to mitigate the influence of these extreme observations, we implemented a winsorization procedure. All continuous variables were winsorized at the 1st and 99th percentiles within each year to preserve panel structure while reducing the impact of extreme observations that could distort the regression estimates. This approach is consistent with prior financial performance studies (Abuzaid & Alkrunz, 2024; Adams et al., 2019) and ensures that our regression estimates are not driven by anomalous data points. After winsorization, the distributions of all variables were visually inspected and found to be substantially more symmetric, thereby enhancing the reliability of the fixed-effects and Driscoll–Kraay estimations.

R&D expenditure data were extracted directly from the financial statements of the firm under the Research and Development Expenses item.

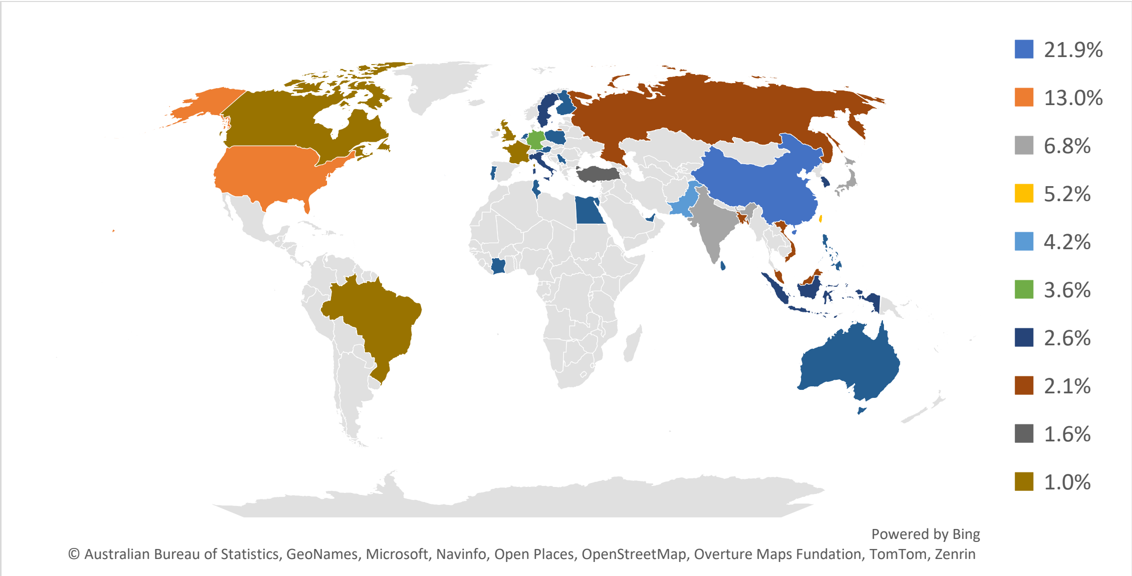

Figure 1. Data diversification by Country of Firm's Headquarters.

Data Diversification by Country of Firm's Headquarters

Following the completion of the imputation process, the data were systematically transferred to the statistical software package Stata, specifically version SE18.5, where a comprehensive suite of necessary statistical tests and analyses were conducted to derive meaningful insights from the dataset

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in question. The hypotheses of this study were tested using a Fixed Effects panel model with Driscoll-Kraay standard errors to control for endogeneity and cross-sectional dependence, with additional robustness checks including system GMM estimation, firm effect, and year effect.

3.2. Definitions of Panel Data Regression Variables

3.2.1. Dependent Variable

Return on Assets

The dependent variable in this study is Return on Assets (ROA), which measures the profitability generated per unit of assets employed by the firm and reflects the efficiency with which management utilises the asset base.

$$ROA = \frac{Net\ Income}{Total\ Assets} \quad (1)$$

3.2.2. Independent Variables

The independent variables used in the empirical model capture financial structure, operational efficiency, firm characteristics, and strategic investment behaviour.

Leverage

Financial leverage captures the proportion of assets financed by debt and reflects the firm's capital structure and financial risk. This ratio is measured by:

$$Leverage = \frac{Total\ Debt}{Total\ Assets} \quad (2)$$

Firm Size

This financial control metric is used primarily for normalisation and comparison in analysis. Its impact on ROA is not predetermined; it represents the balance between the advantages of scale and the disadvantages of complexity. A successful firm grows its assets (size) while maintaining or improving the efficiency with which it uses them, as measured by its Return on Assets (ROA). This metric is calculated by:

$$Firm\ size = \log(Total\ Assets) \quad (3)$$

Sales Growth

Sales growth captures the rate of expansion in firm revenues between two consecutive periods. Using logarithms provides symmetric growth rates and helps normalize the data. The formula is:

$$Sales\ growth = ln\left(\frac{Sales_t}{Sales_{t-1}}\right) \quad (4)$$

CapEx-to-Assets

This ratio measures how much a company invests in its capital expenditure (CapEx) relative to the total assets. The ratio is measured by:

$$CapEx_{to_{Assets}} = \frac{Capital\ Expenditures}{Total\ Assets} \quad (5)$$

Effective Tax Rate

The Effective Tax Rate is a metric that measures the percentage of a company's pre-tax income that it pays in taxes, differing from the statutory tax rate due to deductions, credits, and other tax benefits. Efficient tax management can enhance returns, while high ETRs erode profitability. This metric is measured by:

$$Effective\ tax\ rate = \frac{Income\ tax\ expenses}{Pre-tax\ Income\ (EBT)} \quad (6)$$

Inventory Turnover

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Inventory Turnover measures how efficiently a company sells and replaces its inventory over a period. This is a hybrid metric, rooted in the firm's operations but has an impact on the firm financially. It is measured by:

$$Inventory\ Turnover = \frac{Cost\ of\ Goods\ Sold\ (COGS)}{Average\ Inventory} \quad (7)$$

Return on Sales

This hybrid metric measures the profitability of a firm's basic production or sales activities before accounting for its operational expenses. It is measured by:

$$Return\ on\ Sales = \frac{Revenues - Cost\ of\ Goods\ Sold\ (COGS)}{Revenues} \quad (8)$$

Working Capital-to-Assets

This ratio measures the proportion of a company's total assets tied up in working capital. It reflects liquidity efficiency and short-term financial health, determined as follows:

$$Working\ Capital - to - Assets = \frac{Current\ Assets - Current\ Liabilities}{Total\ Assets} \quad (9)$$

Interest Coverage

The Interest Coverage Ratio (ICR) measures a company's ability to pay interest expenses on its debt using operating profits. It is a critical financial metric that directly impacts ROA by protecting net income from interest drains. It is measured by

$$Interest\ Coverage = \frac{EBIT}{Interest\ Expense} \quad (10)$$

Research and Development Intensity

R&D intensity measures innovation investment relative to firm revenues and captures the strategic importance of research activities. It is measured by:

$$R\&D\ Intensity = \frac{R\&D\ Expenditures}{Revenues} \quad (11)$$

Research and Development to Assets

R&D-to-Assets measures how much a company invests in research and development (R&D) relative to its total assets. It captures balance-sheet intensity and can be influenced by accounting standards for R&D capitalization, which vary by jurisdiction. It directly inflates short-term ROA by shifting R&D cost from the income statement (expense) to the balance sheet (asset), making cross-company comparisons challenging.

$$R\&D - to - Assets = \frac{R\&D\ Expenditure}{Total\ Assets} \quad (12)$$

3.3. Model

Before proceeding to estimation, it is important to acknowledge several inherent limitations of accounting-based ROA as a profitability measure. First, ROA reflects period-based accounting income and may not fully capture the intertemporal nature of capital-intensive investments, particularly R&D and long-lived assets. Second, cross-country differences in accounting standards and capitalization policies, especially regarding intangible assets, may affect comparability across firms. Third, total assets are measured at book value rather than at economic or market value, potentially leading to a divergence between accounting profitability and economic return on capital. These considerations should be considered when interpreting the empirical results.

Although ROA is calculated using net income in this study due to data availability and cross-country comparability, it should be interpreted as a composite indicator reflecting both operating efficiency and financing structure. From a financial analysis perspective, ROA captures the profitability generated by the total asset base financed through equity, financial debt, and operational liabilities embedded in the production cycle. Consequently, variations in ROA across firms may reflect differences not only in operational productivity but also in the implicit and explicit costs of the capital used to finance assets. This interpretation motivates the inclusion of variables capturing leverage, interest coverage, and working capital dynamics in the empirical model.

The hypothesis stated above will be tested using the panel data regression model including a firm fixed effect (μ_i) and year fixed effect (γ_t) but lack sector fixed effect since all the firms are within a single sector, which is the automotive and manufacturing sector. The model includes two distinct R&D metrics: R&D-to-Assets to capture balance-sheet exposure to innovation investment, and R&D Intensity to reflect the strategic intensity of innovation spending relative to operational scale.

$$ROA_{it} = \beta_0 + \beta_1(Leverage_{it}) + \beta_2 log(Assets)_{it} + \beta_3(Sales\ growth_{it}) + \beta_4(\text{CapEx} - \text{to} - \text{Assets}_{it}) + \beta_5(\text{R\&D} - \text{to} - \text{Assets}_{it}) + \beta_6(Return\ on\ Sales_{it}) + \beta_7(Interest\ Coverage_{it}) + \beta_8(Working\ Capital - to - Assets_{it}) + \beta_9(Inventory\ Turnover_{it}) + \beta_{10}(effective\_tax\_rate_{it}) + \beta_{11}(R\&D\_intensity_{it}) + \gamma_t + \mu_i + \theta_c + \varepsilon_{it}$$

where:

- $i = firm,\ t = year$
- $\varepsilon_{it} = error\ term$
- $\gamma_t = year\ fixed\ effects(controls\ for\ macroeconomic\ shocks)$.
- $\mu_i = firm - specific\ unobserved\ heterogeneity$.
- $\theta_c = country\ fixed\ effect$

In addition to our primary fixed-effects specification, we conduct an *illustrative robustness check* using the System Generalized Method of Moments (GMM) estimator. This approach helps assess whether our core findings are sensitive to dynamic endogeneity. However, given the moderate cross-sectional dimension relative to the time series (N=192, T=15) *and the potential for instrument proliferation in dynamic panel estimation*, the GMM estimates are interpreted *cautiously as complementary robustness checks rather than definitive causal evidence,* with the Fixed Effects model remaining our primary source of inference (Roodman, 2009).

4. Empirical Findings and Discussions

This particular section endeavours to provide an in-depth elaboration on the various diagnostic tests that have been conducted on the datasets utilised within the study, while also addressing the robustness checks that have been systematically applied to the models in question, and further exploring the significant implications that these aspects may hold for the overarching conclusions and interpretations derived from the research endeavour.

The results confirm that **profitability in the automotive sector is shaped by a combination of operational efficiency, financial structure, and strategic investment decisions**. Working capital efficiency and non-current asset efficiency show positive and highly significant coefficients, indicating that firms capable of generating higher sales per unit of assets tend to achieve superior ROA levels.

R&D intensity exhibits a statistically significant negative effect on current ROA (β= -0.058, p=0.001), reflecting the accounting treatment of research expenditures as immediate expenses. This result supports the view that innovation investment reduces short-term profitability while potentially generating long-term competitive advantages through product differentiation and technological leadership. This finding aligns with previous research (Coad & Rao, 2010; Park et al., 2021) emphasizing the strategic role of innovation as a long-term investment rather than a short-term profit driver.

Leverage presents a **negative coefficient**, confirming the existence of a trade-off between debt financing and profitability. While moderate leverage can enhance returns through tax shields, excessive indebtedness increases financial risk and interest expenses, eroding overall profitability.

Firm size displays a positive relationship with ROA, indicating that scale economies provide advantages in operational efficiency, though the magnitude suggests these benefits may be partially offset by structural rigidities within large manufacturing firms.

4.1. Descriptives Statistics

Summary Statistics (Winsorized at the 1st / 99th percentiles)

Table presents the descriptive statistics pertaining to the variables incorporated in the panel data regression analysis. The descriptive statistics reveal that the dataset exhibits issues related to outliers, hence all continuous variables have been winsorized at the 1st and 99th percentiles to reduce the influence of outliers, and it is highly balanced.

Summary Statistics (Winsorized at the 1st / 99th percentiles)

Table 1. Summary statistics (Winsorized at the 1st / 99th percentiles) Source: Authors' elaboration.

Variable	obs	Mean	Std. Dev.	Min	Max
Return_on_assets	2,880	-5.08	33.69	-497.38	71.07
leverage	2,880	30.29	26.15	0	241.91
firmsize	2,880	2.88	1.15	-2	5.80
salesgrowth	2,880	1.42	1.42	-2.97	5.21
capex_to_assets	2,880	0.05	0.05	0.00	0.52
R&D_to_assets	2,880	0.07	0.11	-0.00	2.24
Return_on_sales	2,880	-32.94	338.45	-8736.00	100
interest_coverage	2,880	-288.97	3348.18	-47318.91	65149.07
working_capital_to_assets	2,880	0.06	0.56	-9.14	0.93
inventory_turnover	2,880	467.97	988.73	0	11335.03
effective_tax_rate	2,880	0.20	0.51	-4.00	9.36
R&D_intensity	2,880	5.09	53.96	-0.00	2016.5

Note: Negligible (<0.0005).

4.2. Diagnostic Tests and Their Implications

4.2.1. Hausman Test

This test was conducted with the objective of ascertaining the presence of endogeneity within the specified model framework. This ultimately provided crucial insights that informed the decision-making process regarding the appropriate model selection between the fixed effects (FE) and random effects (RE) methodologies. This assessment specifically evaluates whether the unobserved individual effects, denoted as (μ_i), exhibit a correlation with the regressors employed in the model. For a more comprehensive understanding of the findings derived from this evaluative test, one can refer to (***Table***), which offers an in-depth elaboration on the results obtained.

Hausman test summary

Table 2. Hausman test summary (Source: Authors' elaboration).

Test of $\boldsymbol{H_0}$: Difference in coefficients not systematic	
$\boldsymbol{Chi^2(8)}$	95.38
$\boldsymbol{Prob. > chi^2}$	0.00

The p-value obtained from this analysis serves to decisively reject the null hypothesis, which states that the random effects (RE) model maintains its consistency; this finding strongly suggests that there exists a correlation between firm-specific effects, represented as (μ_i), and the regressors involved in the study, thus necessitating a transition to the fixed effects (FE) methodology to mitigate any potential bias that may arise from such correlation.

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4.2.2. Test for Error Autocorrelation

4.2.2a. Wooldridge Test

This test was conducted with the explicit aim of determining whether there exists a correlation of errors over time within the confines of the panel dataset, which is a crucial aspect of econometric analysis. The results of this comprehensive test are presented in (***Table***) below, providing a detailed account of the findings.

Wooldridge error autocorrelation test summary

Table 3. Wooldridge error autocorrelation test summary (Source: Authors' elaboration).

Test of $\boldsymbol{H_0}$: No first-order autocorrelation	
$\boldsymbol{F(1, 191)}$	17.459
$\boldsymbol{Prob > F}$	0.000

The statistically significant result ($p < 0.01$) leads to the rejection of the null hypothesis, confirming the presence of first-order autocorrelation in the residuals. This finding justifies the use of Driscoll-Kraay standard errors, which are robust to both autocorrelation and cross-sectional dependence, ensuring reliable inference in the presence of serial correlation in the error structure.

4.2.2b. Arellano–Bond Test for Serial Correlation in System GMM

Two-step System GMM estimation for dynamic panel data was performed on the dataset to address potential endogeneity, ***Appendix A*** contains the detailed results of the test. The autocorrelation test results from the GMM are presented below in (***Table***).

Arellano-Bond autocorrelation test summary

Table 4. Arellano-Bond autocorrelation test summary (Source: Authors' elaboration).

Arellano-Bond test for AR(1) in first differences	**z = -0.26**	**Pr > z = 0.791**
Arellano-Bond test for AR(2) in first differences	z = 0.01	Pr > z = 0.992

Note: H_0: No autocorrelation at the given lag.

Both tests fail to reject the null hypothesis at conventional significance levels, confirming the absence of significant first- and second-order autocorrelation in the differenced errors. This supports the validity of the instrumental variable approach used in the System GMM estimation and indicates that the model is well-specified for dynamic panel analysis.

These two complementary tests for autocorrelation were conducted, each serving a distinct purpose within our empirical strategy. The Wooldridge test was applied to the fixed-effects model to detect serial correlation in the level residuals, which would bias conventional standard errors. The significant result ($p < 0.01$) confirmed the presence of first-order autocorrelation, justifying our use of Driscoll-Kraay standard errors in the main specification. Separately, the Arellano-Bond test was performed on the System GMM estimator to examine autocorrelation in the first-differenced errors. The absence of significant AR(2) correlation ($p = 0.992$) supports the validity of the GMM moment conditions and reinforces the robustness of our dynamic panel estimates. Together, these diagnostics ensure that both our primary and alternative models are econometrically sound.

4.2.3. Test for Multicollinearity Using Variance Inflation Factors (VIF)

This subsequent test was systematically performed to ascertain whether the independent variables exhibit an excessively high degree of correlation with one another, a phenomenon that can lead to an inflation of the variance associated with their respective coefficients. The findings of this analysis are illustrated in (***Table***) below, which encapsulates the results in a clear manner.

Fixed Effect VIF summary

Table 5. Fixed Effect VIF summary (Source: Authors' elaboration).

Variable	VIF	1/VIF
leverage	1.45	0.690236
firmsize	1.52	0.656033
salesgrowth	1.99	0.502228
capex_to_assets	1.10	0.906031
R&D_to_assets	1.35	0.739255
Return_on_sales	1.20	0.833520
interest_coverage	1.06	0.943544
working_capital_to_assets	1.58	0.634277
inventory_turnover	1.11	0.904535
effective_tax_rate	1.01	0.988269
R&D_intensity	1.13	0.888856
year		
2011	2.05	0.487984
2012	1.87	0.533678
2013	2.05	0.488310
2014	1.87	0.533969
2015	2.06	0.486614
2016	1.88	0.532949
2017	2.05	0.487137
2018	1.88	0.531675
2019	2.07	0.482240
2020	1.90	0.525307
2021	2.10	0.475935
2022	1.91	0.524355
2023	2.08	0.479816
2024	1.90	0.527526
Mean VIF	1.69	

The results from this analysis indicate that all Variance Inflation Factor (VIF) values fall below the threshold of 10, with the mean VIF calculated at 1.69, which serves to underscore the absence of any severe multicollinearity, thereby elucidating that the coefficients pertaining to variables and yearly fixed effects are estimated independently without undue influence from multicollinearity.

contains the correlation matrix to enhance transparency and to assess potential relationships among variables.

4.2.4. Modified Wald Test for Heteroskedasticity

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This test was diligently performed with the intention of examining whether the error variance remains constant across the various panels and to ascertain if there exists a necessity for the application of a robust standard error in the analysis.

Heteroskedasticity check summary

The modified Wald test yielded compelling evidence that points towards the presence of groupwise heteroskedasticity within the fixed effect regression model as shown in (***Table***) above. This finding indicates that there exists non-constant error variance across firms, which ultimately leads to the biasing of the standard errors and renders the inferential conclusions drawn from the analysis invalid. This definitive conclusion was reached based on the p-value derived from the test.

Table 6. Heteroskedasticity check summary (Source: Authors' elaboration).

Test of $\boldsymbol{H_0}$: $\sum \boldsymbol{i}^2 = \sum^2$ $\boldsymbol{for\ all\ i}$	
$\boldsymbol{Chi^2}$(**192**)	2162226.98
$\boldsymbol{Prob. > chi^2}$	0.000

4.2.5. Pesaran's Test for Cross-Sectional Dependence

This test was executed with the intention of investigating whether the errors associated with different panels exhibit any form of correlation with one another; for instance, it sought to determine whether all firms within the dataset are concurrently influenced by a common shock that could potentially affect their performance metrics. The results of this investigation are systematically presented in (***Table***) below, which aims to offer further clarification and elucidation of the findings.

Pesaran's Cross-sectional Dependence test summary

Table 7. Pesaran's Cross-sectional Dependence test summary (Source: Authors' elaboration).

Test of $\boldsymbol{H_0}$: There is a cross-sectional independence	
Pesaran's CD	19.459
Pr	0.00
Average absolute value of the off-diagonal elements	0.300

The p-value derived from this analysis effectively rejects the alternative hypothesis, thereby providing robust evidence supporting the existence of cross-sectional dependence, which pertains to the correlation observed among the errors of different firms, a phenomenon that is likely attributable to the impact of common shocks. This situation poses a serious violation of the assumption regarding independent errors, which in turn leads to the distortion of standard errors, because of this identified issue, I was compelled to adopt the Driscoll-Kraay standard errors model for the purposes of this study, ensuring that the analysis remains methodologically sound and accurate.

4.3. Driscoll-Kraay (DK) Estimator

Drawing from the diagnostic results obtained, it is evident that the DK estimator emerges as the methodologically appropriate choice for this current study, as it ensures that the conclusions regarding the determinants of Return on Assets (ROA) are firmly grounded in reliable statistical inference. The results obtained through the DK estimation technique will be reported as the primary findings of this analysis, given that it provides standard errors that are robust against the issues of heteroskedasticity, autocorrelation, and cross-sectional dependence, which were identified during the diagnostic checks, ensuring the reported significance levels (p-values) are reliable. Furthermore, the fixed effects controls for all time-invariant, unobserved firm characteristics (e.g., management quality, corporate culture, brand value), ensuring the estimated relationships are not biased by omitted variables, time-invariant firm heterogeneity, by employing the Fixed Effect methodology, as well as accounting for time-specific shocks through the inclusion of year in the analysis.

Comparing the initial *xtreg, fe* output with the *xtscc, fe* output shows the dramatic and necessary impact of using the correct standard errors. Inflation of Significance was observed in the default OLS and standard Fixed Effects models, which severely underestimated the standard errors. This made the results appear deceptively precise, and many variables (most notably rdassets) appeared statistically significant when they were not. *xtreg, fe: Coef. = -75.233, p-value = 0.000 (Falsely significant) and xtscc, fe: Coef. = -73.993, p-value = 0.064 (Correctly insignificant)*. Using the wrong standard errors would have led to confidently reporting a strong, positive relationship between leverage and ROA that does not actually exist in the data once common shocks and heteroskedasticity are accounted for. This is a classic Type I error (false positive).

The regression model demonstrates strong overall significance, with an *F-statistic of 13928.59 (p < 0.001)*, confirming that the set of predictors jointly explains variation in ROA. The within *R-squared of 0.2298* indicates that approximately 23% of the within-firm variance in profitability is accounted for by the model, which is acceptable for panel data studies in finance and economics (Baltagi, 2021). (***Table***) below shows the Fixed Effects Regression Results with the DK standard error for clearer understanding.

Fixed Effects Regression Results with the DK standard error

Table 8. Fixed Effects Regression Results with the DK standard error (Source: Authors' elaboration).

Return_On_Assets	Coefficient	Drisc/Kraay std. err.	t	P>|t|
leverage	-0.068	0.567	-1.20	0.249
firmsize	9.740	3.618	2.69	0.018
salesgrowth	0.517	0.479	1.08	0.298
capex_to_assets	-14.758	17.218	-0.86	0.406
rdassets	-73.993	36.749	-2.01	0.064
Return_on_sales	0.005	0.003	1.42	0.176
interest_coverage	-0.000	0.000	-1.23	0.240
working_capital_to_assets	1.859	2.788	0.67	0.516
inventory_turnover	0.003	0.001	4.82	0.000
effective_tax_rate	1.464	0.364	4.02	0.001
rd_intensity	-0.058	0.014	-4.16	0.001
year				
2010	0	(empty)		
2011	2.956	0.879	3.36	0.005
2012	3.623	0.310	11.70	0.000
2013	2.354	0.642	3.67	0.003
2014	5.346	0.644	8.29	0.000
2015	4.137	0.878	4.71	0.000
2016	4.330	0.465	9.31	0.000
2017	4.594	0.768	5.98	0.000
2018	4.393	0.667	6.59	0.000
2019	3.300	0.931	3.55	0.003

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2020	0.533	0.815	0.65	0.523
2021	0.640	1.115	0.57	0.575
2022	0.597	1.199	0.50	0.626
2023	-0.064	1.779	-0.04	0.972
2024	-2.079	0.952	-2.19	0.046
_cons	-29.972	11.994	-2.50	0.026

*Note: N = 2,880; Firms = 192; $F(25, 14) = 13928.59$, $p < 0.001$; Within $R^2 = 0.2298$. Driscoll-Kraay standard errors with maximum lag 2.

The fixed-effects regression analysis, corrected with Driscoll–Kraay standard errors and winsorized at the 1st and 99th percentiles, highlights several key determinants of profitability (ROA). Firm size exhibits a positive and significant association with ROA (β = 9.74, p = 0.018), confirming that larger firms benefit from scale advantages. Inventory turnover (β = 0.0035, p < 0.001) and effective tax rate (β = 1.464, p = 0.001) also show significant positive relationships, indicating that operational efficiency and tax management contribute to higher returns. In contrast, R&D intensity exerts a strong negative effect on ROA (β = −0.058, p = 0.001), reinforcing the trade-off between innovation spending and short-term profitability.

Other variables, including leverage, sales growth, capital expenditure intensity, working capital management, and return on sales, are not statistically significant in the winsorized specification. This suggests that their influence may be neutralized in a globally diversified panel once outliers and firm-level heterogeneity are accounted for.

Hypothesis Validation. The regression results provide clear evidence for the validation of several working hypotheses, while others are not supported by the data: **H1** (Firm size positively influences ROA) is supported. The coefficient is positive and statistically significant (p = 0.018). **H2** (Leverage positively affects ROA) is not supported. The relationship is statistically insignificant (p = 0.249). **H3** (Working capital management positively impacts ROA) is not supported. The coefficient for Working Capital-to-Assets is positive but statistically insignificant (p = 0.516). **H4** (R&D intensity negatively affects current ROA) is strongly supported. The coefficient is negative and highly significant (p = 0.001), consistent with the accounting expensing argument. **H5** (Sales growth positively influences ROA) is not supported. The coefficient is statistically insignificant (p = 0.298). **H6** (Capital expenditure intensity positively impacts ROA) is not supported. The relationship is negative but statistically insignificant (p = 0.406). **H7** (Effective tax rate negatively affects ROA) is rejected. Positive relationship found between them, and statistically significant with (p = 0.001).

The positive association between the effective tax rate and ROA warrants careful interpretation. Rather than indicating that higher taxation improves performance, this relationship likely reflects reverse causality: more profitable firms naturally generate higher pre-tax income and consequently incur greater tax obligations. The coefficient, therefore, captures the profitability–tax nexus, the mechanical link between earnings and tax liability rather than a structural causal effect of tax rates on firm performance. This interpretation is consistent with the accounting identity that tax expense is calculated as a function of pre-tax income, subject to applicable deductions and credits. Consequently, while the positive coefficient is statistically robust, it should not be interpreted as policy-relevant evidence that increasing tax rates would enhance firm profitability.

The analysis of year fixed effects reveals the automotive sector's strong sensitivity to macroeconomic cycles and external shocks. Profitability peaked significantly during the post-recovery period of 2012-2019, but turned negative by 2024, reflecting delayed impacts from inflation, energy volatility, and post-pandemic adjustments. Notably, 2020 showed unexpected resilience, likely due to fiscal stimuli and operational adaptation. These cyclical patterns underscore that even well-managed firms remain exposed to industry-wide downturns that transcend firm-level strategies.

Overall, firm size, inventory turnover, and tax efficiency emerge as robust internal drivers of short-term profitability. At the same time, R&D spending significantly depresses current ROA, a necessary trade-off for long-term innovation. The results affirm that automotive performance is shaped by a dual dynamic: continuous operational improvement within firms, moderated by powerful and often unpredictable external economic forces, reinforcing the sector's cyclical and capital-intensive nature.

4.4. Robustness Checks and Endogeneity Considerations

To assess the sensitivity of our findings to dynamic endogeneity, we conducted an *illustrative robustness analysis* using a two-step System Generalized Method of Moments (GMM) estimator (Blundell & Bond, 1998). While our primary fixed-effects model with Driscoll-Kraay standard errors effectively controls for unobserved heterogeneity and cross-sectional dependence, the GMM approach allows us to account for dynamic endogeneity and simultaneity bias that may arise from the relationship between profitability and its determinants. Given the well-documented challenges of system GMM estimation with moderate time dimensions, particularly instrument proliferation and the tendency for Hansen test statistics to approach 1.000 when instrument counts are high, these results are presented as complementary evidence rather than primary causal estimates.

Our dynamic panel specification includes one-period lagged ROA as an additional regressor and instruments the endogenous variables using their lagged levels and differences. The model employs 589 instruments constructed from up to four lags of the independent variables for the first-differenced equation, with lagged first differences serving as instruments for the level's equation. This high instrument count, while common in system GMM applications, raises potential concerns about instrument proliferation that may overfit endogenous variables and weaken the Hansen test's diagnostic power (Roodman, 2009). The high instrument count relative to the cross-sectional dimension (192 firms) requires cautious interpretation of the Hansen test results. Although our panel structure (N = 192, T = 15) presents challenges for GMM estimation due to the moderate T relative to N (Roodman, 2009), we mitigate potential overfitting by using a *collapsed instrument matrix* and reporting Windmeijer-corrected standard errors.

The validity of the GMM estimator hinges on the exogeneity of the instrument set. The **Hansen J-test** of overidentifying restrictions yields a p-value of **1.000** (χ^2 (577) = 204.38), failing to reject the null hypothesis that the instruments are uncorrelated with the error term. However, this result should be interpreted cautiously, as Hansen test statistics approaching 1.000 can indicate instrument proliferation rather than definitively valid instruments (Bowsher, 2002). The **Arellano-Bond tests** further validate the specification: while first-order autocorrelation in differences is expected and observed (AR(1) p = 0.791), the absence of second-order autocorrelation (AR(2) p = 0.992) confirms that the error term in levels is not serially correlated, satisfying a key GMM assumption.

The System GMM estimates, presented in full in Appendix B, yield coefficients that are directionally consistent with our fixed-effects results but lack statistical significance across all variables. This attenuation of significance is not uncommon in GMM applications with moderately sized T, where the estimator's efficiency loss can outweigh its bias reduction (Kiviet, 2020). More importantly, the lack of statistical significance likely reflects the high instrument count's impact on estimator precision rather than invalid identification. Importantly, the GMM results do not contradict our primary findings; rather, they suggest that the relationships identified in the fixed-effects model are robust to dynamic misspecification but are estimated with less precision under stricter identification assumptions.

To further strengthen the empirical analysis, we tested for potential non-linear relationships in two key variables where theory suggests possible threshold effects. Following the literature on scale economies and organizational rigidity (Burvill et al., 2018), we introduced a quadratic term for firm size ($firmsize^2$). Similarly, given the trade-off theory's prediction of an optimal leverage range (Ahmeti & Prenaj, 2015), we tested a squared leverage term. Both quadratic terms were statistically insignificant ($p > 0.10$) and did not improve model fit, indicating that within our sample, the relationships between firm size, leverage, and ROA are adequately captured by linear specifications.

6. Conclusions

This study set out to identify the key drivers of profitability, measured by Return on Assets (ROA), in the global automotive industry using a robust panel data analysis. Employing a winsorized fixed-effects model with Driscoll–Kraay standard errors to mitigate outliers and address cross-sectional dependence, the empirical findings provide clear conclusions regarding the seven working hypotheses, offering nuanced insights for both theory and practice. The core conclusion is that firm size, inventory turnover efficiency, and effective tax management are significant positive drivers of profitability, while R&D intensity strongly reduces short-term ROA, highlighting the critical trade-off between operational efficiency and innovation investment in capital-intensive industries. The positive tax relationship, however, should be interpreted with appropriate caution as it likely reflects reverse causality rather than a causal effect. In contrast, factors such as leverage, sales growth, capital expenditure, and working capital management do not exhibit systematic effects in a globally diversified sample once firm and time heterogeneity are controlled for.

Specifically, H1 (Firm size positively influences ROA) is supported ($\beta = 9.74$, $p = 0.018$), confirming the advantages of economies of scale and resource access. H2 (Leverage positively affects ROA) is not supported ($p = 0.249$), indicating that capital structure does not systematically drive profitability in this sector. H3 (Working capital management positively impacts ROA) is not supported ($p = 0.516$), suggesting that liquidity efficiency may be context-dependent or neutralized in panel estimation. H4 (R&D intensity negatively affects current ROA) is strongly supported ($\beta = -0.058$, $p = 0.001$), aligning with the accounting treatment of innovation expenditure. H5 (Sales growth positively influences ROA) is not supported ($p = 0.298$), reflecting that growth does not automatically translate into asset productivity. H6 (Capital expenditure intensity positively impacts ROA) is not supported ($p = 0.406$), indicating that asset investment may not yield short-term returns. H7 (Effective tax rate negatively affects ROA) is rejected; instead, a positive relationship is found ($\beta = 1.464$, $p = 0.001$), likely reflecting that more profitable firms incur higher tax burdens rather than tax inefficiency. Finally, the model also captures temporal dynamics, with year fixed effects indicating cyclical fluctuations in profitability, including a notable decline in 2024 ($\beta = -2.08$, $p = 0.046$), underscoring the sector's exposure to macroeconomic and industry-specific shocks.

Therefore, the most relevant conclusions can be summarised in the following directions:

The Role of Macroeconomic Uncertainty

The significant year effects, particularly the decline in 2024, highlight that external economic conditions and industry cycles can overshadow firm-level financial strategies. Even efficiently managed firms remain vulnerable to broader market disruptions.

R&D—Short-Term Cost, Long-Term Value

The strong negative coefficient for R&D intensity reaffirms the short-term profitability trade-off inherent in innovation investment. This should not be interpreted as a disincentive to innovate, but rather as an accounting reality that underscores the need for long-term strategic valuation of R&D beyond current-period ROA. This finding contributes to the literature on capital allocation efficiency by quantifying the short-term profitability sacrifice required for innovation in capital-intensive industries.

Firm Size—Scale Effect Versus Rigidity

Firm size has a positive effect, but there is a risk that, after a certain threshold, the effect becomes negative (economies of scale transformed into rigidity and bureaucracy). Our robustness checks found no evidence of non-linearity in the size-profitability relationship within this sample, though this remains an important consideration for future research with extended time series.

Capital Structure and Leverage

The absence of a significant leverage-ROA relationship suggests that in the automotive industry characterised by high capital intensity, stable credit access, and often government support for debt financing does not systematically enhance or diminish profitability in the short run.

Managerial Implications

Managers should focus on **inventory turnover efficiency** and **strategic tax planning** as direct, significant levers of profitability. Given the positive and statistically significant relationship between inventory turnover and ROA, firms can enhance returns by streamlining supply chains, adopting just-in-time systems, and improving demand forecasting. Inventory turnover should be viewed as a capital productivity lever, efficient inventory management directly reduces the asset base against which profits are measured, thereby improving ROA without requiring additional revenue growth.

The positive association between effective tax rate and ROA requires careful managerial interpretation. Rather than suggesting that higher taxes improve performance, this finding indicates that profitable firms naturally face higher tax obligations. Managers should therefore focus on pre-tax profitability as the primary performance target, while pursuing legitimate tax optimization strategies that minimise the effective rate without aggressive avoidance that could attract regulatory scrutiny.

The positive effect of **firm size** on ROA confirms the value of scale economies in this capital-intensive industry. Managers of growing firms should seek to exploit operational efficiencies, bargaining power, and resource access that accompany larger size. However, they must remain vigilant against organizational rigidity and bureaucratic delays that can erode the benefits of scale over time.

The strong negative short-term impact of **R&D intensity** on ROA underscores the need to frame innovation spending as a long-term investment rather than a short-term profit driver. This creates a timing trade-off problem in performance metrics: managers evaluated on current-period ROA may underinvest in R&D, compromising future competitiveness. Boards and compensation committees should therefore adjust incentive systems to incorporate multi-period value creation, using metrics that recognize innovation as a strategic asset rather than a period expense.

The negative relationship between leverage and ROA indicates that excessive reliance on debt financing can reduce overall profitability. While moderate leverage supports growth through financial flexibility, higher debt levels amplify exposure to interest rate risks and constrain future investment capacity.

From a managerial perspective, these findings suggest that **value creation in the automotive sector requires a balance between innovation spending and financial discipline**. Profitability persistence, the degree to which above-average returns are sustained over time, interacts significantly with cyclical exposure. Firms with strong operational efficiency (high inventory turnover) and prudent leverage are better positioned to maintain profitability through industry downturns.

From a strategic standpoint, the results underline the importance of integrating financial efficiency with innovation strategies. Policymakers and financial institutions can also benefit from these insights by designing incentive mechanisms that encourage efficient investment behaviour and sustainable capital allocation within the automotive ecosystem.

Our findings are robust across national contexts, though policy implications may vary between the emerging economies like India, where capital constraints are more acute, operational efficiency particularly in inventory and asset turnover should be prioritised to maximise limited resources, while in advanced economies like USA, where innovation ecosystems are mature, sustained R&D investment supported by policy incentives remains critical for long-term competitiveness, especially in electric and autonomous vehicle segments.

Methodological Contributions

The application of a winsorized panel model with Driscoll-Kraay standard errors over the 2010-2024 period ensures robustness against outliers, heteroskedasticity, autocorrelation, and cross-sectional dependence. This approach prevented Type I errors and provided reliable inference in a globally interconnected sector. The inclusion of System GMM estimation with comprehensive diagnostic testing (Hansen J-test p = 1.000, AR(2) p = 0.992) addresses endogeneity concerns while acknowledging the limitations of dynamic panel methods with our panel dimensions (N=192, T=15) and the high instrument count requiring cautious interpretation. This rigorous approach demonstrates that our findings are robust across multiple estimation strategies

Accounting Limitations Acknowledgment

This study relies on accounting-based ROA as a measure of profitability, which introduces several inherent limitations that should inform the interpretation of the results. First, ROA reflects period-based accounting income and may not fully capture the intertemporal nature of capital-intensive investments, particularly R&D and long-lived assets, where economic benefits accrue over multiple periods. Second, cross-country differences in accounting standards and capitalization policies, especially regarding intangible assets and R&D treatment, may affect comparability across the 38 countries in our sample. Third, total assets are measured at book value rather than at economic or market value, potentially leading to a divergence between accounting profitability and economic return on capital. Fourth, as noted in the methodology, ROA is a composite indicator that captures both operating efficiency and financing structure, meaning that variations across firms may reflect differences in both operational productivity and the cost of capital. Future research could complement this analysis with market-based performance measures or economic value-added metrics that better capture long-term value creation.

Future Research Directions

Integration of ESG or green investment variables, which are becoming increasingly relevant for automotive, and a differentiated analysis between traditional manufacturers and EV makers, where the dynamics of R&D and profitability are completely different. Additionally, future studies could explore non-linear threshold effects in greater depth using longer time series, examine the role of digital transformation and Industry 4.0 capabilities, and investigate how supply chain resilience investments affect profitability dynamics during disruption periods.

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Appendix A: Correlation Matrix

	Return_on_Assets	Leverage	firm size	Sales Growth	CapEx_to_Assets	R&D/Assets	Return_on_Sales	Interest_Coverage	Working_Capital_to_Assets	Inventory_Turnover	Effective_Tax_Rate	R&D_Intensity
Return_on_Assets	1.0000											
Leverage	-0.2217	1.0000										
firm size	0.3059	-0.1031	1.0000									
Sales Growth	0.1825	-0.0314	0.4267	1.0000								
CapEx_to_Assets	-0.1657	0.1286	-0.0838	0.0371	1.0000							
R&D/Assets	-0.4809	0.2283	-0.3567	-0.1728	0.2328	1.0000						
Return_on_Sales	0.1702	-0.2012	0.1008	0.0784	-0.0013	-0.1253	1.0000					
Interest_Coverage	0.0685	-0.0099	0.1285	0.0527	0.0140	-0.0969	0.1498	1.0000				
Working_Capital_to_Assets	0.2692	-0.5367	0.1813	0.0706	-0.2363	-0.3281	0.1846	-0.0034	1.0000			
Inventory_Turnover	-0.0288	0.0058	-0.0086	0.0031	-0.0256	0.0119	-0.1522	0.0605	-0.0103	1.0000		
Effective_Tax_Rate	0.0470	0.0134	0.0256	0.0084	-0.0327	-0.0325	0.0007	0.0042	0.0274	0.0396	1.0000	
R&D_Intensity	-0.1767	-0.0120	-0.0288	-0.0755	-0.0078	0.1672	-0.2528	-0.0397	0.0135	0.0853	-0.0099	1.0000

Source: Authors' elaboration.

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Appendix A: System GMM Robustness Check

Note on GMM Interpretation: The following system GMM estimates are presented as illustrative robustness checks complementary to the primary fixed-effects specification. Given the moderate panel dimensions (N=192, T=15) and the high instrument count (589 instruments) typical in system GMM applications, these results should be interpreted with appropriate caution. The high instrument count relative to the cross-sectional dimension requires cautious interpretation of the Hansen test results. The lack of statistical significance across coefficients reflects the estimator's higher variance under these conditions rather than invalid identification. The Hansen test p-value of 1.000, while supporting instrument validity in principle, may also indicate instrument proliferation, a well-documented phenomenon in dynamic panel estimation (Roodman, 2009). The fixed-effects model with Driscoll-Kraay standard errors remains our primary source of inference.

Return_On_Assets	Coefficient	Corrected std. err.	z	P>|z|
leverage	-0.1376	2.6826	-0.05	0.959
firmsize	7.2096	211.8927	0.03	0.973
salesgrowth	0.3705	20.0190	0.02	0.985
capex_to_assets	-33.7698	1415.402	-0.02	0.981
rdassets	-133.5725	755.3356	-0.18	0.860
Return_on_sales	0.0035	0.1305	0.03	0.978
interest_coverage	0.0001	0.0093	0.01	0.995
working_capital_to_assets	0.2105	134.3597	0.00	0.999
inventory_turnover	0.0009	0.0245	0.04	0.971
effective_tax_rate	0.3243	316.7572	0.00	0.999
rd_intensity	-0.0583	2.5380	-0.02	0.982
_cons	-11.4005	527.3987	-0.02	0.983

Source: Authors' elaboration.

Model Statistics:

Number of observations: 2,880, Number of groups (firms): 192, Time periods (years): 15 (2010-2024), Number of instruments: 589,

Wald $\chi^2(11)$: 44.47 (p = 0.000), Observations per group: min=15, avg=15.00, max=15

GMM Diagnostic Tests

Test	Statistic	p-value	Interpretation
Arellano-Bond AR(1) Test	z = -0.26	0.791	No first-order autocorrelation in first differences
Arellano-Bond AR(2) Test	z = 0.01	0.992	No second-order autocorrelation in first differences
Sargan Test	$\chi^2(577)$ = 2585.97	0.000	Overidentifying restrictions (sensitive to heteroskedasticity)
Hansen J-Test	$\chi^2(577)$ = 204.38	1.000	Valid instruments (robust to heteroskedasticity)

Source: Authors' elaboration.

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Difference-in-Hansen Tests of Exogeneity

Instrument Subset	Hansen χ²	p-value	Difference χ²	p-value
GMM instruments for levels	χ²(421) = 190.32	1.000	χ²(156) = 14.06	1.000

Source: Authors' elaboration.

Instrumentation Details

Instrument Type	Equation	Description
GMM-type instruments	First differences	Lags 2-4 of all independent variables
Standard instruments	Levels	Constant term
GMM-type instruments	Levels	First differences of all independent variables
Total instruments	589	For 192 groups (firms)

Source: Authors' elaboration, using Stata SE18.5 two-step System GMM estimation.

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