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*Research article*

# Econometric analysis of supply chain disruptions: financial performance in the European automotive sector

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**Abstract:** We investigated the relationship between supply chain disruptions (SCD) and the financial performance (FP) of European automotive companies across emerging and developed nations. Addressing gaps in the literature, it offers a comprehensive, industry-specific analysis using panel data from 73 automotive firms across 21 European countries from 2013 to 2022. We examined the impact of SCD on return on assets (ROA), return on equity (ROE), and stock returns (SR), while controlling for factors such as age, leverage, size, economic growth, inflation, and unemployment. Our findings revealed that disruptions related to industrial materials and iron prices (IRAW) positively influence stock market performance, with a 99.5% increase in SR per 1% rise in IRAW, suggesting increased demand. Conversely, precious metal prices negatively affected all financial metrics, reducing ROE by 17.3% and SR by 55.5% per 1% increase. Heightened shipping costs showed varied impacts on ROA and ROE but contributed to a 12.9% average increase in SR, indicating effective cost transfer to consumers. The pandemic years significantly decreased ROA, ROE, and SR, highlighting challenges faced by the automotive sector. Rising oil prices showed no significant association, underscoring the importance of hedging strategies. The control variable outcomes emphasize the need for detailed evaluation in assessing financial performance. This study's contribution lies in its detailed analysis of specific disruptions within the automotive industry and their distinct impacts on financial performance metrics, providing a nuanced understanding that addresses significant gaps in the existing literature.

**Keywords:** supply chain disruptions; financial performance; automotive sector; developed; emerging; oil prices; industrial materials and iron; shipping costs

## 1. Introduction

In today's globalized and fiercely competitive business environment, the effective and efficient management of supply chains (SCs) has become a critical priority for organizations worldwide. The concept of SCs has gained significant traction across both emerging and developed nations and is recognized for its adaptability across various industries. As companies strive to reduce costs, many have turned to outsourcing essential raw materials and offshoring manufacturing activities to low-cost countries. This trend, however, has increased the vulnerability of SCs, heightening the risk of disruptions. Consequently, identifying and mitigating the impact of these disruptions on organizational performance has become a matter of utmost importance.

As a commonly accepted definition, SCD refer to unforeseen and unanticipated events that disrupt the normal flow of goods and materials within a SC and, as a result, expose companies within the SC to operational and financial risks. Disruptions can be regular or irregular, short-term or long-term, and can result in either significant or insignificant problems for the affected company. There is considerable literature that labels and examines the reasons for disruptions in SCs [1,2], with the majority of the studies grouping them into two main categories: Natural disasters and human factors. Natural disasters refer to catastrophic events that are believed to have a low probability of occurrence but have a high impact on SCs and encompass pandemics, earthquakes, tsunamis, floods, bushfires, hurricanes, droughts, and heatwaves. Human factors can be classified as either intentional or inadvertent behaviors. Intentional disruption can arise from vendors choose to use inferior quality materials or fail to deliver goods to increase their price. They also include targeted strikes, port closures, and attempts by rivals or terrorists to interrupt the flow of goods in a company's SC. Inadvertent disruptions include economic and financial crises, political instability, quality problems due to poor quality control, fires or accidents, and supplier bankruptcy, among others. More particularly, supply bottlenecks have emerged as a significant disruption in recent times, with their impact magnified by the disruptive consequences of the COVID-19 pandemic on businesses' supply chains. These bottlenecks have triggered inflationary pressures, particularly evident by the unprecedented surge in international shipping costs and the escalating prices of essential input materials. These challenges arose from congested logistical systems, shortages in labor and materials, a consequence of prolonged lockdowns, and shifts in consumer spending [3].

The repercussions of these disruptions are manifold, significantly impacting firms' profitability and operational effectiveness in various ways. First, these disruptions often force companies to seek materials or components from alternative, often more costly sources, thereby increasing procurement expenses and potentially reducing profit margins if cost increases cannot be passed on to customers. Second, disruptions frequently cause production delays and downtime by disrupting the steady flow of essential materials and components needed for manufacturing. These delays disrupt production schedules and decrease output and sales revenue, negatively impacting overall profitability [4]. Managing these disruptions also introduces operational complexities, necessitating resource allocation to mitigate impacts through alternative sourcing or logistical rerouting, which in turn increases operational costs and reduces efficiency. Financial instability arising from prolonged disruptions compounds these challenges, straining resources and potentially limiting future growth prospects. These disruptions manifest as detrimental impacts on short-term and long-term financial performance, often resulting in decreased sales, market share erosion from inventory markdowns, and missed business opportunities due to supply shortages [2].

While numerous researchers have investigated how SCD affects company performance, they have shown certain limitations. Some of these studies included a wide range of companies operating across various industries, which limited their ability to deliver specific insights into firms operating sectors within specific geographic areas. Other studies took a broad approach, encompassing all disruption announcements that emerged during the period under examination, which hindered a thorough understanding of the overall research landscape. This situation highlights the need for a more balanced approach to ensure a holistic and nuanced exploration of the impact of SCD on the FP of companies operating within the same industry. Thus, we attempt to address the question: Is there a relationship between supply chain disruptions and the financial performance of the automotive sector in Europe?

To address this research question, we employ panel data drawn from a sample of 73 automotive companies operating across 21 emerging and developed nations in Europe, spanning the period from 2013 to 2022. The FP is assessed through three primary metrics: ROA, ROE, and SR. The selected set of SCD encompasses the fluctuation in the price of raw materials, assessed through the S&P GSCI Industrial Metals & Iron Ore Index and the S&P GSCI Precious Metals, Platinum & Palladium Index, as well as energy prices, measured using West Texas Intermediate, and shipping costs, assessed by the Baltic Dry Index. Additionally, this paper considers the impact of the coronavirus pandemic, recognizing it as a global event with far-reaching consequences on supply chains worldwide. This study employs feasible generalized least squares (GLS) and Random Effects with GLS Regression methodologies to address various econometric assumptions. To ensure robustness, outliers in the data were mitigated using winsorization. Pre-regression assumptions such as multicollinearity, serial correlation, and stationarity were tested using the Pearson correlation matrix, Wooldridge test, and Fisher-type unit-root test, respectively. Post-regression, heteroskedasticity was assessed using the Breusch-Pagan / Cook-Weisberg test, and the normality of residuals was tested with the Shapiro-Francia test. The Hausman test was utilized to determine the appropriate model between fixed effect (FE) and random effect (RE) models, ensuring the reliability and validity of the results. To provide a clearer focus and direction for the study, we propose the following hypotheses:

$H_1$: SCDs significantly and negatively affect the return on assets of automotive firms.

$H_2$: SCDs significantly and negatively impact the return on equity of automotive firms.

$H_3$: SCDs significantly and adversely affect the annual stock returns of automotive firms.

The choice of the automotive sector depends largely on this sector as being one of the most exposed to SCD. Trends within this sector such as outsourcing and globalization are much more prevalent than in other industries, exposing automotive firms to higher risks of SCD. This vulnerability arises from the complex nature of automotive SCs. A typical vehicle comprises approximately 20,000 distinct parts, and the absence or delayed delivery of even one part can halt the production and shipment of the entire vehicle. Additionally, the sector's SCs are characterized by multiple tiers of suppliers and the critical importance of effectively coordinating materials and information flow. Consequently, automotive companies have experienced recurring disruptions due to natural and human-made disasters over the past few decades. For instance, natural disasters such as earthquakes, hurricanes, and floods have disrupted supply chains by damaging production facilities, interrupting transportation routes, and causing shortages of critical components [2]. Human-made disasters like geopolitical conflicts, trade disputes, and economic sanctions have also impacted supply chains by restricting access to raw materials, increasing tariffs on imports, and disrupting global trade flows. Despite being the most susceptible sector to disruptions, comprehensive studies of how SCD impacts FP within the automotive industry are very limited.

The structure of this paper is as follows: in Section 2, we review pertinent literature on supply chain disruptions in the automotive sector. In Section 3, we detail the methodology, including the sample and variables selected. In Section 4, we present the empirical findings. Finally, we conclude the study by discussing the results and their implications in Section 5.

## 2. Literature review

Due to the increasing complexity and interdependence of modern SCs, the type and nature of uncertain events or the effect of any action have become very complex or even impossible to predict [5]. Firm survival in the modern business environment does not depend on companies and organizations competing against each other, instead, it revolves around one SC competing against another [6]. As a result, top executives who are focusing primarily on SCDs and their corresponding operational and financial risks [7] should not come as a surprise. Existing research has not only validated the costly nature of disruptions but has also added significant insight into measuring the impact of these disruptions on the financial and non-financial performance of companies. While these studies have greatly contributed to the literature in identifying and measuring the effects of disruptions, they have lacked industry-specific insights, leaving a gap in the knowledge regarding firms operating in specific sectors.

The automotive sector is widely recognized for its efforts to enhance its SC practices, driven by the complex and dynamic business environment in which companies operate [8]. The automotive sector operates in a unique, challenging business environment characterized by high competition, global supply chain dependencies, and stringent regulatory pressures. Globalization has intensified competition among automotive manufacturers and suppliers, leading to pressure to innovate, reduce costs, and improve efficiency throughout the supply chain [9]. Geopolitical uncertainties, such as trade disputes and tariffs, further contribute to volatility in supply chain operations by disrupting global trade flows and supply routes. Additionally, the sector is highly sensitive to economic cycles and fluctuations in commodity prices, particularly for raw materials like steel, aluminum, and petroleum products, which directly impact production costs and profitability [10]. These factors collectively necessitate robust and agile supply chain management to ensure resilience and efficiency in the face of ongoing challenges.

Researchers have primarily examined three key areas. First, there has been a concentrated effort to identify and assess the various types of disruptions and risks this sector confronts, methodically studying potential threats and challenges it faces. Second, the spotlight has been on evaluating the influence of supply chain management (SCM) practices on the overall performance and competitiveness of automotive companies. Last, research has consistently underscored the role of SC resilience. It has focused on strategies and practices that reinforce the sector's ability to withstand and mitigate the impact of disruptions, thereby ensuring its robustness and adaptability in the face of uncertainty [11,12]. However, these researchers have often overlooked the dimension of assessing the financial repercussions of disruptions, creating a gap in the automotive sector's literature.

In order to demonstrate whether SCD leads to lower operational and organizational performance, Bavarsad et al. [13] developed a questionnaire that was distributed to 300 managers and senior experts working in major Iranian car manufacturing companies. The results indicate that SCDs negatively and significantly affect organizational performance measured using a combination of finance, flexibility, responsiveness, and SC relationship factors. Filbeck et al. [14] explored the automotive stock movements from disruptions under several market cycles and firm domicile for three American companies and two Japanese. They used 408 announcements of disruptions revolving around supplier breakdown, design issues, production delays, inventory shortfall, poor planning, inaccurate forecast, strikes, transportation delays, accidents, data breaches, fire, earthquake, and ethical complaints between 1990 and 2010. The event study showed negative and significant cumulative abnormal returns for the whole sample, with more negative returns during bear markets. Pal and Mitra [15] explored the co-movement between returns of major stock market indices in the automotive sector and oil prices using wavelet coherent analysis. Daily price series from 1996 to 2017 were used, and the results indicated that the co-movement between oil price and automobile stock return is strong during the years 2000 to 2002 and 2006 to 2009. Wen et al. [16] provided a comprehensive analysis of COVID-19 impacts on China's electric vehicle industry. The results indicated that the coronavirus outbreak has reduced electric vehicle sales in the short term, interrupted material supplies, and disrupted production and operations. A case study approach was conducted by Eldem et al. [17] and a questionnaire was distributed to 174 participants working in the automotive sector in Turkey. The results showed that disruptions such as shortage of raw materials and spare parts, availability of transportation, availability of labor, and demand fluctuations among others, had a significant impact on the Turkish automotive industry, causing loss in earnings and losses in production. Sudan and Taggar [18] also attempted to analyze the impact of COVID-19-induced SCD on the Indian automotive industry using a case study of Maruti Suzuki India Limited. The results indicated that the company is unlikely to achieve its financial targets for 2021−2022 due to a fall in production and sales caused by the pandemic-induced lockdowns. Frieske and Stieler [19] used quantitative market analysis to depict the effects of semiconductor shortages on the German automotive industry. The outcome showed that supply bottlenecks resulted in a drastic reduction in production volumes with the number of vehicles not produced because of the semiconductor crisis adding up to about 9.7 million light-duty vehicles in 2021 alone. Manley et al. [20] aimed to evaluate the impact of disruptions in mineral commodities used in the automotive and electronics industries, as the automotive SC depends on the electronics and semiconductor industries. After modeling disruptions for 56 mineral commodities, the results showed that disruptions in aluminum, magnesium metal, and platinum resulted in large declines in output for the automotive sample firms. More interestingly, the results showed that supply disruptions in mineral commodities that are generally considered semiconductor materials, such as gallium, can significantly impact the automotive sector.

The literature pertaining to the automotive sector displays several limitations. It predominantly centers on event-driven and case-study approaches, often neglecting the exploration of alternative empirical testing methods. Additionally, none of these studies was able to examine how SCD influences FP, utilizing comprehensive and representative financial indicators such as return on assets (ROA) and return on equity (ROE). This paper endeavors to address this gap by introducing a novel empirical approach that aims to quantify the impact of SCD on corporate financial performance. This will be achieved through multivariate regression analysis of panel data involving automotive firms operating in emerging and developing markets.

## 3. Data, variables and econometric models

### *3.1. Sample*

We examine the impact of supply chain disruptions on the financial performance of publicly traded automotive companies in Europe from 2013 to 2022. The sample includes all companies listed under the Automobiles & Auto Parts sector in Europe on Refinitiv Workspace, resulting in 162 initial constituents. Companies that issued an IPO on or after 2022 and those outside the Auto Components and Automobiles industries were excluded, narrowing the sample to 78. Further exclusions were made for companies lacking the required data, leading to a final sample of 73 companies. To account for differences between emerging and developed countries, the sample was divided into two sub-groups, consisting of 13 firms operating in 5 emerging countries and 60 firms in 16 developed countries based on IMF's classification (refer to Table A1 for the distribution of companies by country). The remaining data was sourced either from the london stock exchange group (LSEG)/Refinitiv, S&P Global or the World Bank database.

### *3.2. Variables*

#### 3.2.1. Financial performance

In line with previous studies, we adopted a comprehensive approach to evaluate firm financial performance. We employed two widely recognized accounting-based measures: ROA and ROE [21]. ROA is computed as earnings before interest and taxes divided by average total assets, providing insights into how efficiently a company utilizes its assets to generate earnings. ROE, on the other hand, measures profitability relative to shareholders' equity, calculated as earnings before interest and taxes divided by average total equity, indicating how effectively a company generates profits from shareholders' investments. Additionally, we included a market-value measure, specifically SR, to offer a comprehensive assessment of firm performance. SR is defined as the natural logarithm of the ratio of two consecutive stock prices, reflecting the percentage change in a company's stock price over a specific period. This metric is crucial for investors and analysts as it captures the overall financial health and market perception of a company, integrating both internal profitability metrics and external market sentiment. The comprehensive use of these metrics aligns with established literature [22,23] providing a robust framework to analyze and compare the financial performance of firms within the European automotive sector.

#### 3.2.2. The independent variables

The independent variables represent SCD and include increases in the prices of raw materials, energy prices, and shipping costs.

Industries closely tied to raw materials, like the automotive sector, are particularly vulnerable to price fluctuations in raw material supply [10]. To quantify this risk, we utilize the S&P GSCI industrial metals & iron ore equal weight index (IRAW) as a proxy. This index tracks industrial metal prices used in automobile production. Another variable, the S&P GSCI precious metals, platinum & palladium equal weight (PRAW), monitors the prices of precious metals utilized in catalytic processes within vehicle exhaust systems [24], making it an essential input for the automotive sector. The third variable is oil prices using the west texas intermediate (WTI) crude oil price, which is known to influence the European automotive sector's performance [25]. Last, to evaluate the influence of shipping costs, we employed the baltic dry index (BDI), a widely recognized indicator of global shipping costs [1]. Fluctuations in shipping costs can substantially affect SC operations, triggering reactions in stock markets due to both local and global SCD [26].

In addition, and in response to the coronavirus pandemic, we included a dummy variable, taking the value of one for the years 2020, 2021, and 2022, to account for the significant disruptions and consequences of the pandemic on the automotive sector [27]. The SCD faced during this period ranged from manufacturers not being able to rapidly bridge the gap between supply and demand due to the ongoing material shortages, to lockdowns, and shipping delays [28]. During this period, automakers saw their car sales plummeting to new lows, leading the manufacturers to cut production and cause significant losses [3].

**Table 1**. Summary of all variables with expected signs.

| Variable (Abbreviation) | Definition | Expected Sign | Source |
|---|---|---|---|
| Dependent Variables | | | |
| Return on Assets (ROA) | EBIT divided by average total assets | | Refinitiv |
| Return on Equity (ROE) | EBIT divided by average total equity | | Refinitiv |
| Stock Return (SR) | Ln ($P_t/P_{t-1}$) | | Refinitiv |
| Independent Variables | | | |
| Industrial Metals and Iron ($IRAW_t$) | S&P GSCI Industrial Metals & Iron Ore Equal Weight at time t | Negative | S&P Global |
| Precious Metals, Platinum and Palladium ($PRAW_t$) | S&P GSCI Precious Metals, Platinum & Palladium Equal Weight at time t | Negative | S&P Global |
| Oil ($OIL_t$) | The West Texas Intermediate at time t | Negative | Refinitiv |
| Baltic Dry Index ($BDI_t$) | The Baltic Dry Index at time t | Negative | Refinitiv |
| Covid (COV) | Dummy variable with a value of 1 if the year is pandemic, 0 otherwise. | Negative | |
| Firm-Specific Control Variables | | | |
| Age ($AGE_{i,t}$) | One plus the difference between the year t and the IPO date of company i | Positive | Refinitiv |
| Size ($SIZE_{i,t}$) | The natural logarithm of total assets of company i at time t | Positive | Refinitiv |
| Leverage ($LEV_{i,t}$) | Total debt divided by total assets for company i at time t | Negative | Refinitiv |
| Country-Specific Control Variables | | | |
| GDP Growth ($GDPG_{j,t}$) | Annual percentage rate of GDP at market prices of country j at time t | Positive | World Bank |
| Inflation ($CPI_{j,t}$) | The annual percentage change in consumer prices of country j at time t | Negative | World Bank |
| Unemployment ($UNEMP_{j,t}$) | Unemployment of country j at time t | Negative | World Bank |

### 3.2.3. The control variables

We incorporated four control variables, categorized into firm-specific and country-specific factors. Firm-specific variables included firm age, size, and leverage, widely utilized in previous studies dealing with SC and the automotive sector [21].

Firm age, defined as one plus the time difference between the year under investigation and the IPO date [29], is expected to positively impact FP and SCM practices. Size, measured as the natural logarithm of total assets, is also expected to positively affect SCM [30] and FP of the automotive sector [21]. Leverage, defined as total liabilities divided by total assets [31], was included to assess its impact on financial performance. While agency theory predicts that higher leverage may exacerbate agency problems, potentially leading to decreased efficiency and negatively impacting FP [32], certain studies reported a positive effect on a company's earnings within the automotive sector [33]. Country-specific control variables encompass GDP growth (GDPG), inflation, and unemployment. GDPG plays a pivotal role in automobile demand and is expected to positively influence FP [34]. Inflation, measured as the annual percentage change in consumer prices, can affect production costs and, consequently, profits. Last, unemployment rates can have a negative impact on FP [35], as lower employment levels may lead to reduced consumer spending. Data for these country-specific control variables was extracted from the World Bank database. Table 1 contains a summary of all variables with their expected sign.

### *3.3. Econometric models*

To investigate the effect of SCD on the FP of the European automotive sector from 2013 to 2022, panel data was used with the following regression:

$$ROA_{i,t} = \alpha + \beta_1 IRAW_t + \beta_2 PRAW_t + \beta_3 OIL_t + \beta_4 BDI_t + \beta_5 COV + \beta_6 AGE_{i,t} + \beta_7 SIZE_{i,t} + \beta_8 LEV_{i,t} + \beta_9 GDPG_{j,t} + \beta_{10} CPI_{j,t} + \beta_{11} UNEMP_{j,t} + \varepsilon_i \quad (1.1)$$

$$ROE_{i,t} = \alpha + \beta_1 IRAW_t + \beta_2 PRAW_t + \beta_3 OIL_t + \beta_4 BDI_t + \beta_5 COV + \beta_6 AGE_{i,t} + \beta_7 SIZE_{i,t} + \beta_8 LEV_{i,t} + \beta_9 GDPG_{j,t} + \beta_{10} CPI_{j,t} + \beta_{11} UNEMP_{j,t} + \varepsilon_i \quad (1.2)$$

$$SR_{i,t} = \alpha + \beta_1 IRAW_t + \beta_2 PRAW_t + \beta_3 OIL_t + \beta_4 BDI_t + \beta_5 COV + \beta_6 AGE_{i,t} + \beta_7 SIZE_{i,t} + \beta_8 LEV_{i,t} + \beta_9 GDPG_{j,t} + \beta_{10} CPI_{j,t} + \beta_{11} UNEMP_{j,t} + \varepsilon_i \quad (1.3)$$

These equations aim to evaluate the effect of SCD on the FP of the automotive sector measured by ROA in Model 1.1, ROE in Model 1.2, and SR in Model 1.3 of company *i* in year *t*.

The main independent variables are IRAW, PRAW, OIL, BDI, and COV.

Firm-specific control variables are represented by AGE, SIZE, and LEV, while country-specific control variables are denoted by GDPC, CPI, and UNEMP.

$\alpha$ represents the constant, $\beta_1$–$\beta_{11}$ represents the coefficients of the independent and control variables, and $\varepsilon$ is the error term, *i* refers to firm, *t* to time, and *j* to the concerned country.

To ensure the robustness and reliability of our findings, we specifically addressed outliers present in our dataset by applying winsorization. Winsorization mitigates the impact of extreme values on statistical analyses, which assume normality or are sensitive to outliers, thereby making statistical tests and models more robust and less influenced by these extreme observations. By winsorizing our variables, we aimed to reduce the potential skewing effects of outliers on the analysis.

#### 3.3.1. Pre-regression CLRM assumptions

It is essential to find a set of assumptions that are both sufficiently specific and realistic to allow taking the best possible advantage of the data available. In this study, the assumptions are categorized into two distinct phases: pre-regression and post-regression.

The initial phase involves evaluating multicollinearity through the Pearson correlation matrix. The correlation coefficient r between two sequences x and y can be expressed as follows:

$$r(x,y) = \frac{cov(x,y)}{\sqrt{\sigma(x)\sigma(y)}} = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2(y_i-\bar{y})^2}} \quad (2)$$

where $\bar{x}$ and $\bar{y}$ are the mean values of the two sequences, and n is the number of samples of the sequences.

A second assumption to be tested is serial correlation. Various statistical tests can be employed to identify the presence of autocorrelation in a regression, but in this research, the Wooldridge test was used, as it was demonstrated to be useful for addressing the issue of serial correlation for both fixed-effect and random-effect [36] panel data models.

The Wooldridge test uses the residuals from a regression in first differences. By employing first differencing in the panel data regression model, this technique effectively removes the individual-level effect, the component linked to time-invariant covariates, and the constant term.

This transformation can be represented by the equation:

$$y_{it} - y_{it-1} = (X_{it} - X_{it-1})\beta_n + \varepsilon_{it} - \varepsilon_{it-1}$$

$$\Delta y_{it} = \Delta X_{it}\beta_i + \Delta\varepsilon_{it} \quad (3)$$

where $\Delta$ is the first difference operator.

Wooldridge's method starts with estimating the parameters $\beta$ by regressing $\Delta y_{it}$ on $\Delta X_{it}$, thereby obtaining the residuals $\Delta\varepsilon_{it}$. A key insight in this process is Wooldridge's observation that, under the assumption of no serial correlation in the residuals, the Corr ($\Delta\varepsilon_{it}$, $\Delta\varepsilon_{(it-1)}$) = −0.5. Given this, the procedure regresses the residuals $\varepsilon_{it}$ from the first-differenced regression on their lagged values and tests whether the coefficient on the lagged residuals equals −0.5.

Another assumption to be tested is stationarity. In this paper, the Fisher-type unit-root test, by removing cross-sectional means, is employed – and more specifically - the Im-Pesaran-Shin test (IPS). This is a statistical test for the presence of a unit root in a panel data set, where the data consist of multiple individuals or cross-sectional units observed over time [37].

The IPS test is expressed as follows:

$$\Delta\bar{y}_{i,t} = \bar{\alpha}_i + \beta_i\bar{y}_{i,t-1} + \sum_{j=1}^{w_i}\bar{\delta}_{j,i}\Delta\bar{y}_{i,t-j} + \bar{\varepsilon}_{i,t} \quad (4)$$

With $i, j$ = 1, 2, …, N and $t$ = 1, 2, …, T

where:

$$\bar{y}_{i,t} = y_{i,t} - \frac{1}{N}\sum_{i=1}^{N} y_{i,t}$$

$$\bar{\alpha}_i = \alpha_i - \frac{1}{N}\sum_{i=1}^{N} \alpha_i$$

$$\bar{\varepsilon}_{i,t} = \varepsilon_{i,t} - \frac{1}{N}\sum_{i=1}^{N} \varepsilon_{i,t}$$

$\Delta$ is the difference operator, $\beta$ and $\delta$ are the slope coefficients, $p$ is the lag length for lagged differences, and $\bar{\varepsilon}_{i,t}$ is assumed to be uncorrelated over time, and to be mutually uncorrelated across $i$.

The IPS examine the null hypothesis: $H_0$: $\beta_1 = \beta_2 = \cdots = \beta_N = 1$ vs. $H_a$: $\beta_i < 1$, for all $i$.

The next step is to define the t-statistic of $\widehat{\beta_\iota} = 0$ in (3) as $t_{iT}(w_i)$. The t-bar statistic is defined as follows:

$$\bar{z}_{1NT} = \frac{\sqrt{N}[\bar{t}_{NT} - a_{NT}]}{\sqrt{b_{NT}}} \tag{5}$$

where:

$$\bar{t}_{NT} = \frac{1}{N}\sum_{i=1}^{N} t_{iT}(w_i)$$

$$a_{NT} = \frac{1}{N}\sum_{i=1}^{N} E[t_{iT}(w_i)]$$

$$b_{NT} = \frac{1}{N}\sum_{i=1}^{N} V[t_{iT}(w_i)]$$

$E[t_{iT}(w_i)]$ and $V[t_{iT}(w_i)]$ are the mean and variance of $t_{iT}(w_i)$.

### 3.3.2. Choice of model

Before assessing the validity of the remaining CLRM assumptions, the appropriate regression model for the study needs to be determined. Two commonly used models for panel data analysis are the FE and RE regression models. The FE model assumes that the unobserved individual-specific effects are correlated with the explanatory variables, while the RE model assumes no correlation. The choice between FE and RE models is made using the Hausman test, which compares the estimated coefficients of both models to test for statistical significance. The null hypothesis suggests that the preferred model is RE, while the alternative hypothesis suggests FE as the preferred model.

Hausman statistic is calculated using the formula:

$$H = \left(\hat{\beta}^{FE} - \hat{\beta}^{RE}\right)'\left[Avar\left(\hat{\beta}^{FE}\right) - Avar\left(\hat{\beta}^{RE}\right)\right]^{-1}\left(\hat{\beta}^{FE} - \hat{\beta}^{RE}\right) \tag{6}$$

where: $\hat{\beta}^{RE}$ are the corresponding estimated coefficients from the RE model. $\hat{\beta}^{FE}$ are the coefficient estimates of the time-varying covariates from the FE model. $Avar\left(\hat{\beta}^{FE}\right)$ and $Avar\left(\hat{\beta}^{RE}\right)$ are estimators for the asymptotic covariance matrix of the FE and RE estimators respectively.

This test statistic has an asymptotic $\chi^2$distribution with $K$ degrees of freedom

### 3.3.3. Post-regression CLRM assumptions

Heteroskedasticity can have important implications for statistical inference and can lead to biased and inefficient estimates of regression coefficients, standard errors, and hypothesis tests. Therefore, detecting and correcting for heteroskedasticity is an important aspect of statistical analysis. The statistical test employed to identify and address heteroskedasticity in our regression models is the Breusch-Pagan / Cook-Weisberg test [38]. This test is based on the null hypothesis that the variance of the errors is homoscedastic and the alternative hypothesis that the variance of the errors is heteroscedastic.

Let us specify a simple random effect regression model with generalized least square estimators:

$$y_{it} = X_{it}'\beta + \alpha_i + \varepsilon_{it}$$

where $X'_{it}$ is the transpose of the vector of independent variables for individual $i$ at time $t$. β is the coefficient vector for the independent variables. $\alpha_i$ is the individual-specific random effect. $\varepsilon_{it}$ is the idiosyncratic error term.

Compute the residuals $\varepsilon_{it} = y_{it} - X'_{it}\hat{\beta} - \widehat{\alpha_i}$ and the squared residuals $\hat{\varepsilon}_{it}^2$ and then regress the squared residuals on the independent variables and their lagged values:

$$\hat{\varepsilon}_{it}^2 = \alpha_0 + \alpha_1 X_{1it} + \alpha_2 X_{2it} + \cdots + \beta_1 \hat{\varepsilon}_{1it-1} + \varepsilon_i \quad (7)$$

If the coefficient $\beta_1$ is statistically different from zero, it suggests the presence of heteroskedasticity in the model.

The normality of residuals is the final assumption to test in our regression analysis. When errors follow a normal distribution, the estimated regression coefficients also tend to be normally distributed, ensuring valid statistical inference [39]. Even if data deviate from perfect normality, regression analysis remains valid with mild deviations, provided they are appropriately addressed. The Shapiro-Francia (SF) test is employed in order to test for the normality of the residuals as it was found to outperform the other normality tests.

The Shapiro-Francia test is expressed as follows:

$$SF = \frac{\left[\sum_{i=1}^{n} m_i X_i\right]^2}{\sum_{i=1}^{n}(X_i - \bar{X})^2} \quad (8)$$

where: $m_i$ denotes a vector of standard normal ordered statistics, $X_i$ is the $i$th largest order statistic $\bar{X}$ is the sample mean.

Because the distribution of SF under the null hypothesis of normality is not known, Royston [40] demonstrated using simulation that (7) was approximately a standard normal distribution.

$$Z = \frac{(\log(1-SF) - \mu)}{\sigma} \quad (9)$$

where:

$$\mu = -1.2725 + 1.0521\,[\log\log n - \log n]$$

$$\sigma = -0.26758\,[\log\log n + \frac{2}{\log n}] + 1.0308 \ \text{ for } \ 5 \le n \le 5000$$

Using Z, properties of the SF test could be studied in detail.

## 4. Results

### 4.1. *Descriptive statistics*

Tables 2 and 3 display the descriptive statistics of variables across both emerging and developed countries. Throughout the entire study period, a consistent pattern emerges in the means and medians of the three dependent variables (SR, ROA, and ROE). Despite the lower performance observed in emerging countries compared to developed ones, the t-test results indicate no significant difference between the two groups for SR and ROA. Consequently, we merged the data into a unified dataset encompassing firms operating in both emerging and developed countries.

**Table 2.** Descriptive statistics of the dependent variables.

| | Dependent Variables | | | | | |
|---|---|---|---|---|---|---|
| | Emerging | | | Developed | | |
| | SR | ROA | ROE | SR | ROA | ROE |
| Mean | −5.90% | 5.20% | 9.79% | −2.10% | 5.99% | 15.58% |
| St. Dev | 49.42% | 9.63% | 27.63% | 44.96% | 5.41% | 19.92% |
| Median | −4.86% | 4.02% | 9.07% | −1.62% | 6.21% | 17.09% |
| Min | −163.21% | −12.02% | −71.46% | −163.21% | −12.02% | −71.46% |
| Max | 164.17% | 27.98% | 58.90% | 164.17% | 19.56% | 58.90% |
| Skewness | 0.05 | 0.87 | (1.00) | (0.11) | (0.51) | (0.94) |
| Kurtosis | 2.01 | 0.66 | 2.02 | 1.11 | 0.52 | 1.97 |

**Table 3.** Descriptive statistics of the independent variables.

| | Independent Variables | | | |
|---|---|---|---|---|
| | BDI | PRAW | IRAW | OIL |
| Mean | 7.62% | 2.59% | 5.63% | 0.18% |
| St. Dev | 58.06% | 16.72% | 18.25% | 32.38% |
| Median | 22.57% | 4.02% | 11.68% | 7.26% |
| Min | −106.88% | −21.69% | −29.45% | −60.85% |
| Max | 118.10% | 26.02% | 29.89% | 44.36% |
| Skewness | (0.08) | 0.01 | −0.54 | −0.31 |
| Kurtosis | 2.65 | 1.63 | 2.09 | 1.95 |

### *4.2. Diagnostic tests*

We assess multicollinearity using the Pearson correlation matrix. In accordance with the criteria provided by [41], the correlation coefficients (Table 4) falling within the range of −0.8 to +0.8 indicate the absence of multicollinearity. Also, the Im-Pesaran-Shin test (Table 5) confirms the stationarity of all variables (p-value of 0.000 for all the variables).

The Hausman test presented in Table 6, whose primary purpose is to compare whether the coefficients estimated through a fixed effects model or a random effects model are consistent and efficient, reveals that the Random Effect regression model is suitable for all three models, with p-values exceeding 0.1 in all cases.

Models 1.1 and 1.2 exhibit significant first-order serial correlations at 5% and 1% levels, respectively (with p-values of 0.0333 and 0.0003), while Model 1.3 does not (p-value above 0.1). Additionally, both Models 1.1 and 1.2 indicate the presence of heteroskedasticity (p-value of 0.000), whereas Model 1.3 demonstrates homoscedastic residuals (p-value of 0.152).

Since Models 1.1 and 1.2 indicate the presence of autocorrelation and heteroskedasticity within the random effect framework, and following Wooldridge's recommendation [42], feasible generalized least squares (FGLS) is used to address these issues. FGLS is specifically designed to correct for heteroskedasticity and autocorrelation, simultaneously by transforming the data to rectify unequal variance by giving more weight to observations with smaller variances and less weight to observations with larger variances and adjusting the covariance structure of error terms, effectively accounting for the correlation between errors in a manner that appropriately incorporates this relationship into the estimation process. Conversely, Model 1.3 showed no evidence of autocorrelation and exhibited homoscedasticity, thus confirming the appropriateness of random effect with generalized least squares (GLS) for this specific model. This approach ensures robust estimation and enhances the reliability of our regression results by accounting for varying error structures across different models.

**Table 4.** Pearson correlation Matrix.

| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) BDI | 1.000 | | | | | | | | | | |
| (2) PRAW | 0.042 | 0.042 | | | | | | | | | |
| (3) IRAW | 0.630 | 0.630 | 0.630 | | | | | | | | |
| (4) OIL | 0.648 | 0.648 | 0.648 | 0.648 | | | | | | | |
| (5) COV | 0.045 | 0.045 | 0.045 | 0.045 | 0.045 | | | | | | |
| (6) AGE | −0.012 | −0.012 | −0.012 | −0.012 | −0.012 | −0.012 | | | | | |
| (7) LEV | 0.010 | 0.010 | 0.010 | 0.010 | 0.010 | 0.010 | 0.010 | | | | |
| (8) SIZE | 0.006 | 0.006 | 0.006 | 0.006 | 0.006 | 0.006 | 0.006 | 0.006 | | | |
| (9) GDPG | −0.058 | −0.058 | −0.058 | −0.058 | −0.058 | −0.058 | −0.058 | −0.058 | −0.058 | | |
| (10) CPI | −0.152 | −0.152 | −0.152 | −0.152 | −0.152 | −0.152 | −0.152 | −0.152 | −0.152 | −0.152 | |
| (11) UNEMP | 0.037 | 0.037 | 0.037 | 0.037 | 0.037 | 0.037 | 0.037 | 0.037 | 0.037 | 0.037 | 1.007 |

**Table 5.** Stationarity results.

| Variable | Coeff | P-value |
|---|---|---|
| SR | 872.575 | 0.000*** |
| ROE | 277.181 | 0.000*** |
| ROA | 261.865 | 0.000*** |
| BDI | 863.033 | 0.000*** |
| PRAW | 338.948 | 0.000*** |
| IRAW | 426.813 | 0.000*** |
| OIL | 699.201 | 0.000*** |
| AGE | 911.196 | 0.000*** |
| LEV | 333.722 | 0.000*** |
| SIZE | 241.237 | 0.000*** |
| GDPG | 565.427 | 0.000*** |
| CPI | 272.011 | 0.000*** |
| UNEMP | 258.637 | 0.000*** |

**Table 6.** Diagnostic tests.

| Variables | Model 1.1<br>ROA | | Model 1.2<br>ROE | | Model 1.3<br>SR | |
|---|---|---|---|---|---|---|
| | Coeff | p-value | Coeff | p-value | Coeff | p-value |
| Hausman | 13.119 | 0.280 | 4.975 | 0.932 | 16.117 | 0.137 |
| Wooldridge Test | 4.710 | 0.0333** | 15.084 | 0.0002*** | 0.513 | 0.4761 |
| Breusch and Pagan Lagrangian Multiplier | 623.36 | 0.000*** | 396.11 | 0.000*** | 1.05 | 0.152 |
| Results | Random Effect with autocorrelation and heteroskedasticity | | Random Effect with autocorrelation and heteroskedasticity | | Random Effect with no autocorrelation and homoscedasticity | |
| Regression Used | Feasible GLS with heteroskedastic error structure and an AR (1) autocorrelation | | Feasible GLS with heteroskedastic error structure and an AR (1) autocorrelation | | Random Effect with GLS Regression | |

*Note: *, **, and *** denote significance levels of 10%, 5%, and 1%, respectively.*

### *4.3. Regression results*

Table 7 displays the results of the regression analysis, presenting the effects of SCD on the FP of companies.

**Table 7.** Regressions' results.

| Variables | Model 1.1<br>ROA | | Model 1.2<br>ROE | | Model 1.3<br>SR | |
|---|---|---|---|---|---|---|
| | Coefficients | p−value | Coefficients | p−value | Coefficients | p−value |
| IRAW | 0.062 | 0.000*** | 0.134 | 0.000*** | 0.995 | 0.000*** |
| PRAW | −0.067 | 0.000*** | −0.173 | 0.000*** | −0.555 | 0.004*** |
| OIL | −0.004 | 0.314 | 0.001 | 0.932 | −0.069 | 0.502 |
| BDI | −0.007 | 0.003*** | −0.027 | 0.000*** | 0.129 | 0.021** |
| COV | −0.037 | 0.000*** | −0.081 | 0.000*** | −0.197 | 0.000*** |
| AGE | 0.000 | 0.032** | −0.001 | 0.003*** | −0.002 | 0.319 |
| LEV | −0.074 | 0.000*** | −0.12 | 0.000*** | −0.100 | 0.261 |
| SIZE | 0.018 | 0.000*** | 0.066 | 0.000*** | 0.028 | 0.085* |
| GDPG | 0.012 | 0.723 | 0.155 | 0.075* | −0.889 | 0.196 |
| CPI | 0.121 | 0.002*** | 0.230 | 0.020** | −0.113 | 0.865 |
| UNEMP | −0.279 | 0.000*** | −0.060 | 0.711 | 0.439 | 0.425 |
| CONSTANT | −0.056 | 0.009*** | −0.372 | 0.000*** | −0.216 | 0.162 |
| R−square | 0.1972 | | 0.1952 | | 0.1877 | |
| N | 662 | | 662 | | 662 | |

*Note: *, **, and *** denote significance levels of 10%, 5%, and 1%, respectively.*

Our aim of this study is to examine the impact of supply chain disruptions on the financial performance of automotive firms, specifically focusing on return on assets, return on equity, and annual stock returns. The hypotheses tested are:

$H_1$: SCDs negatively affect the return on assets of automotive firms.

$H_2$: SCDs negatively impact the return on equity of automotive firms.

$H_3$: SCDs adversely affect the annual stock returns of automotive firms.

In all three models, the selected independent variables representing SCD exhibit statistical significance, except for OIL. Notably, a 1% increase in IRAW results in average increases of 6.2% in ROA, 13.4% ROE, and 99.5% in SR. Conversely, a 1% rise in PRAW is associated with average decreases of 6.7% in ROA, 17.3% in ROE, and 55.5% in SR. A 1% increase in shipping costs, represented by BDI leads to average decreases of 0.7% in ROA and 2.7% in ROE, while yielding an average increase in SR of 12.9%. The dummy variable for COVID-19 (COV) suggests that during pandemic years, there were average decreases of 3.7% in ROA, 8.1% in ROE, and 19.7% in SR. These results underscore the significant role of SCD in influencing the financial performance of the European automotive sector. Regarding control variables, firm-based and country-level factors do not significantly impact SR, though they are significant predictors for changes in ROA (excluding GDP growth) and ROE (excluding unemployment rates). While our findings indicate a notable relationship between SCD and the financial performance of European automotive companies in both emerging and developed nations, the specifics of this relationship vary across different variables, as detailed in Table 6.

Based on these findings, the hypotheses are evaluated as follows:

H1: Rejected for IRAW and OIL, as the former records a significant positive relationship and the latter has no significant relationship with ROA. Not rejected for PRAW, BDI, and COV, as they negatively and significantly affect ROA.

H2: Rejected for IRAW and OIL, as they do not negatively impact ROE. Not rejected for PRAW, BDI, and COV, as they negatively impact ROE.

H3: Rejected for IRAW, OIL, and BDI, as they do not adversely affect SR. Not rejected for PRAW and COV, as they adversely affect SR.

Please refer to Table 8 for a comprehensive summary of the hypotheses' results for all supply chain disruptions evaluated in this study.

**Table 8.** Summary of findings.

| | Accounting-based | | Market-based |
|---|---|---|---|
| Variable | ROA | ROE | SR |
| IRAW | Positive | Positive | Positive |
| | Reject $H_1$ | Reject $H_2$ | Reject $H_3$ |
| PRAW | Negative | Negative | Negative |
| | Do not Reject $H_1$ | Do not Reject $H_2$ | Do not Reject $H_3$ |
| BDI | Negative | Negative | Positive |
| | Do not Reject $H_1$ | Do not Reject $H_2$ | Reject $H_3$ |
| OIL | None | None | None |
| | Reject $H_1$ | Reject $H_2$ | Reject $H_3$ |
| COV | Negative | Negative | Negative |
| | Do not Reject $H_1$ | Do not Reject $H_2$ | Do not Reject $H_3$ |

### 4.4. Discussion

In line with our hypotheses, the findings reveal a negative impact of supply chain disruptions on the financial performance of European automotive firms. As expected, disruptions related to PRAW exhibit a consistent adverse effect across all financial metrics. The results align with the initial premise of this paper, indicating that increases in PRAW lead to significant decreases in both ROA and ROE, as well as substantial declines in stock returns, which is in line with the findings of Manley et al. [48]. Contrary to expectations, disruptions associated with IRAW demonstrated unexpected positive relationships with FP metrics. Our results suggest that higher IRAW positively influence ROA, ROE, and SR. This outcome may appear counterintuitive; however, it aligns with narratives presented in financial news media, which underscore the significance of industrial metal returns as crucial leading indicators for both the economy and equity markets. The ascent in industrial metals prices could signify heightened demand propelled by economic growth. In such scenarios, an increased demand for industrial metals may indicate a thriving manufacturing sector, positively influencing the revenue and profitability of automotive companies. Paradoxically, while elevated metal prices could increase production costs, they might positively impact financial indicators if the surge in demand results in higher sales volume. This, in turn, enables automotive companies to distribute fixed costs over a larger output, potentially enhancing their financial performance by leveraging economies of scale. The ability to transfer increased material costs to consumers through higher prices may help maintain or improve profit margins, supporting positive financial metrics. Our findings align with existing literature, as demonstrated by Sockin and Xiong [43]. The BDI, a key indicator of shipping costs that reflects the demand for raw materials and indicates trends in global industrial production, demonstrates a positive impact on accounting-based financial metrics but has a negative influence on stock returns within our selected sample, which is in line with our third hypothesis only. This indicates increased demand for raw materials, leading to capacity constraints and subsequently impacting accounting performance negatively. The positive relationship between the BDI and SR can be rationalized by the BDI’s role in predicting future economic activity and growth potential for industries. This fosters positive expectations among investors, thereby driving stock prices upward. This upward trend reflects optimism regarding future growth and profitability despite short-term cost pressures. Our findings are consistent with previous research suggesting that higher shipping charges positively affect stock returns. Results observed during the coronavirus pandemic showcased a detrimental effect on the FP of companies in the European automotive industry. The spread of COVID-19 imposed social and personal restrictions, negatively affecting company revenues and contributing to a decline in the financial performance of the companies. Specifically, our results are in line with El Baz and Ruel [44] and Devi et al. [45]. Conversely, disruptions linked to rising OIL does not exhibit significant associations with FP metrics. This differs from the conclusions drawn by Park and Ratti [46] and Arouri and Nguyen [47] who observed that fluctuations in oil prices had a negative impact on stock returns within the European automobile industry. However, our results align with the findings of Pal and Mitra [15] who noted an insignificant correlation between oil prices and stock returns in the automotive sector. The absence of a direct impact of oil price disruptions on the FP of automotive companies can be attributed to several offsetting factors. On a microeconomic level, an increase in oil prices typically affects equity returns by raising input costs and production expenses, leading to reduced profits and, subsequently, lower stock returns. Conversely, from a macroeconomic perspective, fluctuations in oil prices might indicate a flourishing economy, correlating with increased consumer demand, thereby fostering a positive relationship between oil prices and stock returns. Moreover, automotive companies often employ hedging strategies against oil price fluctuations. These strategies involve adjusting vehicle prices without impacting consumer demand, maintaining profit margins, and establishing long-term contracts with fuel providers to shield themselves from short-term oil price fluctuations. Examining control variables, age exhibits mixed effects on FP. The positive effect on ROA suggests that older firms exhibit superior financial performance due to accumulated experience and the advantages of "learning by doing". Conversely, the negative impact on ROE indicates that aging may negatively affect FP due to "inertia effects", resulting in inflexibility and challenges in adapting to a rapidly changing business environment. Leverage consistently exerted a negative impact on FP, aligning with findings in various studies. The positive influence of company size on all FP measures also aligns with the findings of Dahlan et al. and Tinoco and Wilson [48,49]. Larger companies benefit from economies of scale, leading to higher profit margins and enhanced financial performance. Additionally, their broader range of products or services helps them manage risks effectively and sustain growth during economic downturns. The larger market influence of these companies often facilitates more favorable negotiations with suppliers and customers, resulting in higher profit margins and improved overall performance. Country-level variables such as GDP Growth showed nuanced impacts, with no significant impact on ROA and SR and a significant impact on ROE only at a 10% significance level. This suggests that the performance of the European automotive sector is not significantly tied to the economic conditions in these countries, contradicting Patra and Rao [34]. The unexpected positive impact of inflation on financial performance contrasts with the usual expectation that inflation erodes consumer purchasing power, increases production costs, and leads to higher interest rates—factors negatively impacting firms in the automotive sector [50]. The positive impact might indicate anticipated inflation, high demand, and pricing power, enabling automotive companies to timely adjust prices, resulting in higher revenues. Last, unemployment rates negatively impacted ROA, reflecting consumer sensitivity to economic conditions affecting automotive purchasing decisions.

In summary, while some findings align with our initial hypotheses regarding the detrimental effects of certain SCDs on automotive FP, such as PRAW, shipping costs, and pandemic disruptions, others, like IRAW and OIL, diverge from expectations. These insights underscore the complexity of SCD impacts within the automotive sector and highlight the sector-specific strategies that mitigate or capitalize on these disruptions.

## 5. Conclusion and implications

We elucidate the relationship between SCD and the FP of the emerging and developed European automotive sector. The findings reveal intriguing dynamics affecting the financial performance of European automotive companies, with notable distinctions between ROA, ROE, and SR. First, disruptions tied to fluctuations in IRAW defy conventional assumptions by showing a positive correlation. This suggests that automotive companies should view increased metal prices not just as cost burdens but also as indicators of heightened demand and improved financial health. IRAW notably influences SR more than ROA and ROE, with a 1% increase in IRAW correlating with a remarkable 99.5% surge in SR, underscoring its critical role in stock market performance. Although the impact on ROA (6.2%) and ROE (13.4%) is also positive, the significant boost in SR highlighted the crucial impact of industrial metals prices on stock returns. Investors should consider this strong correlation as a vital factor influencing overall stock performance. Second, rising prices of precious metals negative impact all financial metrics. A 1% increase in PRAW is associated with a substantial 17.3% decline in ROE and a significant 55.5% decrease in SR. While the negative effect on ROA (6.7%) is significant, it is comparatively less severe. Third, disruptions due to heightened shipping costs reveal an intriguing contrast between financial metrics. Despite average decreases of 0.7% in ROA and 2.7% in ROE, the increase in BDI leads to an average SR increase of 12.9%. This indicates that, despite challenges in operational efficiency and profitability, companies may have effectively passed on increased costs to consumers, resulting in a notable rise in stock returns. Automotive companies should consider the broader economic context, as reflected by the BDI, in their strategic planning and risk management. Fourth, the analysis of the COVID-19 dummy variable during pandemic years show consistent average decreases in ROA (3.7%) and ROE (8.1%), with the most significant impact observed in SR, which has an average decrease of 19.7%. This underscores the severe challenges faced by the automotive sector during pandemic-induced disruptions, particularly in terms of stock market performance, and highlights the importance of building resilience and adaptability into business models. Companies should have proactively assessed and enhanced their capacity to navigate unforeseen disruptions. Investors need to be mindful of the lingering effects of such disruptive events on overall financial performance, highlighting the necessity for strategic risk management and resilience in the face of unforeseen challenges. Fifth, and conversely, the impact of rising OIL shows no significant association with financial performance metrics, underscoring the importance of hedging strategies and long-term contracts in stabilizing costs for automotive companies. This also indicates that macroeconomic indicators should be considered alongside microeconomic factors when evaluating the impact of oil price fluctuations. Analyzing control variables, the effect of age on FP yielded mixed results, leverage consistently has a negative impact, and larger company size correlates with higher profit margins and improved financial performance.

The theoretical and managerial implications of this study are multifaceted, providing actionable insights for both automotive firms and regulators. Automotive firms can mitigate the adverse effects of SCDs by diversifying their supplier base geographically and exploring alternative materials less susceptible to price volatility. This strategy reduces dependency on single sources and enhances resilience against unforeseen disruptions in the supply of critical materials. Specific measures may include establishing partnerships with local suppliers in different regions, investing in research and development to innovate new or substitute materials, and integrating sustainability criteria into supplier selection processes to ensure long-term viability.

Given the significant impact of shipping costs on financial performance, firms should prioritize optimizing logistics operations. This involves leveraging advanced technologies such as the internet of things (IoT) for real-time tracking of shipments, adopting predictive analytics to forecast demand and optimize routing, and utilizing blockchain technology for enhanced transparency and traceability throughout the supply chain. Implementing just-in-time inventory practices and adopting lean principles can further reduce excess inventory and minimize storage costs, thereby improving overall supply chain efficiency and responsiveness.

The COVID-19 pandemic underscores the necessity of digital transformation and agile supply chain strategies. Automotive firms should invest in digital technologies such as artificial intelligence (AI) and machine learning to forecast demand more accurately and simulate various disruption scenarios. Developing agile supply chains involves fostering a culture of adaptability and responsiveness within the organization, enabling quick adjustments to changing market conditions or unforeseen disruptions. This may include cross-training employees, establishing backup suppliers, and implementing flexible manufacturing processes.

Regulators play a decisive role in fostering a resilient automotive supply chain through policy development and enforcement. This includes incentivizing automotive firms to adopt best practices in risk management, diversification, and sustainability through regulatory frameworks and industry guidelines. Regulators can also support research and development initiatives focused on improving supply chain visibility, enhancing material efficiency, and advancing sustainable manufacturing practices. Providing funding or tax incentives for investments in renewable energy sources, recycling technologies, and eco-friendly materials can encourage automotive firms to adopt environmentally sustainable practices while reducing reliance on scarce or volatile resources. By focusing on these practical implications, both automotive firms and regulators can collaboratively work towards building a resilient and sustainable automotive supply chain capable of effectively navigating the challenges posed by supply chain disruptions.

While this study provides valuable insights, it is important to note some contextual considerations. The focus on the European automotive sector limits the generalizability of the findings to other regions and industries. The dynamics and challenges of SCD may differ significantly across countries and sectors. Additionally, the study's time frame, limited to the years 2013 to 2021, may not capture longer-term trends and the evolving nature of SCD and resilience strategies, particularly post-pandemic and in light of recent geopolitical events. By expanding the scope of future studies, a more holistic understanding of the dynamics of SCD across various contexts can be achieved.

## Use of AI tools declaration

The authors declare that they have not used Artificial Intelligence (AI) tools in the creation of this article.

## Conflict of interest

The authors declare there is no conflict of interest.

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## Appendices

**Table A1.** Distribution of companies by country.

| Country Name | Number of Companies | Country's Classification* |
|---|---|---|
| Austria | 3 | Developed |
| Bulgaria | 3 | Developed |
| Croatia | 1 | Emerging |
| Cyprus | 1 | Developed |
| Denmark | 1 | Developed |
| Finland | 1 | Developed |
| France | 9 | Developed |
| Germany | 13 | Developed |
| Ireland | 2 | Developed |
| Italy | 10 | Developed |
| Netherlands | 2 | Developed |
| Norway | 1 | Developed |
| Portugal | 1 | Developed |
| Poland | 4 | Emerging |
| Romania | 3 | Emerging |

*Continued on next page*

| | | |
|---|---|---|
| Russia | 4 | Emerging |
| Spain | 2 | Developed |
| Serbia | 1 | Emerging |
| Sweden | 5 | Developed |
| Switzerland | 2 | Developed |
| United Kingdom | 4 | Developed |

***** *Based on IMF's classification*.