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Challenging the Industry Effect: Evidence of Fundamental Risk Heterogeneity Across Sectoral and Industry Tiers

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Abstract
Purpose: The study challenges the industry effect concept by analysing total volatility and idiosyncratic risk in the firms listed in the Indonesia equity market to investigate whether firms in the same sector industry share similar risk profiles.
Methodology: While previous work has largely focused on the time series of average idiosyncratic volatility, the study uses a novel cross-sectional approach to identify industry-wide mispricing in the normalisation of both total and idiosyncratic volatility, by using data from 601 publicly traded firms in the Indonesia Equity Market (IDX) and several robust statistical tests, including the Coefficient of Variance, the Shapiro-Wilk Test for Data Normality, the Kruskal-Wallis H test, and Levene's Test.
Result: The findings show significant variation across industries, with coefficients of variation for total volatility and idiosyncratic risk at the market level higher than typically observed in homogeneous groups. Deviating from the traditional Structure-Conduct-Performance (SCP) view.
Conclusions: This study found that the traditional Structure-Conduct-Performance (SCP) model is too simple to capture how firms really behave, especially when compared to the Resource-Based View (RBV) using modern risk analysis.
Limitations: The study focuses on standard deviation and *STEY X* as measures of risk and does not cover other external factors, such as macroeconomic or geopolitical factors.
Contributions: The results contribute to the existing capital market literature by providing empirical evidence that challenges the traditional concept of the industry effect, showing that sectoral and industry classifications fail as measures of firm risk profile.

Keywords: *Capital Asset Pricing Model (CPAM), Industry Effect, Risk*

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1. Introduction

The industry effect is an important concept in finance, particularly in empirical asset pricing and systematic risk decomposition (Kohls, Mager, & Regele, 2023; Momani & AlZboon, 2025; Pal & Garg, 2019). It suggests that industry or sectoral identity shape a company's risk-return profile (Ahinful, Boakye, & Osei Bempah, 2023; Chen, Huang, & Jiang, 2026; Haslanger, Lehmann, & Seitz, 2023). This seminal financial theory fits the Structure-Conduct-Performance (SCP) paradigm Bhat, Seth, Rasheed, and Malik (2025); Habaibeh, Alkhalaileh, and Al-Mohareb (2025); Pietrzak (2025), which states that firms in similar industries respond similarly to common external fundamentals, including economic cycles, technological advancements and changes in regulations as well as supply chain vulnerabilities (Garcia-Castro & Ariño, 2026; Hudson, 2025; Nwoba, Osisiogu, Okoro, & Nduka, 2025). The Global Industry Classification Standard (GICS) captures this shared experience by effectively grouping assets into distinct categories (Teske, Niklas, Talwar, & Atherton, 2022; Ure, South, Farnsworth, Bown, & Thompson, 2024; Wang & Guo, 2025).

This study questions the validity of the industry effect concept by showing significant risk heterogeneity across and within sectors and industries. The idea comes from the fact that risk is not a single property of a sector or industry, but a multidimensional factor. The study explores differences in the metrics of total volatility *(σ)* and idiosyncratic risk *(STEY X)* between firms grouped by industrial similarity. It finds that sub-industries within sectors are often statistically different from their parent-sector portfolios. The results indicate significant risk heterogeneity even within stable sectors and industry groups. While financial measurements, such as the Capital Asset Pricing Model (CAPM) or Fama-French models, have addressed noise at the firm level Arnott and Hsu (2008); Bartholdy and Peare (2005), they cannot ignore that intra-industry variance will challenge generic sectoral and industrial benchmarks. When it is found that the standard deviations of companies in the same industry differ significantly, it may indicate that research on volatility polarisation by generation cannot be reduced to an industry level, as issues regarding total volatility cannot be captured by a mere aggregate picture. When idiosyncratic risk also varies significantly, it implies that firm-specific risk is more pronounced than industry effects. In particular, earlier studies have shown a trend of aggregate market-level idiosyncratic volatility (Campbell, Lettau, Malkiel, & Xu, 2001; Chiah, Gharghori, & Zhong, 2023) however, very little research has been devoted to intra-industry dispersion and its implications for these risk components. The current literature does not completely explain why firms under similar regulatory and competitive conditions can exhibit such extreme differences in total standard deviation.

This study is unique in its examination of the intra-industry risk paradox, which challenges the traditional belief among scholars and practitioners that industry classification is significant to sector-level risk. Whereas previous work has largely focused on the time series of average idiosyncratic volatility, the study uses a novel cross-sectional approach to identify industry-wide mispricing in the normalisation of both total and idiosyncratic volatility, by using several robust statistical tests, including the Coefficient of Variance, the Shapiro-Wilk Test for Data Normality, the Kruskal-Wallis H test, and Levene's Test.

2. Literature Review and Hypotheses Development

There is a long-standing debate among financial researchers over whether industry-level or firm-level factors have a greater impact on risk and return profiles. The classical Structure-Conduct-Performance (SCP) theory Chai, Liu, Zhang, and Zhang (2025); Khan, Afridi, Tahir, and Burki (2026); Ku and Chang (2026) argues that industry structure mainly determines how firms behave and their risk-return profiles. According to this theory, firms within the same Global Industry Classification Standard (GICS) classification exhibit similar levels of return variance, as they face relatively similar business environments and economic cycles (Imran et al., 2024; Ure et al., 2024; Wang & Guo, 2025). On the other hand, the Resource-Based View (RBV) explains that a firm's ability to manage risk comes from its firm-specific unique characteristics, both tangible and intangible Kanoujiya, Agarwal, Rastogi, Tarode, and Bodne (2026); Zhang (2026), which cannot be easily transferred and copied by other firms in a similar sector or industry. As a result, even if two firms face the same industry-wide challenges, their volatility might differ depending on their management capacity and business strategy.

However, this traditional view is currently being questioned by several researchers. Innovation may vary greatly within similar groups, leading to distinct risk profiles. For example, two firms in the pharmaceutical industry can exhibit very different risk levels depending on how their research and development processes operate at different stages. In a pivotal study, Campbell et al. (2001) found that while overall market and industry volatilities remained stable during the research period, the risk specific to individual firms known as idiosyncratic risk increased significantly. This study suggests that unique firm-specific factors are becoming more important than shared industry traits. Despite this trend, the risk models still assume that the overall volatility of firms within the same sector will be similar. However, this assumption is becoming less accurate due to differences in business models and the growing importance of intangible assets. Other researcher argues that traditional industry classifications, such as the GSIC classification, fail to capture the dynamic nature of today's markets Hoberg and Phillips (2016), leading to firms in the same sector having very different products and cost structures. Therefore, it is essential to consider risk variability at the firm level rather than treating all firms as the same.

These two assumptions leave a gap in how overall risk is measured. If industry classifications worked well to standardise risk, firms in the same sector would show little difference in their standard deviations. But other research suggests that firm's risk profile unique to each firm play the biggest role in total volatility (Andersen, 2008; Kanoujiya et al., 2026). Based on these premises, the study proposes that industry membership does not fully explain a firm's total volatility profile.

H_{1a}: Firms within the same sector exhibit significantly different standard deviations, indicating varying levels of volatility that industry membership alone fails to explain

H_{1b}: Firms within the same industry exhibit significantly different standard deviations, indicating varying levels of volatility that industry membership alone fails to explain

The earlier study reviewed how standard deviations help measure volatility and show differences in risk among firms in the same sector or industry. This premise raises another question whether industry classifications are sufficient to assess risk. Standard deviation gives a general sense of volatility, but it does not capture the specific factors behind each firm's unique risk. Therefore, it is important to use a more detailed approach to evaluate risk-adjusted performance, focusing on the part of a firm's returns that cannot be explained by overall market trends.

According to Capital Asset Pricing Model (CAPM), an asset's expected return depends on its systematic risk, which is usually measured by beta. A beta coefficient measures how the asset's returns move with the market. However, this model does not capture idiosyncratic risk, which is unique to each company. To address this issue, the study uses *STEY X*, a tool that gives a more detailed view of risk-adjusted performance. By looking at *STEY X*, the study sees how well companies handle this unexplained risk, which matters for asset pricing models. If a significant difference is observed, it means the industry effect is insufficient to predict idiosyncratic risk. If firm-specific risk were mostly tied to industry, *STEY X* values would be similar across sectors. Since factors such as operational leverage and innovation strategies vary across companies, this study examines the following second hypothesis.

H_{2a}: Firms within the same sector exhibit significantly different *STEY X* values, indicating that industry membership is an insufficient predictor of idiosyncratic risk levels

H_{2b}: Firms within the same industry exhibit significantly different *STEY X* values, indicating that industry membership is an insufficient predictor of idiosyncratic risk levels

3. Methodology

3.1 Data and Sample

This research uses all companies listed on the Indonesian Stock Exchange as its sample. The dataset includes daily stock prices for 601 firms traded on the Indonesian Equity Market (IDC) from January 1, 2024, to December 31, 2024. We calculated alpha and beta values based on this data and the market index for the same period. The data came from www.idx.go.id, the official website of the market.

3.2 Measuring Volatility and Volatility Gap

Standard deviation serves as a proxy for volatility in this study, quantifying the extent to which stock returns deviate from their mean, driven by both systematic and idiosyncratic factors. The standard deviation is calculated using the following equation (Borlinghaus, Coblenz, Grothe, & Kächele, 2026).

$$\sigma = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} (R_i - \bar{R})^2} \quad (1)$$

Where:

σ = standard deviation;

R_i = individual return;

$\bar{R}$ = average return over the selected period;
N = total number of returns.

The analysis proceeds by measuring the volatility gap. To evaluate the volatility gap within a GICS Industry Group, the variance of the standard deviations is calculated by using the following equation (Lane et al., 2017; Martinez & Bartholomew, 2017).

$$\Delta\sigma_j = \frac{\sum_{i=1}^{N}(\sigma_i - \bar{\sigma}_j)^2}{N_j - 1} \tag{2}$$

Where:

σ_j = The Intra-Industry Volatility Spread within Industry Group *j;*
σ_i = The calculated standard deviation for firm *i;*
$\bar{\sigma}_j$ = The average volatility of all firms within GICS Industry Group *j;*
N_j = The sample size of firms within the GICS Industry Group *j;*
$N_j - 1$ = the degrees of freedom used to calculate an unbiased sample variance.

3.3 Measuring Standard Error of the Estimate (STEY X)

Within the Market Model, *STEY X* measures a firm's risk contribution relative to market movements. In a statistical sense, *STEY X* is the standard deviation of the regression residuals, which indicates how the data are distributed around the regression line. The *STEY X* equation for calculating is as follows (Lane et al., 2017):

$$STEY\ X = \sqrt{\frac{\sum_{i=1}^{N}(R_i - \bar{R})^2}{n-2}} \tag{3}$$

Where:

R_i = the observed return of the firm;
$\bar{R}$ = the predicted return based on the regression line (where $\bar{R} = \alpha_i + \beta_i R_m + \epsilon_i$);
n = the number of observations (sample size) used in the regression period;
n – 2 = the degrees of freedom, accounting for the two parameters (α and β).

The study continues to assess the Intra-Industry *STEY X* Spread, which evaluates how effectively sector and industry membership predict firm characteristics. Significant variation in *STEY X* values within an industry indicates that industry labels alone do not capture individual firm risk profiles. The *STEY X* variance is defined by the following equation.

$$\Delta STEY\ X_j = \frac{\sum_{i=1}^{N}(STEY\ X_i - ST\bar{E}Y\ X_j)^2}{N_j - 1} \tag{4}$$

Where:

$STEY\ X_j$ = The Idiosyncratic Risk Dispersion within Industry Group *j.*
$STEY\ X_i$ = The idiosyncratic risk value for individual firm *i.*
$ST\bar{E}Y\ X_j$ = The Mean Idiosyncratic Risk for all firms within that GICS Industry Group.
N_j = The sample size of firms within the GICS Industry Group *j.*
$N_j - 1$ = the degrees of freedom used to calculate an unbiased sample variance.

3.4 Significance of Measurement

To test the hypothesis, the study uses a two-stage statistical approach to study the consistency of industry groups and the extent to which sector classifications explain differences across them. In the first phase, this research uses the Coefficient of Variation (CV) to measure within each sector the degree of risk variation. The CV is calculated as a firm-level volatility standard deviation divided by a sector's or industry's average volatility (Mahmoudvand & Oliveira, 2018), using the following equation.

$$CV_j = \frac{\sigma_j}{\mu_j} \quad (4)$$

Where:

CV_j = Coefficient of Variation for sector or industry j;
σ_j = Standard deviation of total volatility for all firms within or industry j;
μ_j = Mean total volatility for all firms within or industry j.

This study measures total market dispersion using the following equation.

$$CV_{Market} = \frac{\sigma_{Market}}{\mu_{Market}} \quad (4)$$

Where:

CV_{Market} = The aggregate Coefficient of Variation for the entire population of firms;
σ_{Market} = The standard deviation of total volatility (σ) calculated across all firms;
μ_{Market} = The arithmetic mean of total volatility (σ) for all firms in the sample.

If the Coefficient of Variation (CV) is 0.30 or less, the sectors are considered homogeneous. This means a company in the sector is similar to the industry average and can represent other firms in the group. On the other hand, sectors with a CV above 0.30 are considered highly dispersed or heterogeneous (Lin, Chu, & Hodges, 2017). In these cases, the differences among firms are large enough that the sector label does not create a clear, shared risk profile.

$$\sigma_i = \beta_0 + \beta_1 X_{i,1} + \beta_2 X_{i,2} + \cdots + \beta_k X_{i,k} + \epsilon_i \quad (4)$$

Where:

σ_i = Total volatility (firm standard deviation of daily stock returns);
β_0 = The intercept (constant), representing the baseline volatility level in the market;
$X_{i,k}$ = Binary dummy variables (0 or 1) representing firm *i*'s classification;
β_k = The sectoral coefficients of k industry;
ϵ_i = The idiosyncratic error term (Residual).

The Coefficient of Determination (R^2) is calculated based on the preceding model. A low R^2 value indicates significant dispersion that cannot be explained by sector of industry membership.

4. Results and Discussions

4.1 Data Clean Up and Descriptive Statistic

Table 1 shows summary statistics for 601 publicly traded firms, grouped by GICS industry. Standard deviations and the STEYX risk measure were used. Z-score filtering was applied to remove missing values and outliers, thereby improving statistical reliability, as indicated by lower standard deviations.

Table 1. Descriptive statistics of the refined sample

VariableS	N	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis
STEY X	601	0	0.122415	0.030679	0.018973	1.443692	3.32057
σ	601	0.005473	0.08667	0.022896	0.012827	1.602548	3.74508

The aggregate descriptive statistics of the refined sample shown above reveal several interesting aspects that will be important for understanding subsequent analyses and interpreting results especially in relation to distributions and statistics for both *STEY X* and σ. The variable *STEY X* has a mean of 0.030679 and a standard deviation of 0.018973. This variable ranges from 0 to about 0.122 (the values are widely scattered). This variable has a positive skewness of 1.44, indicating that most of the data points are concentrated on the negative end with an obvious tail toward the positive side (tailing out to the right). In addition, the value of the kurtosis is 3.32, indicating a leptokurtic distribution, a sharper peak, and fatter tails than those of a normal distribution, meaning it has more extreme values than one would expect under the normal model.

The mean of the σ variable is 0.022896, and the standard deviation is 0.012827, an indication that data values are nearer to the mean than those for *STEY X*. The data are distributed in a narrow range and with a small standard deviation (from 0.005473 to 0.08667). This variable is more positively skewed than *STEY X* (skew coefficient 1.60), suggesting a strong concentration of observations at low values. The higher peak and fatter tails are indicated by the kurtosis of about 3.75. While both are positively skewed and peaked, standard deviation is more concentrated with a flatter tail than *STEY X*.

4.2 Heterogeneity of Volatility (σ)

4.2.1 Analysis from Sectoral Level

Table 2 below provides the sector-level heterogeneity. This table summarises the mean and variance of total volatility across sectors. This data excludes extreme statistical outliers to prevent the measures of central tendency and dispersion from being skewed. The empirical results in the table support H1a, which suggests that firms in the same sectors exhibit markedly different standard deviations. Volatility is definitely not similar across industries; this finding suggests differences beyond the industry membership. Analysis of the risk distribution reveals considerable intra-sector heterogeneity, questioning the historical GICS top-down risk assessment models.

Given the heterogeneous nature of eleven sectors with Coefficient of Variation (CV) values above 0.30, each sector was identified as heterogeneous. These heterogeneities are very pronounced in sectors such as Utilities (CV = 0.770) and Health Care (CV = 0.745), with high or above-average risk. In these industries, firms exhibit substantially divergent risk profiles, making average sector volatility less meaningful. As a result, firms in these sectors are at risk in significantly different ways. This is not just an isolated event; the study observes a similar trend across the entire market, with a CV of 0.560. That finding has revealed that risks are not uniform across the market and often cross traditional sector lines.

Table 2. Sectoral volatility and dispersion analysis

GICS Sector Name	Mean of *σ*	Variance of *σ*	CV Value	Conclusion
Utilities	0.026556	0.000418	0.769938	Heterogenic
Consumer Discretionary	0.026153	0.000186	0.521014	Heterogenic
Information Technology	0.024085	0.000251	0.657922	Heterogenic
Industrials	0.024003	0.000192	0.577206	Heterogenic
Communication Services	0.023908	0.000123	0.464659	Heterogenic
Materials	0.023279	0.000115	0.460681	Heterogenic
Health Care	0.023185	0.000298	0.744665	Heterogenic
Real Estate	0.022499	0.000178	0.593518	Heterogenic
Financials	0.021062	0.000155	0.591024	Heterogenic
Consumer Staples	0.020374	0.000129	0.556823	Heterogenic
Energy	0.020126	0.000079	0.440989	Heterogenic
Total Market	**0.022896**	**0.000165**	**0.560222**	**Heterogenic**

The data provided in Table 3 below also support a similar conclusion. The table shows the R^2 value from the ANOVA model, indicating that industry membership makes a small contribution to overall firm volatility, as evidenced by a market-wide CV of 0.5602. This finding indicates that the risk from idiosyncratic factors specific to individual firms, rather than from their GICS industry. The Kruskal-Wallis H test ($p = 0.0808$) and Levene's test ($p = 0.3183$) confirm it, quantifying what can be described as a universal heterogeneity paradox. Yet these tests imply a homogeneous sectoral classification. No individual industry could be statistically deemed riskier or more dispersed than the others, and intra-sector data reveal all groups as equally diverse.

Table 3. Sectoral volatility and dispersion analysis

Statistic	Market-Wide Value	Conclusion for H_{1a}
Market-wide CV	0.5602	The market is highly heterogenic; dispersion is 56% of the mean.
R-squared (R^2)	0.0227	Industry membership explains only 2.27% of risk variation.
Prevalence Rate	90.91%	Over 90% of all sectors are individually heterogenic.
Kruskal-Wallis H Test	H=16.72, p=0.0808	No significant difference (p>0.05) in median risk across sectors.
Levene's Test	W=1.16, p=0.3183	Population variances are statistically similar (p>0.05) across sectors.

4.2.2 Analysis from Industry Level

This section analyses volatility heterogeneity at the industry level. Table 4 shows total volatility and internal dispersion for all industries in the dataset, which supports the conclusion presented at the sectoral level. The next level down, from sector to industry, reveals that most industries are heterogeneous. This observation further strengthens the finding that even narrower classifications often fail to create a consistent risk profile.

Table 4. Volatility and Dispersion Analysis - Industry Level Analysis

GICS Industry Name	N	Mean of σ	Variance	CV Value	Conclusion
Pharmaceuticals	9	0.026118	0.000625	0.956991	Heterogenic
Renewable Electricity	6	0.030208	0.000521	0.755829	Heterogenic
Software	5	0.026261	0.000336	0.697576	Heterogenic
Building Products	7	0.021256	0.000217	0.693388	Heterogenic
Insurance	18	0.027106	0.00034	0.679913	Heterogenic
Trading Companies & Distrib.	12	0.026832	0.000324	0.670401	Heterogenic
Capital Markets	12	0.021681	0.000206	0.662082	Heterogenic
Passenger Airlines	3	0.03708	0.000601	0.66129	Heterogenic
Beverages	6	0.020878	0.000187	0.655384	Heterogenic
Containers & Packaging	15	0.027045	0.000303	0.643338	Heterogenic
Tobacco	4	0.016674	0.000114	0.640483	Heterogenic
Interactive Media & Services	3	0.027656	0.000303	0.629439	Heterogenic
Electronic Equip., Inst. & Comp.	5	0.031832	0.00038	0.612656	Heterogenic
Real Estate Mgmt & Develop.	64	0.022499	0.000178	0.593518	Heterogenic
Electrical Equipment	4	0.025721	0.000231	0.590719	Heterogenic
Food Products	49	0.021371	0.000151	0.574888	Heterogenic
Air Freight & Logistics	5	0.03032	0.000302	0.572831	Heterogenic
Construction & Engineering	26	0.026058	0.000217	0.565645	Heterogenic
Textiles, Apparel & Luxury Goods	16	0.028564	0.000254	0.558287	Heterogenic
IT Services	3	0.01327	0.000055	0.556714	Heterogenic
Transportation Infrastructure	9	0.013379	0.000053	0.545633	Heterogenic
Hotels, Restaurants & Leisure	26	0.030171	0.000261	0.535817	Heterogenic
Ground Transportation	11	0.026851	0.000206	0.535166	Heterogenic
Broadline Retail	4	0.019619	0.00011	0.533745	Heterogenic
Diversified Telecom Services	14	0.021296	0.000119	0.512935	Heterogenic
Oil, Gas & Consumable Fuels	33	0.019115	0.000075	0.454368	Heterogenic

Consumer Staples Dist. & Retail	9	0.018098	0.000065	0.445129	Heterogenic
Consumer Finance	13	0.020979	0.000084	0.436611	Heterogenic
Media	13	0.026973	0.000137	0.433599	Heterogenic
Banks	44	0.017364	0.000056	0.43205	Heterogenic
Paper & Forest Products	7	0.021883	0.000084	0.418633	Heterogenic
Specialty Retail	16	0.020684	0.000073	0.412159	Heterogenic
Commercial Services & Supplies	8	0.015808	0.00004	0.401679	Heterogenic
Construction Materials	6	0.022539	0.000073	0.379472	Heterogenic
Chemicals	15	0.018909	0.00005	0.375706	Heterogenic
Energy Equipment & Services	8	0.024298	0.000081	0.369461	Heterogenic
Health Care Providers & Serv.	11	0.020785	0.000052	0.348545	Heterogenic
Financial Services	3	0.036929	0.000152	0.334013	Heterogenic
Household Products	2	0.014852	0.000024	0.327461	Heterogenic
Machinery	5	0.026528	0.000074	0.324352	Heterogenic
Marine Transportation	12	0.021575	0.000049	0.323251	Heterogenic
Household Durables	4	0.023333	0.000057	0.323046	Heterogenic
Distributors	5	0.024458	0.000061	0.319309	Heterogenic
Entertainment	4	0.023639	0.000057	0.318989	Heterogenic
Personal Care Products	4	0.018993	0.000036	0.317196	Heterogenic
Metals & Mining	24	0.024248	0.000054	0.302526	Heterogenic
Automobile Components	7	0.020969	0.000032	0.271272	Homogenic
Tech. Hardware & Peripherals	2	0.017996	0.00002	0.247692	Homogenic
Industrial Conglomerates	2	0.016889	0.000015	0.228633	Homogenic
Wireless Telecom Services	2	0.017194	0	0.019377	Homogenic
Gas Utilities	2	0.015602	0	0	Homogenic
Aerospace & Defense	1	0.021318	0	0	Single data
Communications Equipment	1	0.019092	0	0	Single data
Diversified Consumer Services	1	0.052796	0	0	Single data
Professional Services	1	0.04141	0	0	Single data
Total Market	**601**	**0.022896**	**0.000165**	**0.560222**	**Heterogenic**

A deeper analysis of individual industries reveals that the details illuminate the deep asymmetries in risk profiles that industry membership alone cannot explain. The study uses statistics in Table 5 to fairly strongly confirm H_{1b} that firms within the same industry, based on their risk characteristics, can differ widely from one another. The essential measure for this is the Coefficient of Variation (CV), which describes firm-level volatility dispersion relative to the industry mean (Standard Deviation). The high CV across most sectors in the market indicates that most industries are Heterogeneous, with values many times exceeding 0.30. For instance, the industries Pharmaceuticals (CV = 0.957), Renewable Electricity Producers (CV = 0.756), and Software (CV = 0.698), show pronounced within-industry variation in joint risk levels, suggesting that an average industry risk level is a poor proxy for the actual volatility.

The heterogeneity was so prevalent that H_{1b} became a systemic market characteristic rather than an exceptional event. In about 83.64%–85.19% of cases across all industries, the results show that idiosyncratic elements dominate over industry-wide commonalities. The data demonstrated that these firm-level disparities across sectors are consistent even in relatively stable industries; for example, Banks and Real Estate with CVs of 0.504 and 0.593, respectively. As such, industry classification provides a poor, noisy signal for assessing risk. Findings from analyses reject the industry-based risk homogeneity hypothesis and show that idiosyncratic operational differences, management quality, and firm-specific leverage are the main drivers of volatility in the capital market.

Table 5. Volatility and Dispersion – Industry Level Analysis

Statistic	Market-Wide Value	Conclusion
Market-wide CV	0.5602	The market is highly heterogenic; dispersion is 56.02% of the mean.
R-squared (R2)	0.1218	Industry membership explains only 12.18% of the variation in firm risk.
Prevalence Rate	90.20%	90.20% of all valid industries (with N>1) are internally heterogenic.
Kruskal-Wallis H Test	H=70.75, p=0.0627	No significant difference (p>0.05) in median risk levels between industries.
Levene's Test	W=1.23, p=0.1310	Population variances are statistically similar (p>0.05) across industries.

4.3 Heterogeneity of Idiosyncratic Risk (STEY X)

4.3.1 Analysis from Sectoral Level

Table 6 shows the idiosyncratic risk metrics for each GICS sector. Understanding how this risk is structured is important for H_{2a}, as it determines whether firm-specific risks are grouped together or spread out within industry groups. The table shows that all 11 GICS sectors are classified as 100% Heterogenic for idiosyncratic risk (STEY X). Each sector is well above the 0.50 CV threshold, with Real Estate (1.162) and Industrials (1.081) showing the highest levels of internal risk fragmentation. This finding adds to the earlier volatility analysis. It shows that unique, firm-specific factors vary even more than total volatility (σ). This result supports H_{2a}, which postulates that industry labels do not support group firms with similar idiosyncratic risk profiles. The large differences in idiosyncratic risk suggest that firm-level details are most important in the market, so comparing risk by sector is less helpful for judging individual firm risk. The results for H2a show a clear gap between how industries are classified and how firms actually behave with respect to risk. The GICS system groups companies by similar business models and economic factors, but our analysis finds that these similarities do not translate into consistent firm-specific risk.

Table 6. Sectoral Idiosyncratic Risk (STEY X) Dispersion Analysis

GICS Sector Name	N	Mean of Stey X	Variance of Stey X	CV Value	Conclusion
Utilities	8	0.036169	0.00088656	0.823231	Heterogenic
Health Care	20	0.030927	0.00063486	0.814714	Heterogenic
Information Technology	16	0.031977	0.00058013	0.753216	Heterogenic
Financials	90	0.027759	0.00034307	0.667238	Heterogenic
Real Estate	64	0.030074	0.00039321	0.659367	Heterogenic
Industrials	106	0.032301	0.00041986	0.634354	Heterogenic
Consumer Staples	74	0.027009	0.00028289	0.62272	Heterogenic
Consumer Discretionary	79	0.035583	0.00039809	0.560733	Heterogenic
Energy	41	0.026574	0.00018577	0.51289	Heterogenic
Communication Services	36	0.032314	0.00026852	0.507105	Heterogenic
Materials	67	0.03148	0.00024273	0.494905	Heterogenic
Total Market	**601**	**0.030679**	**0.00035996**	**0.618419**	**Heterogenic**

Analysis in Table 7 also shows this fragmentation, with a Market-wide Coefficient of Variation (CV) of 0.6184, which is well above the 0.30 threshold for homogeneity. All 11 GICS sectors show this heterogeneity, so the lack of cohesion is a market-wide issue, not just limited to certain industries. The Kruskal-Wallis p-value of 0.249 indicates that there is no statistically significant difference in median idiosyncratic risk across sectors. This means that the variation within each sector is so high that comparing sectors does not provide much useful information. The OLS R^2 value of 0.0235 also indicates that a firm's sector explains 2.35% of its unique risk. This means that industry effects are almost absent, and 100% of the risk differences come from factors within each company, such as management quality, operational efficiency, and capital structure. This pattern appears across all 11 GICS sectors with a CV above 0.30, indicating that it is not just a feature of one industry, such as Tech or Finance, but a consistent trait of the market as a whole. Even across all industry subgroups, diversity persists, showing that the problem is not that sectors are too broad, but that each company has its own unique risk profile.

The study uses the Kruskal-Wallis H Test MacFarland and Yates (2016) and Levene's Test O'Neill and Mathews (2000) to examine risk patterns in the market. The Kruskal-Wallis H Test tests for significant differences in median risk across groups and yields a p-value of 0.0663 for sectoral idiosyncratic risk. Since the p-value of 0.3036 is above the usual 0.05 cutoff, the study does not reject the idea that all sectors have the same risk medians. This means the study cannot say that any sector is different from the others; firms across the market have similar risk tail shapes. Levene's Test was also used to assess whether risk is evenly distributed across sectors. The p-value for risk spillover across sectors is 0.2940, indicating no evidence of spillover. This suggests risk is fragmented across the market. The overall median and variance of the sectors show some similarities. However, the high Coefficient of Variation (CV) of 0.6184 and the low R^2 of 0.0235 indicate clear differences. When sector medians are not statistically different, the distribution shows little internal variation.

Table 7. Statistical Analysis for Sectoral Idiosyncratic Risk (STEY X) Dispersion

Statistic	Market-Wide Value	Conclusions
Market-wide CV	0.6184	Highly Heterogenic: The market-wide dispersion of idiosyncratic risk significantly exceeds the 0.30 threshold.
R-squared (R2)	0.0235	Sector membership explains only 2.35% of the variation in firms' individual residual risk.
Prevalence Rate	100.00%	100% of the sectors in the sample are internally heterogenic regarding idiosyncratic risk.
Kruskal-Wallis H Test	H=17.38, p=0.0663	No Significant Difference: Median idiosyncratic risk levels do not vary significantly across different sectors (p>0.05).
Levene's Test	W=1.19, p=0.2940	Equal Variances: The spread of residual risk is statistically uniform across all sectoral groups (p>0.05).

4.3.2 Analysis from Industry Level

Looking at risk across all 54 industries in the market provides a better understanding of the overall risk landscape. In Table 8 , the focus is on residual or firm-specific risk, which is the volatility that general market trends cannot explain. By analysing the coefficient of variation for each industry, the study examines whether firms within the same industry share similar unique risk profiles or are quite different. The findings show a high level of diversity, with the market-wide coefficient of variation for STEY X at 0.6184, which is more than double the usual threshold of 0.30 that separates diverse from similar groups. This fragmentation is widespread, not just in a few unusual cases, as it occurs in 90.38% of industries. In other words, in nearly 9 out of 10 industries, the differences in firm-specific risk are so large that the industry average is not a reliable benchmark for any individual firm.

The results show that fragmentation is especially strong in certain industries. For instance, the Pharmaceuticals sector has a CV of 1.054, meaning risk varies more among pharmaceutical firms than the industry average. Similarly, sectors with high growth or volatility, such as Software (CV = 0.842) and Renewable Electricity (CV = 0.797), show that even within specific industry groups, firms can have very different risk-return profiles. The findings for H_{1b} clearly reject the idea that industry membership predicts firm risk. Grouping firms by identifiers like SIC codes may suggest they are similar, but the data indicate that factors unique to each firm, such as management style and financial or operational leverage, are much more important than industry affiliation. For investors or researchers, this means that relying on industry-level shortcuts is not sufficient; stock price movements and volatility are shaped more by individual firms than by their industries.

Table 8. Industrial Idiosyncratic Risk (STEY X) Dispersion Analysis

GICS Industry Name	N	Mean_Steyx	Variance	CV Value	Conclusion
Pharmaceuticals	9	0.034754	0.00134201	1.05407	Heterogenic
IT Services	3	0.01522	0.00019727	0.922839	Heterogenic
Software	5	0.034198	0.0008294	0.842122	Heterogenic
Renewable Electricity Producers	6	0.041587	0.00110026	0.797609	Heterogenic
Capital Markets	12	0.028577	0.0004745	0.762268	Heterogenic
Building Products	7	0.028492	0.0004709	0.761632	Heterogenic
Transportation Infrastructure	9	0.016062	0.00014163	0.74092	Heterogenic
Insurance	18	0.03684	0.00072599	0.731376	Heterogenic
Trading Companies & Distrib.	12	0.036683	0.00068372	0.712812	Heterogenic
Beverages	6	0.027595	0.00038639	0.712336	Heterogenic
Tobacco	4	0.021082	0.0002187	0.701474	Heterogenic
Interactive Media & Services	3	0.03772	0.00066458	0.683438	Heterogenic
Containers & Packaging	15	0.036887	0.00063434	0.682796	Heterogenic
Passenger Airlines	3	0.051836	0.00124854	0.681666	Heterogenic
Real Estate Mgmt & Develop.	64	0.030074	0.00039321	0.659367	Heterogenic
Food Products	49	0.028459	0.00033538	0.643509	Heterogenic
Electronic Equip., Inst. & Comp.	5	0.044124	0.00079572	0.639295	Heterogenic
Construction & Engineering	26	0.034856	0.00049155	0.636083	Heterogenic
Broadline Retail	4	0.025773	0.00026541	0.632104	Heterogenic
Electrical Equipment	4	0.035292	0.00048903	0.6266	Heterogenic
Air Freight & Logistics	5	0.041529	0.00063183	0.605276	Heterogenic
Textiles, Apparel & Luxury Goods	16	0.039002	0.00055192	0.602353	Heterogenic
Ground Transportation	11	0.036528	0.00044928	0.580281	Heterogenic
Diversified Telecom Services	14	0.028527	0.00026344	0.568953	Heterogenic
Hotels, Restaurants & Leisure	26	0.041545	0.00054426	0.561546	Heterogenic
Oil, Gas & Consumable Fuels	33	0.024997	0.00018048	0.537439	Heterogenic
Consumer Staples Dist. & Retail	9	0.02373	0.00014887	0.514167	Heterogenic
Consumer Finance	13	0.027869	0.00020523	0.514038	Heterogenic
Banks	44	0.022177	0.00012506	0.504265	Heterogenic
Specialty Retail	16	0.027367	0.00017574	0.484405	Heterogenic
Commercial Services & Supplies	8	0.020602	0.00009339	0.469076	Heterogenic
Media	13	0.036729	0.0002957	0.46818	Heterogenic
Paper & Forest Products	7	0.029693	0.00018198	0.454318	Heterogenic
Chemicals	15	0.025234	0.0001106	0.41677	Heterogenic
Construction Materials	6	0.030152	0.00015457	0.412321	Heterogenic

Energy Equipment & Services	8	0.033082	0.00017636	0.401428	Heterogenic
Household Products	2	0.019364	0.00005723	0.390669	Heterogenic
Health Care Providers & Serv.	11	0.027795	0.00010865	0.375013	Heterogenic
Personal Care Products	4	0.025507	0.00008273	0.356596	Heterogenic
Marine Transportation	12	0.029176	0.00010403	0.349582	Heterogenic
Household Durables	4	0.031887	0.00012145	0.345614	Heterogenic
Entertainment	4	0.032008	0.0001215	0.344366	Heterogenic
Distributors	5	0.03361	0.00013323	0.343422	Heterogenic
Machinery	5	0.036335	0.00015545	0.343137	Heterogenic
Financial Services	3	0.051407	0.00029491	0.334057	Heterogenic
Metals & Mining	24	0.032858	0.00011409	0.325068	Heterogenic
Automobile Components	7	0.028198	0.00006895	0.294464	Homogenic
Industrial Conglomerates	2	0.022002	0.00004189	0.294163	Homogenic
Tech. Hardware & Peripherals	2	0.024232	0.00004518	0.277393	Homogenic
Wireless Telecom Services	2	0.022621	0.00000128	0.050095	Homogenic
Gas Utilities	2	0.019914	0	0	Homogenic
Aerospace & Defense	1	0.028524	0	0	Single Firm
Communications Equipment	1	0.025903	0	0	Single Firm
Diversified Consumer Services	1	0.072877	0	0	Single Firm
Professional Services	1	0.058256	0	0	Single Firm
Total Market	**601**	**0.030679**	**0.00035996**	**0.618419**	**Heterogenic**

In addition to the above analysis, Table 9 below outlines key metrics extracted from the GICS industry to rigorously establish support for *H_{2b}* at the most granular level possible. This summary of industry-level market-wide volatility dispersion for STEYX strongly supports the view that idiosyncratic risk remains a predominant factor in the market. With a Market-wide CV of 0.6184, the results show substantial and dynamic systemic heterogeneity, indicating that firm-specific risk has been more widely decoupled than overall volatility. The prevalence rate of 90.20% supports this observation, suggesting that almost all industries with multiple firms are internally heterogeneous. Hence, using industry-level residual risk as a proxy for firm-specific effects can be misleading. Differences between firms in the same industry are often greater than the similarities arising from their common sector classification. The structural disconnect between industry grouping and risk is also evident in the R-squared (R^2) value of 0.1219. Therefore, industry membership explains only about 12% of the variation in firm-specific risk, meaning that almost 88% of the volatility is due to idiosyncratic factors, such as the quality of management, operational efficiency, and financial leverage, operating at a firm-by-firm level. The Kruskal-Wallis H Test (p=0.0471) also finds a significant difference in medians among certain industries. Unlike Levene's Test (p=0.1170), further evidence indicates that there is no significant difference, suggesting that the measured fragmentation or dispersion persists similarly across sectors.

These findings confirm *H_{1b}* Even within narrow industries; homogeneous risk groups do not form. Idiosyncratic risk noise is large enough to challenge industry-based predictions. These results urge researchers and market participants to move beyond the industry effect concept and adopt firm-level risk models. In conclusion, market volatility is primarily driven by firm-specific factors rather than industry-wide parameters.

Table 9. Statistical Analysis for Industrial Idiosyncratic Risk (STEY X) Dispersion

Statistic	Market-Wide Value	Conclusions
Market-wide CV	0.6184	Highly Heterogenic: Total market residual risk is highly dispersed, well above the 0.30 threshold.
R-squared (R2)	0.1219	Industry membership explains only 12.19% of the variation in firms' individual residual risk.
Prevalence Rate	90.20%	90.20% of all valid industries (with N>1) are internally heterogenic.
Kruskal-Wallis H Test	H=72.52, p=0.0471	Marginally Significant: There are statistically detectable differences in median idiosyncratic risk across industries (p<0.05).
Levene's Test	W=1.26, p=0.1170	Equal Variances: The spread of idiosyncratic risk is statistically uniform across most industrial groups (p>0.05).

5. Conclusions

5.1 Conclusion

This study provides a rigorous empirical test that challenges the traditional concept of industry effect by showing that sectoral and industry classification fail as measures of firm risk profile. An analysis of 601 publicly traded firms across total volatility and idiosyncratic risk reveals a universal heterogeneity paradox that holds across almost all sectors at the Global Industry Classification Standard level. Empirical results show that market-level dispersion exceeds the threshold typically associated with homogeneity for total volatility and the idiosyncratic risk measure, indicating that systemic macroeconomic risks are in excess. This means that risk is not one-size-fits-all. Additional regression analysis confirms our finding that industry labels are an insufficient descriptor of firm risk. Thus, it is concluded that most of the firms' volatility is explained by idiosyncratic factors, such as management quality, operational toughness, and capital structure, rather than the industry or sector classification factors.

This wide dispersion is seen even within narrow industry groups that are usually considered close peers, with heterogeneity present for over 90% of the period. Some industries, such as Pharmaceuticals and Utilities, exhibit high internal fragmentation, with CVs close to 0.957. Because of this, using average sector volatility does not help predict performance at the individual-firm level. The Kruskal-Wallis H and Levene’s tests also show that, while industries are diverse within themselves, this pattern is consistent across the market. This means that, once differences within each sector are taken into account, no sector is naturally riskier or safer than another. This study found that the traditional Structure-Conduct-Performance (SCP) model is too simple to capture how firms really behave, especially when compared to the Resource-Based View (RBV) using modern risk analysis. As business models change and intangible assets become more important, standard GICS codes no longer reflect the unique factors that drive volatility for each firm. Because of this, both investors and researchers need to shift from using broad, sector-based climate risk assessments to more detailed, firm-level models.

5.2 Research Limitation

This study primarily focuses on measuring internal risks and does not consider other external factors that could significantly influence market risk. While internal risk factors are critical in understanding organizational vulnerabilities, external factors such as macroeconomic conditions, geopolitical factors, and global market fluctuations play an important role in shaping the overall risk landscape. These external elements can directly or indirectly affect financial performance, market stability, and risk exposure, yet they were not included in the scope of this research. Moreover, the limited geographic and sectoral focus of this study restricts its generalizability to a broader range of industries or countries. Future studies should consider integrating these external factors to provide a more comprehensive risk assessment.

5.3 Suggestion and Direction for Further Research

Considering the limitations mentioned, this study suggests that future research should explore the inclusion of external risk factors, particularly macroeconomic conditions and geopolitical developments, which are integral to understanding market risk in a globalized environment. The role of inflation rates, exchange rate fluctuations, government policies, and international trade relations should be examined, as they can significantly impact an organization's risk profile. Additionally, future research could expand its focus to include a broader range of industries, sectors, and geographical regions to enhance the generalizability of findings. Incorporating external variables will provide a more holistic view of market risks and offer insights for more robust risk management strategies. Furthermore, longitudinal studies could be conducted to analyze the long-term effects of these external factors on organizational risk and performance.

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