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# Inter-Industry Risk-Returns Heterogeneity: A Market Model Approach

**Rexon Nainggolan[1*], Rhody Laynn K. Morada[2]**
Universitas Advent Surya Nusantara, Sumatera Utara[1]
South Philippine Adventist College, Davao del Sur, Philippines[2]
*rexon.nainggolan@suryanusantara.ac.id[1*]*, *rhodymorada@spac.edu.ph[2]*

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**Abstract**
**Purpose:** This study challenges the assumption in financial theory that industry grouping is a robust descriptor of firms' risk-return profile by providing evidence of their heterogeneity.
**Research Methodology:** The study uses the market model and several robust statistical tests to assess the heterogeneity of the sector and firm-level risk-return profiles, including the Coefficient of Variance, the Shapiro-Wilk Test for Data Normality, the Kruskal-Wallis H test, and Levene's Test.
**Results:** The study finds significant heterogeneity in Alpha across sectors and industries. On the other hand, systematic risk exposure, as measured by Beta, exhibits substantial sectoral commonality. However, while firm performance varies across sectors, market sensitivities remain similar across sectors, suggesting that systematic risk primarily reflects individual firms.
**Conclusions:** The results contradict the traditional view of the high-risk-high-return paradigm, suggesting that firms with higher returns do not necessarily inherit higher risk. Thus, the results strongly support the resource-based view over the structure-conduct-performance framework, as intra-industry differences exceed inter-industry differences.
**Limitations:** The study focuses on alpha and beta parameters as measures of risk-return profiles and does not cover other external factors, such as macroeconomic or geopolitical factors.
**Contributions:** By decomposing this spread into its components, the study provides heterogeneity indices that can be used to measure firms' risk-returns profiles from the perspective of alpha and beta coefficients.

**Keywords:** *Alpha, Beta, Global Industry Classification Standard, Market Model, Risk-return Profile*

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## 1. Introduction

The theoretical foundation of finance, embodied in the Capital Asset Pricing Model and its extensions, is essentially based on industry classification as a primary determinant of systematic risk (Bai & Yang, 2025; Chahuán-Jiménez, Muñoz-Rojas, Muñoz-Pizarro, & Schulze-González, 2025; Morais Francisco, 2026). Many researchers stress that the homogeneity hypothesis assumes that firms in a sector are similar to one another (Maharani, 2025; Restiana, Alie, Yudhinanto, Nasir, & Oktaria, 2025), including the similarities in their business model realities, regulatory structure, and risks of operation (Martins & Moutinho, 2025; Peswani & Joshipura, 2022). This basic assumption is also confirmed by the extensive analyses from other researchers (Balla, Chandra, Balla, Pani, & Sahu, 2025; Bi, Chang, & Yang, 2025; Romagosa, Dot, Mlakar, & Gorenak, 2025), which highlight the susceptibility of firms within a particular industry to common shocks. The condition of this complex interrelation among firms in a sector underscores the necessity of making investment decisions and risk assessments based on insights at the sector level.

With a better level of understanding of the individual industries, in this case, investors and analysts should be able to make more robust predictions as to which direction markets will move in, enabling a more complex approach to be taken for investment decisions. However, the assumption of industry homogeneity may pose substantial challenges. The study argues that this observation is especially critical when considering the fact that organizations in an identical industry can, and regularly do not have similar strategies (Y. Chai, Liu, Zhang, & Zhang, 2025) and deploy different technology and facilities (B. Liu, 2025), which can then cause a broad range of varied performance outputs. Moreover, differences in the economic environment (Bose & Srinivasan, 2025; Moshiri & Pourmand, 2025) as well as in consumers' preferences and behavior (C. Liu & Xiang, 2026; Shi, Lin, & Chen, 2026) bear a unique impact on businesses performances, further affirming that a standardised or one-size-fits-all approach (Major & Williams, 2026; Shan, Zhao, Xu, & Xue, 2025; Vavpotič, Fujs, & Hovelja, 2026) to risk assessment is not just irrelevant but perhaps misleading. Furthermore, firms may be operating across multiple regulatory environments (Ma & Zhuo, 2026; L. Zhang & Yong, 2026), which can differ markedly and significantly shape firms' risk profiles and potential returns, even within a specific industry.

Dissimilarity of capital structure (Kansikas & Gustafsson, 2024; Martins Rodrigues & Schneider, 2021; Pham, Do Nguyen, & Nguyen, 2025) and differences in cost-efficiency (Alwashah et al., 2026; Karanki & Yu, 2026) may also contribute to the creation of heterogeneity of firms' growth trajectories and financial capabilities. Studies have examined heterogeneity across similar sectors and industries using several econometric models and contexts; however, this study distinguishes itself by investigating the issue within the framework of a market model. It argues that key financial metrics in the model, specifically alpha and beta, may explain heterogeneity characteristics even in similar sectors and industries. First, the study examines the alpha value, which represents firms expected excess returns, and examines heterogeneity across firms in similar sectors and industries. Second, the study assesses the stock price's sensitivity to market movements by using the beta coefficient and examines heterogeneity across firms in similar sectors and industries. Third, the study examines the correlation between alpha and beta to investigate the linkage between the dispersion of systematic risk and the spread of idiosyncratic returns.

The novelty of this study lies in its departure from predictive modelling to a diagnostic examination of industry heterogeneity through the view of the market model. Our main contribution is the empirical finding that intra-industry differences often exceed inter-industry differences. By decomposing this spread into its components, we provide heterogeneity indices that can be used to measure firms' risk-returns profiles from the perspective of alpha and beta coefficients, both at the sectoral and industrial levels. The indices allow portfolio managers to diversify their investments more accurately based on risk profiles. The intra-industry dispersion analysis allows investors to reduce concentration risk by examining firm-level alpha–beta differences rather than relying on industry labels. The indices are also evidence-based screening tools for analysts and research teams, enabling them to rank firms by heterogeneity and focus on industries with better risk-return opportunities rather than relying on homogeneous risks within industries.

## 2. Literature Review and Hypotheses Development

The traditional sectoral analysis of finance assumes that firms operate within the same industrial boundaries and are exposed to similar market structures, regulations, and macroeconomic cycles, thereby implying expected convergence in risk-adjusted performance. This view is consistent with the Structure-Conduct-Performance (SCP) hypothesis (Y. Chai et al., 2025; Khan, Afridi, Tahir, & Burki, 2026; Ku & Chang, 2026), which argues that industry has a relatively similar structure which affects firm performance. Nonetheless, a few recent empirical findings have begun to question the validity of this homogeneity assumption (L. Chai, Zong, & Lai, 2026; B. Liu, 2025; Moshiri & Pourmand, 2025). Some of them argue that the structure of a firm's industry, in particular its level of ownership concentration, substantially influences firms' returns (Bozhkov, Lee, Sivarajah, Despoudi, & Nandy, 2020). They note that, in a highly concentrated ownership, their firms have different return profiles due to firm-specific strategic decisions. In other words, while industry membership sets the stage, it does not set the performance. If industry were the factor and source of risk-adjusted returns, it would be expected that Alpha (α), one key metric in the Market Model (Nakagawa, Hirano, Minami, & Mizuta, 2024; Zhao, 2024), approximate a sectoral mean. However, the non-persistence of alpha over time suggests that firm-specific idiosyncratic characteristics may enable firms to outperform their sectoral benchmarks.

Researchers have shown that competitive advantages related to sustainability are more firm-specific than industry-specific. This argument is based on the Resource-Based View (Kanoujiya, Agarwal, Rastogi, Tarode, & Bodne, 2026; Yu & Xin, 2026; S. Zhang, Wang, & Zhen, 2026), which posits that firm-specific resources and capabilities are the main factor in determining firm's performance. For example, recent researchers assert that a firm's internal governance competency (Ayurini & Wijayati, 2025) and technology (Mukhlis, Makhya, Yulianto, & Aviv, 2025; Nwosu, Obalum, & Ananti, 2024) has a substantial moderating effect on Environmental, Social, and Governance (ESG) risks (Ali, Subhani, & Zunhuan, 2026). The results indicate that, rather than being purely determined by industrial features, CEOs' experiences are closely linked to their firms' business strategies, which, in turn, determine the level of sustainability.

Along the same lines, other researchers explore how firms' management control aligns with sustainability objectives, suggesting that sustainability is not necessarily industry-driven but rather rooted in the firm's specific fundamentals (Fagerlin, Wen, & Lövstål, 2026). Another group echoed this point when presenting evidence that the effects of firm-specific idiosyncratic volatility endure (Ang, Hodrick, Xing, & Zhang, 2006). As a result, industry labels have become poor proxies for performance. This alteration implies that the aggregate signal across firms is often lost due to competitive reactions specific to those firms. That variety strongly suggests that the industry effect is not just a constant multiplier of risk factors.

This underlying conflict between sectoral similarities and firm uniqueness provides the basis for a critique of industry-based benchmarking in contemporary portfolio management practice, leading the study to investigate the following hypotheses.

$H_{1a}$: Firms within the same sector exhibit significantly different alpha values, indicating that sector membership is not a primary determinant of risk-adjusted excess returns

$H_{1b}$: Firms within the same industry exhibit significantly different alpha values, indicating that industry membership is not a primary determinant of risk-adjusted excess returns

Another critical measure in need of detailed analysis is the Beta coefficient. In accordance with the Capital Asset Pricing Model, beta is an essential measure of systematic risk that indicates how sensitive an asset is to general market movements. Although the traditional formulation of CAPM assumes that a single market factor influences returns ((Shahzad, Bouri, Ahmad, Naeem, & Vo, 2021), empirical observations in the real world indicate that beta estimates are not constant but rather vary, with substantial differences between firms and periods. In other case, Chinese researchers report a statistically significant decline in beta estimates following the COVID-19 outbreak and show that stronger industry characteristics may be inversely related to beta (Valadkhani, Marashdeh, & Ahmmod, 2026). Other team suggested that the risk-return relationship for investments is more firm-specific than industrially contingent (Kim, Kwon, Yoon, & Kim, 2026). This careful analysis of the relationships among beta, size, value, investment, and quality clearly shows how important each of these firm-specific characteristics in determining the firm's overall performance.

The study objective is to assess whether a firm's market risk is indeed driven by its macro-industrial classification, or, conversely, whether other factors may yield high-variance risk profiles that do not conform to the standard classifications. To achieve this objective, the study examines the following hypotheses.

$H_{2a}$: Firms within a similar sector have different beta values, indicating variation in market risk exposure

$H_{2b}$: Firms within a similar industry have different beta values, indicating variation in market risk exposure

The third dimension of our examination focuses on the theoretical relationship between the dispersions in systematic risk and idiosyncratic returns. As per the frameworks and principles set previously in standard financial theory, together with the original homogeneity assumption, firms under a constellation of relatively stable industry dynamics are bound to cluster around a universal Beta (Bose & Srinivasan, 2025). Nevertheless, the latest shifts in market structure have uncovered a concept referred to as heterogeneity coupling. Many researchers and scientists have recognized this important concept that the strategic gap between companies will become much wider, as more industries face disruption or find themselves under extreme regulatory pressure (L. Chai et al., 2026). This divergence is not limited to performance; it also translates into differences in how firms absorb market shocks (Beta) and generate excess returns (Alpha). As a result, the market model serves as a diagnostic test of whether the breakdown of system cohesion ($\Delta_{\beta}$) is antecedent to, or an outcome of, fragmented performance outcomes ($\Delta_{\alpha}$). Therefore, we hypothesize that the degree of fragmentation in risk exposure is intrinsically tied to the degree of heterogeneity in performance, and investigate the following hypothesis.

$H_{3a}$: At the sector level, there is a significant positive correlation between Intra-Sector Beta Dispersion and Intra-Sector Alpha Spread

$H_{3b}$: At the industry level, there is a significant positive correlation between Intra-Industry Beta Dispersion and Intra-Industry Alpha Spread

## 3. Methodology

### *3.1. Research Design*

This study uses a cross-sectional and quantitative approach based on a market model framework. The analysis proceeds in stages: the firm's dollar returns are initially regressed on a market index, represented by the $R_i = \alpha_i + \beta_i R_m + \epsilon_i$ equation, to estimate alpha and beta. Initial explorations reveal substantial skewness and leptokurtosis in risk-return distributions across GICS sectors, suggesting non-normality and invalidating the validity of conventional parametric tests. Therefore, in this report, the robust nonparametric equivalent of ANOVA i.e., the Kruskal-Wallis H test is used. Furthermore, Levene's Test for Equality of Variances is used to examine whether intra-industry heterogeneity in alpha and beta is statistically significant. The paper also examines the relationship between alpha and beta to explore associations between systematic risk spreads and idiosyncratic return spreads using Pearson Correlation (r) and Spearman Rank (rho).

#### *3.1.1. Data and Sample*

The sample for this research consists of all companies listed on the Indonesia Stock Exchange. The dataset includes 957,159 daily measurements from January 1, 2024, to December 31, 2024. By analysing such data, we obtained alpha and beta values using the daily and market index for that period. Data were sourced from www. idx. go. id, the market's official website. As shown in Table 1, the study removed 2 samples with missing values. In addition, a robust screening for outliers was conducted using a Z-score approach (any standardized value greater than |3|), which removed 27 samples. The refined data now show stronger overall adherence to the fundamental statistical assumptions of homoscedasticity and normality compared with prior evaluations. Beta has a standard deviation of 0.45 after extensive cleaning (down from the published 0.64 on the raw unfiltered data). This significant reduction in standard deviation indicates that the clean process successfully removed noise while retaining relevant economic signals, the following can be seen in the table 1.

Table 1. Sample selection

| **Steps** | **Observation Removed** | **Remaining *N*** |
|---|---|---|
| Initial observation | - | 630 |
| Missing Primary Data (Alpha/Beta) | 2 | 628 |
| Outlier Removal (Z-score > 3) | 27 | 601 |

#### *3.1.2 Alpha Coefficient*

The Alpha coefficient of the Market Model is the intercept of its regression line and would be a main characteristic among other regression parameters, such as risk-adjusted excess return. It is a measure of performance that cannot be explained by generalised market trends, and estimates the contribution of factors outside systematic market factors, such as management ability, innovation in operational activities, or any other competitive effects. In this study, Alpha serves as the primary variable for testing hypotheses $H_1$ and $H_3$.

The alpha coefficient (α) is determined using the following formula:

$$\alpha = R_i - \left(R_f + \beta_i(R_m - R_f)\right) \tag{1}$$

Where:

$R_i$ = the actual return;
$R_f$ = the risk-free rate;
$\beta_i$ = the beta coefficient;
$R_m$= market expected returns.

*3.1.3. Beta Coefficient*

The market model also introduced the Beta coefficient (β) as a primary measure of market risk, or systematic risk, which measures how security returns respond to the overall market. In this study, Beta is tested as the main predictor of $H_2$ and $H_3$. By examining variation in Beta within an industry, we seek to determine whether sector membership accurately reflects a firm's market sensitivity or whether individual leverage and operating characteristics create a patchwork of risks. Beta *(β)* is calculated using the following formula.

$$\beta_i = Cov(R_i, R_m)/Var(R_m) \tag{2}$$

Where:

$\beta_i$ = the beta coefficient;
$Cov(R_i, R_m)$ = the covariance between the returns of the stock $R_i$ and the returns of the market $R_m$;
$Var(R_m) =$ the variance of the market returns.

***3.5. GICS Sector and Industry***

This study deliberately restricts the analytical focus to the Global Industry Classification Standard (GICS) at the sector and industry levels for statistical rigor and thematic reach. Level (Level 1) GICS Sectors offer a general business environment for example, the financial sector. On the other hand, the GICS Industry Group (Level 2) is taken in the next step. For example, the Level 1 Financial Sector includes the Level 2 industry group, which covers Banks, Capital markets, Consumer Finance, Financial Services, and Insurance. We maintain a sufficient number of firms (at least 5) per cluster to apply rigorous comparative statistics, such as the Kruskal-Wallis H and Levene's tests.

***3.2. Statistical Modelling***

*3.2.1. Intra-Industry Alpha Spread ($\Delta\alpha_j$)*

The formula for the Intra-Industry Alpha Spread ($\Delta\alpha_j$) is designed to quantify the variability of alphas within a specific industry group $j$. The study calculates the Intra-Industry Alpha Spread for each Industry Group *j* by using the following equation.

$$\Delta\alpha_j = \frac{\sum_{i=1}^{N}(\alpha_i - \bar{\alpha}_j)^2}{N_j - 1} \tag{3}$$

Where:

$\Delta\alpha_j$ = The intra-industry alpha spread;
$\alpha_i$ = The alpha of the $i^{th}$asset within the industry group.
$\bar{\alpha}_j$ = The average alpha of all assets in 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.

*3.2.2 Intra-Industry Beta Variance*

To quantify the risk fragmentation within a GICS Industry Group, we calculate the Intra-Industry Beta Variance, by using the following equation.

$$\sigma^2{}_{b,j} = \frac{\sum_{i=1}^{N}(\beta_i - \bar{\beta}_j)^2}{N_j - 1} = \quad (4)$$

Where:

$\sigma^2{}_{b,j}$ = the Beta Dispersion within Industry Group *j*;
$\beta_i$ = the estimated Beta for individual firm *i*;
$\bar{\beta}_j$ = the mean Beta for all firms within that Industry Group;
$N_j$ = he samples size of firms within the GICS Industry Group *j*.
$N_j - 1$ = the degrees of freedom used to calculate an unbiased sample variance.

*3.2.3 Statistical Validation*

The tests of $H_1$, $H_2$, and $H_3$ use the Coefficient of Variation (CV) as the primary measure of differences within each industry. The CV is calculated by dividing the standard deviation of each company's risk change by the industry's average risk. This gives a measure of risk differences that does not depend on the overall size of the numbers.

$$CV_j = \frac{\sigma_j}{\mu_j} \quad (5)$$

Where:

$CV_j$ = Coefficient of Variation for sector *j*.
$\sigma_j$ = Standard deviation of total volatility (Stdev) for all firms within sector *j*.
$\mu_j$ = Mean total volatility (Stdev) for all firms within sector *j*

The significance of these results in the entire market is measured using a market-wide CV, by using the following equation.

$$CV_{Market} = \frac{\sigma_{Market}}{\mu_{Market}} \quad (6)$$

Where:

$CV_{Market}$ = The aggregate Coefficient of Variation for the entire population of firms;
$\sigma_{Market}$ = The standard deviation of total volatility ($\sigma$) calculated across all firms;
$\mu_{Market}$ = The arithmetic means of total volatility ($\sigma$) for all firms in the sample.

If the CV stays below 1, the sectors or industries are homogeneous, indicating that a member company is similar to the industry average and can therefore be used as a proxy for its member firms. Sectors with a CV higher than 1 are categorized as heterogeneous, meaning the internal variance is so large across firms that sector classification does not provide sufficient cohesion to form a risk identity.

Given that financial and operational metrics in specific industries often exhibit significant skewness and leptokurtosis, the Shapiro-Wilk test is also employed to assess the normality of the distribution. A significant result ($p < 0.01$) necessitates a shift from parametric to non-parametric inferential statistics to maintain the integrity of the findings and avoid Type I errors. Once non-normality is confirmed, the Kruskal-Wallis H test—a rank-based non-parametric alternative to the one-way ANOVA—is utilized to determine if statistically significant differences exist in the medians of Alpha and Beta across different firm clusters or industry segments. To complement this, Levene's test is applied to evaluate the equality of variances. A significant Levene's result ($p < 0.01$) specifically validates the Resource-Based View (RBV) perspective of intra-industry heterogeneity, as it proves that firm-level performance and risk profiles are not uniform despite shared market conditions.

## 4. Results and Discussions

### *4.1. Data Clean Up and Descriptive Statistic*

Table 2 presents the summary of statistics, including 601 cleaned observations for publicly traded firms, organized by GICS industry. The study excludes missing data and outliers using standard Z-score filtering (|Z| > 3), which improves the statistical properties of both parametric and nonparametric estimation, shown by the lower standard deviation of the parameters, especially Beta, which dropped from 0.666 to 0.483.

Table 2. Summary statistics of the refined sample

| Predictor | N | Minimum | Maximum | Mean | Std. Deviation | Skewness | Kurtosis |
|---|---|---|---|---|---|---|---|
| Alpha | 601 | -0.013178 | 0.009912 | -0.001358 | 0.003037 | -1.333385 | 3.76226 |
| Beta | 601 | -1.179203 | 1.946124 | 0.371813 | 0.483124 | 0.348242 | 0.75205 |

As shown in the table above, the Alpha value has a mean of -0.001358 and an SD of 0.0030. The small negative mean, combined with a skewness of -1.333, implies that most firms are indeed focusing on benchmark tracking. The negative skewness specifically indicates that a disproportionate number of firms in our sample have extreme negative Alpha values, meaning their returns frequently fall short of the benchmark, and point to underperformance across these firms. On the other hand, there is an overall bearishness across the industries analyzed, as evidenced by the Beta mean of 0.3718. The largest Beta value is 1.946, while the lowest is -1.179. The numbers indicate a wide range of systematic risk profiles; however, a relatively low average Beta also indicates that the portfolio is typically less risky than the overall market index.

### *4.2. Normality Examination*

Table 2 presented above also shows that the results of formal tests, jointly with descriptive statistics, indicate that the series Alpha and Beta do not follow a normal distribution in both cases. Overall, the p-values for the Shapiro-Wilk and D'Agostino-Pearson tests are far from 0.05 ($p < .001$), indicating a formal rejection of the null hypothesis of normality. This is also confirmed by the skewness and excess kurtosis statistics; Alpha shows a strong negative skew (−1.3334), though Steyx and Stdev show large positive skewness (>1.44). The large positive excess kurtosis values (>3.32) for these variables support a leptokurtic distribution with heavy tails and an acute peak.

### *4.3. Examining $H_1$: Intra-Industry Alpha Variation*

*4.3.1 Sectoral Intra-Industry Alpha Variation*

The findings presented in Table 4 represent a significant index of the performance counterbalancing. Using empirical findings from the Market Model framework, we find substantial performance heterogeneity across GICS-classified sectors, providing strong evidence against intra-industry homogeneity. According to the sectoral dispersion analysis, all 11 sectors analyzed in this part exhibit a Coefficient of Variation (CV) greater than 1, which is our benchmark for relative dispersion. Thus, the industry effect appears inadequate for accounting for cross-sectional variation in firm performance, leading us to provide strong empirical support for Hypothesis $H_{1a}$.

This heterogeneity varies by sector, with the Energy and Utilities sectors continuing to prevail with CV values of 472.05 and 13.13, respectively. These sectors show mean alphas close to zero, suggesting a significant degree of aggregate market efficiency. The efficiency paradox means that, while the sector as a whole closely follows market benchmarks, individual firms in these categories face very different idiosyncratic shocks. By contrast, the Information Technology (CV = 1.37) and Health Care (CV = 1.61) sectors are more uniformly diverse but clearly heterogeneous. The broad Alpha Spread (1.37% to 1.48%) in these innovation-driven sectors reflects the fact that firm-level competitive edges are more decisive than sectoral and industrial-group factors. Additionally, the extremely large Alpha Spread within Consumer Staples (2.24%) implies that a top-down sectoral allocation approach is limited. If sector membership were the main driver of returns, alpha values would all be clustered closely around the mean. Yet these performance gaps by firm-level strategic positioning are pronounced even in non-cyclical industries, as reflected in the observed dispersion. These results are consistent with the Resource-Based View (RBV) of the firm and indicate that alpha is fundamentally driven by internal capabilities.

Table 3. Sectoral Intra-Industry Alpha Variation

| GICS Sector Name | N | Mean Alpha ($\bar{\alpha}$) | Alpha Variance (σα2) | Alpha Spread (Δ) | CV | Conclusion |
|---|---|---|---|---|---|---|
| Energy | 41 | -0.000004 | 0.000004 | 0.0094 | 472.05 | Heterogenic |
| Utilities | 8 | 0.000105 | 0.000002 | 0.003 | 13.13 | Heterogenic |
| Consumer Staples | 74 | -0.000785 | 0.000011 | 0.0224 | 4.24 | Heterogenic |
| Industrials | 106 | -0.001073 | 0.000007 | 0.0164 | 2.48 | Heterogenic |
| Real Estate | 64 | -0.001664 | 0.000012 | 0.018 | 2.1 | Heterogenic |
| Financials | 90 | -0.001178 | 0.000006 | 0.0185 | 2.1 | Heterogenic |
| Materials | 67 | -0.001669 | 0.000009 | 0.0194 | 1.8 | Heterogenic |
| Consumer Discretionary | 79 | -0.002193 | 0.000013 | 0.0174 | 1.62 | Heterogenic |
| Health Care | 20 | -0.002514 | 0.000016 | 0.0148 | 1.61 | Heterogenic |
| Communication Services | 36 | -0.001478 | 0.000004 | 0.0085 | 1.39 | Heterogenic |
| Information Technology | 16 | -0.002746 | 0.000014 | 0.0137 | 1.37 | Heterogenic |
| Total Market | 610 | -0.00136 | 0.000009 | 0.0230 | 2.25 | Heterogenic |

This research tests Hypothesis $H_{1a}$ by switching from absolute variance to the Coefficient of Variation (CV) at the market level. Whereas industry-specific variance provides views particular to each industry, market-wide CVs provide an overall assessment of the market, revealing a market-wide CV of 2.25. This ratio indicates that the standard deviation of risk-adjusted excess returns is more than double the magnitude of the mean alpha. It shows that the Alpha value of firms is not simply a clustered-sector phenomenon but rather a highly heterogeneous, firm-specific element. In a setting where the CV is 2.25 for the market, the study argues that the sector label cannot be used to predict performance groups. The results imply that the intra-industry heterogeneity mentioned earlier is not a series of isolated sectoral anomalies, but a systemic characteristic of the market-wide risk-return profiles. Therefore, the study concludes in accepting Hypothesis $H_{1a}$.

The step from industry analysis to a broader sectoral understanding further supports the plausibility of hypothesis $H_{1a}$. The results of Levene's Test formal application at the sector level ($F=18.452$, $p<0.001$) show that non-constant dispersion in eleven GICS sectors' excess returns is present. Such statistical heterogeneity implies that some sectors, such as Consumer Staples and Energy, behave like high-variance clusters, in which idiosyncratic performance at the individual-firm level is orders of magnitude more important than sector-wide trends. Given the heterogeneity of risk across these broad categories, the study rejects the notion that a single measure of market risk or sector risk can adequately capture firm-level exposure.

The Kruskal-Wallis H-Test ($H=92.14$, $p<0.001$) also provides a similar conclusion by showing median Alpha values that differ across sectors (See Table 4). This cross-level heterogeneity demonstrates that firm-specific idiosyncratic noise is the principal driver of performance, whether an investor considers the 11 broad sectors or the 54 focused industries. This result is important because it suggests that the breakdown of homogeneity is a structural property of the overall market. Therefore, top-down sectoral allocation is mathematically more likely to fail than the bottom-up approach. Furthermore, the Shapiro-Wilk test reported a statistic of 0.812 and a p-value of less than 0.001, leading to rejection of the null hypothesis that the data are normally distributed.

Table 4. Statistical test result for sectoral intra-industry alpha variation

| Statistical Test (Sectoral Level) | Statistic | p-value | Decision | Relevance to $H_{1a}$ |
|---|---|---|---|---|
| Levene's Test | 18.452 | < 0.001* | Reject Null | Confirms that Alpha variance is significantly inconsistent across the 11 sectors. |
| Kruskal-Wallis H-Test | 92.14 | < 0.001* | Reject Null | Confirms that sectoral Alpha distributions are statistically distinct from one another. |
| Shapiro-Wilk Test | 0.812 | < 0.001* | Reject Null | Validates the use of CV by confirming the non-normal, skewed nature of the Alpha data. |

*Note: Significance levels at p < 0.01.

*4.3.2. Industrial Intra-Industry Alpha Variation*

At the industry level, Hypothesis $H_{1a}$ is empirically assessed and evidences a strong structural fragmentation of risk-adjusted performance over the entire market. Using CV as a standardized measure of dispersion, the data suggest that almost all GICS industries are intrinsically diverse (CV > 1). The CV at the level of the entire market is 2.24, a value that indicates that standard deviation (Alpha=0.003037) is more than twice as large as the mean Alpha (-0.001358). This statistical reality suggests that Alpha is not an industry trait, but rather a highly idiosyncratic firm-dependent phenomenon.

This heterogeneity is well illustrated in the capital-intensive sectors, especially in Oil, Gas & Consumable Fuels. There was an almost unbelievable Coefficient of Variation (CV) of 15.38. This figure shows that, in addition to being subject to a common global commodity price cycle, individual firms' operational efficiency varies widely, suggesting that factors beyond the industry group affect risk-adjusted returns. The final picture combines fragments of performances from various sources. Such a phenomenon is not unique; similar patterns exist in the Food Products industry, where the CV is 5.51, and in Construction & Engineering, where the CV is 4.46. The high values here make it clear that firms' industry classifications do not form a single, cohesive cluster. On the contrary, the industry effect may be overshadowed by firm-level idiosyncratic shocks and major management decisions, which together account for the extremely high observed performance spread.

On the other hand, only a slight fraction of the market less than one-quarter (22%) of the examined industries exhibits homogeneity. In contrast, industries such as Construction Materials (0.67) and Textiles (0.72) display near synchronicity in their movements, indicative of higher product commoditization and greater regulatory homogeneity, with these characteristics limiting individual firm maneuverability. But those examples are more the exception than the rule. Idiosyncratic risk is so high for the overwhelming majority of the 2024, that active portfolio management that drives bottom-up firm selection rather than top-down industry allocation is a necessity. The result provides a solid foundation for the study to question the inter-industry homogeneity assumption and shows that excess returns are driven by firm-level characteristics rather than group commonalities.

Table 5. Industrial intra-industry alpha variation

| GICS Industry Name | N | Mean Alpha | Alpha Variance | Alpha Stdev | Alpha Spread | CV | Conclusion |
|---|---|---|---|---|---|---|---|
| Oil, Gas & Consumable Fuels | 33 | -0.00013 | 0.00000 | 0.00198 | 0.00943 | 15.381 | Heterogenic |
| Machinery | 5 | -0.00058 | 0.00003 | 0.00586 | 0.01447 | 10.101 | Heterogenic |
| Food Products | 49 | -0.00060 | 0.00001 | 0.00332 | 0.02237 | 5.511 | Heterogenic |
| Construction & Engineering | 26 | -0.00060 | 0.00001 | 0.00267 | 0.01372 | 4.456 | Heterogenic |
| Transportation Infrastructure | 9 | 0.00026 | 0.00000 | 0.00115 | 0.00377 | 4.349 | Heterogenic |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Air Freight & Logistics | 5 | -0.00104 | 0.00001 | 0.00382 | 0.00926 | 3.685 | Heterogenic |
| Metals & Mining | 24 | -0.00087 | 0.00001 | 0.00316 | 0.01568 | 3.626 | Heterogenic |
| Distributors | 5 | -0.00064 | 0.00000 | 0.00217 | 0.00568 | 3.405 | Heterogenic |
| Energy Equipment & Services | 8 | 0.00051 | 0.00000 | 0.00167 | 0.00547 | 3.272 | Heterogenic |
| Consumer Staples Distribution & Retail | 9 | -0.00047 | 0.00000 | 0.00134 | 0.00440 | 2.886 | Heterogenic |
| Automobile Components | 7 | 0.00029 | 0.00000 | 0.00078 | 0.00217 | 2.667 | Heterogenic |
| Beverages | 6 | -0.00221 | 0.00003 | 0.00551 | 0.01656 | 2.495 | Heterogenic |
| Banks | 44 | -0.00068 | 0.00000 | 0.00159 | 0.01011 | 2.350 | Heterogenic |
| Specialty Retail | 16 | -0.00111 | 0.00001 | 0.00259 | 0.01158 | 2.320 | Heterogenic |
| Independent Power and Renewable Electricity Producers | 6 | -0.00047 | 0.00000 | 0.00103 | 0.00276 | 2.186 | Heterogenic |
| Consumer Finance | 13 | -0.00163 | 0.00001 | 0.00352 | 0.01332 | 2.155 | Heterogenic |
| Interactive Media & Services | 3 | -0.00206 | 0.00002 | 0.00437 | 0.00764 | 2.120 | Heterogenic |
| Real Estate Management & Development | 64 | -0.00166 | 0.00001 | 0.00350 | 0.01799 | 2.102 | Heterogenic |
| Trading Companies & Distributors | 12 | -0.00146 | 0.00001 | 0.00300 | 0.01139 | 2.046 | Heterogenic |
| Insurance | 18 | -0.00139 | 0.00001 | 0.00281 | 0.01235 | 2.023 | Heterogenic |
| Building Products | 7 | -0.00167 | 0.00001 | 0.00338 | 0.00957 | 2.018 | Heterogenic |
| Chemicals | 15 | -0.00110 | 0.00000 | 0.00200 | 0.00806 | 1.829 | Heterogenic |
| Personal Care Products | 4 | 0.00148 | 0.00001 | 0.00269 | 0.00575 | 1.819 | Heterogenic |
| Diversified Telecommunication Services | 14 | -0.00071 | 0.00000 | 0.00122 | 0.00451 | 1.708 | Heterogenic |
| Commercial Services & Supplies | 8 | -0.00130 | 0.00000 | 0.00202 | 0.00673 | 1.552 | Heterogenic |
| Paper & Forest Products | 7 | -0.00164 | 0.00001 | 0.00251 | 0.00675 | 1.537 | Heterogenic |
| Pharmaceuticals | 9 | -0.00364 | 0.00003 | 0.00558 | 0.01479 | 1.534 | Heterogenic |
| Capital Markets | 12 | -0.00111 | 0.00000 | 0.00171 | 0.00568 | 1.534 | Heterogenic |
| Hotels, Restaurants & Leisure | 26 | -0.00330 | 0.00002 | 0.00494 | 0.01744 | 1.498 | Heterogenic |
| Marine Transportation | 12 | -0.00147 | 0.00000 | 0.00216 | 0.00755 | 1.475 | Heterogenic |
| Containers & Packaging | 15 | -0.00260 | 0.00001 | 0.00351 | 0.01316 | 1.351 | Heterogenic |
| Health Care Providers & Services | 11 | -0.00160 | 0.00000 | 0.00207 | 0.00685 | 1.298 | Heterogenic |
| Electrical Equipment | 4 | -0.00172 | 0.00000 | 0.00220 | 0.00480 | 1.277 | Heterogenic |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Electronic Equipment, Instruments & Components | 5 | -0.00156 | 0.00000 | 0.00197 | 0.00549 | 1.268 | Heterogenic |
| Passenger Airlines | 3 | -0.00212 | 0.00001 | 0.00251 | 0.00502 | 1.188 | Heterogenic |
| Ground Transportation | 11 | -0.00155 | 0.00000 | 0.00158 | 0.00565 | 1.018 | Heterogenic |
| Software | 5 | -0.00571 | 0.00003 | 0.00569 | 0.01287 | 0.997 | Homogenic |
| Entertainment | 4 | -0.00162 | 0.00000 | 0.00157 | 0.00308 | 0.965 | Homogenic |
| Tobacco | 4 | -0.00335 | 0.00001 | 0.00306 | 0.00671 | 0.913 | Homogenic |
| Media | 13 | -0.00240 | 0.00000 | 0.00216 | 0.00772 | 0.903 | Homogenic |
| IT Services | 3 | -0.00076 | 0.00000 | 0.00068 | 0.00129 | 0.889 | Homogenic |
| Financial Services | 3 | -0.00554 | 0.00002 | 0.00492 | 0.00913 | 0.888 | Homogenic |
| Household Durables | 4 | -0.00127 | 0.00000 | 0.00100 | 0.00213 | 0.789 | Homogenic |
| Industrial Conglomerates | 2 | -0.00257 | 0.00000 | 0.00197 | 0.00278 | 0.765 | Homogenic |
| Textiles, Apparel & Luxury Goods | 16 | -0.00300 | 0.00000 | 0.00217 | 0.00661 | 0.721 | Homogenic |
| Construction Materials | 6 | -0.00400 | 0.00001 | 0.00266 | 0.00707 | 0.666 | Homogenic |
| Broadline Retail | 4 | -0.00150 | 0.00000 | 0.00092 | 0.00215 | 0.615 | Homogenic |
| Wireless Telecommunication Services | 2 | 0.00029 | 0.00000 | 0.00018 | 0.00025 | 0.604 | Homogenic |
| Technology Hardware, Storage & Peripherals | 2 | -0.00132 | 0.00000 | 0.00078 | 0.00111 | 0.594 | Homogenic |
| Household Products | 2 | -0.00183 | 0.00000 | 0.00062 | 0.00088 | 0.340 | Homogenic |
| Gas Utilities | 2 | 0.00184 | 0.00000 | 0.00000 | 0.00000 | 0.000 | Homogenic |
| Aerospace & Defense | 1 | -0.00199 | | | 0.00000 | | Homogenic |
| Communications Equipment | 1 | -0.00270 | | | 0.00000 | | Homogenic |
| Diversified Consumer Services | 1 | -0.00948 | | | 0.00000 | | Homogenic |
| Professional Services | 1 | 0.00231 | | | 0.00000 | | Homogenic |
| **Total Market** | **601** | **-0.00136** | **0.00001** | **0.00304** | **0.02309** | **2.23636** | **Heterogenic** |

Besides CV analysis, the validation of Hypothesis $H_{1a}$ is supported by a rejection of the null hypothesis in Levene's Test of Homogeneity of Variance (F=24.812, p<0.001). The results presented in Table 6 suggest that the internal risk (as measured by dispersion) across GICS industries is heterogeneous, providing a theoretical basis for the heterogeneity we expect to observe. Moreover, the Kruskal-Wallis H-Test (H=114.56, p<0.001) indicates that despite the presence of industry labels, these distributions of Alpha are statistically disjoint yet similar at high-variance profiles. Together with the Shapiro-Wilk results, which indicate fat tails and non-normality, the results justify the use of the Coefficient of Variation (CV) as a primary measure of dispersion. The overall conclusion is that the assumption of intra-industry homogeneity, as typically used in standard linear models, is clearly not appropriate, thereby supporting $H_{1a}$.

Table 6. Industrial intra-industry alpha test results

| Statistical Test | Statistic | p-value | Decision | Relevance to $H_{1a}$ |
|---|---|---|---|---|
| Levene's Test | 24.812 | < 0.001* | Reject Null | Confirms alpha variance is significantly different across industries (Heterogenic). |
| Kruskal-Wallis H-Test | 114.56 | < 0.001* | Reject Null | Confirms that industry-level performance distributions are not identical. |
| Shapiro-Wilk Test | 0.812 | < 0.001* | Reject Null | Confirms non-normality, justifying the use of Coefficient of Variation (CV). |

*Note: Significance levels at p < 0.01.

### *4.4. Examining $H_2$: Inter-Industry Beta Heterogeneity*

*4.4.1. Inter-Industry Beta Heterogeneity at Sectoral Level*

Table 7 below shows that firms within the same GICS sectors in the sample had different market risk exposure (Beta). Hypothesis $H_{2a}$ shows that, at the sectoral level, no strong beta proxies are found in favor of firm-specific risk profiles. The result challenges common academic finance literature, which suggests that sectors are homogeneous groups of firms with similar market responsiveness. The empirical data presented in the table do not support this expectation, as Beta CVs exceed 1.0 for all 11 GICS sectors. For example, the Information Technology sector has a CV of 4.85, meaning that the internal variation in market risk exposure is 4.85 times the sector's mean Beta. Indeed, this finding indicates that the sector label "Tech" is a largely uninformative predictor of a firm's systematic risk.

This fragmentation is also supported by the Consumer Discretionary (CV = 1.52) and Industrials (CV = 1.33) sectors, with large sample sizes (N = 79 and N = 106, respectively). These sectors, despite their sizes, do not exhibit a common risk profile. Rather, the Beta standard deviations (0.5167 and 0.3393, respectively) mask any sectoral signal due to risk noise. This pervasive heterogeneity evidence leads to rejection of the null hypothesis for $H_{2a}$, suggesting that firms within a market sector do not share a common exposure to market risk. Thus, the presumption that a Beta on an industry basis of group measurement is statistically invalid.

Table 7. Beta dispersion at sectoral level

| GICS Sector Name | N | Mean Beta | Beta Stdev | CV (Beta) | Conclusion |
|---|---|---|---|---|---|
| Information Technology | 16 | 0.0759 | 0.3685 | 4.8538 | Heterogenic |
| Consumer Discretionary | 79 | 0.3393 | 0.5167 | 1.523 | Heterogenic |
| Real Estate | 64 | 0.3103 | 0.4149 | 1.3373 | Heterogenic |
| Industrials | 106 | 0.3647 | 0.4866 | 1.3343 | Heterogenic |
| Health Care | 20 | 0.384 | 0.5048 | 1.3145 | Heterogenic |
| Consumer Staples | 74 | 0.3383 | 0.4428 | 1.3088 | Heterogenic |
| Financials | 90 | 0.4349 | 0.5553 | 1.277 | Heterogenic |
| Utilities | 8 | 0.3508 | 0.442 | 1.2603 | Heterogenic |
| Materials | 67 | 0.4302 | 0.4774 | 1.1097 | Heterogenic |
| Communication Services | 36 | 0.4515 | 0.4916 | 1.0889 | Heterogenic |
| Energy | 41 | 0.4194 | 0.4266 | 1.0173 | Heterogenic |
| **Total Market** | **601** | **0.3718** | **0.4831** | **1.2994** | **Heterogenic** |

Thus, the examination of systematic risk via the aggregate market measures an empirical metric for assessing Hypothesis $H_{2a}$. These results show an overall market Beta Mean of 0.3718, Standard Deviation (Stdev) of 0.4831, and a Coefficients of Variation (CV) of 1.30 by aggregating data across all 601 firms. This market-wide CV is very high and far exceeds the threshold that generally signifies homogeneity. The fact that the standard deviation is larger than the mean at the aggregate level suggests that systematic risk exposure is not a centralized force but is instead highly fragmented across the entire economy.

As extensive secondary evidence of Hypothesis $H_{2a}$, Table 8 presents Beta distributions across the entire market. Beyond the CV analyses shown above, the study rejects the null hypothesis of normality of systematic risk exposure based on the Shapiro-Wilk Test ($W = 0.9828$, $p < 0.001$). The non-normal distribution of Beta is indicated by skewness and outliers, which proves that it is not concentrated around the center of the data. Thus, the results justify the use of non-parametric dispersion measures (e.g., the Coefficient of Variation) for assessing risk heterogeneity. Levene's Test and the Kruskal-Wallis H-Test also report similar results that lead to the failure to reject the null hypothesis. Analysis of Levene's Test shows a p-value result of 0.5319, implying that Beta variance is statistically homogeneous across all GICS sectors. Simultaneously, the Kruskal-Wallis Test ($p = 0.1821$) also implies that median Beta values are not meaningfully different between sectors. Taken together with the significant intra-sector CV values, these observations point to an intriguing conclusion that the sector label does not provide a meaningful value for market risk measurement.

Table 8. Beta heterogeneity test for the entire market from sectoral level perspective

| Statistical Test | Scope | Statistic | p-value | Decision |
|---|---|---|---|---|
| Shapiro-Wilk Test | Normality of Global Beta | 0.9828 | < 0.001* | Reject Null (Non-Normal) |
| Levene's Test | Homogeneity of Variance across Sectors | 0.901 | 0.5319 | Fail to Reject (Homogeneous Variance) |
| Kruskal-Wallis H-Test | Equality of Beta Medians across Sectors | 13.8036 | 0.1821 | Fail to Reject (Equal Medians) |

*Note: Significance at p < 0.01.

The study concludes that sector membership does not determine a firm's exposure to systematic risk. Rather, this risk is uniform and heterogeneous across a broad array of sectors that are statistically indistinguishable from one another. This universal heterogeneity corroborates the view that $H_{2a}$ is the idiosyncratic feature of systematic risk. As a result, sector-based Beta proxies are insufficient for determining the true level of firms' risk profile.

*4.4.2 Inter-Industry Beta Heterogeneity at Industry Level*

As shown in Table 9, the examination results provide evidence in favour of $H_2$, showing that systematic risk (Beta) varies at the granular level. The rejection of risk homogeneity is almost universal at the specific industry level. As for the Electronic Equipment & Components sector, it is not only above average in intensity but has also recorded a CV of up to 7.1519, meaning that firm-level Beta divergence from the industry mean is very strong. The result is similar across other industries, such as Textiles, Apparel & Luxury Goods (CV = 3.3658) and Air Freight & Logistics (CV = 2.7323), which illustrate that even in narrowly defined competitive groups, systematic risk remains decidedly idiosyncratic. The result shows a large decoupling Beta coefficient across the entire market, with a coefficient of variation of 1.2994, indicating that the market risk standard deviation is almost 130% of the mean. The high degree of heterogeneity means the market as a whole is not following a single risk profile, leading to even greater divergences at the sub-sector level. The result challenges the traditional view that industry groups exhibit similar sensitivity to market direction.

Table 9. Beta heterogeneity test result at industry level

| GICS Industry Name | N | Mean Beta | Beta Stdev | Min Beta | Max Beta | CV Beta | Conclusion |
|---|---|---|---|---|---|---|---|
| Electronic Equipment, Instruments & Components | 5 | 0.0759 | 0.5429 | -0.8629 | 0.5059 | 7.1519 | Heterogenic |
| Electrical Equipment | 4 | 0.0993 | 0.3393 | -0.1623 | 0.5557 | 3.4152 | Heterogenic |
| Textiles, Apparel & Luxury Goods | 16 | 0.1875 | 0.6311 | -1.0936 | 1.4986 | 3.3658 | Heterogenic |
| Air Freight & Logistics | 5 | 0.3304 | 0.9028 | -1.0301 | 1.3702 | 2.7323 | Heterogenic |
| Passenger Airlines | 3 | 0.0888 | 0.2426 | -0.1365 | 0.3456 | 2.7317 | Heterogenic |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Entertainment | 4 | 0.3498 | 0.7797 | -0.2313 | 1.4281 | 2.2289 | Heterogenic |
| Hotels, Restaurants & Leisure | 26 | 0.2340 | 0.5164 | -0.8522 | 1.9461 | 2.2069 | Heterogenic |
| Building Products | 7 | 0.1410 | 0.2863 | -0.2847 | 0.5990 | 2.0308 | Heterogenic |
| Independent Power and Renewable Electricity Producers | 6 | 0.2207 | 0.4386 | -0.1276 | 0.9553 | 1.9873 | Heterogenic |
| Financial Services | 3 | -0.3939 | 0.7448 | -1.1792 | 0.3024 | 1.8911 | Heterogenic |
| Containers & Packaging | 15 | 0.3091 | 0.5703 | -0.6891 | 1.6013 | 1.8450 | Heterogenic |
| Software | 5 | 0.2010 | 0.3642 | -0.1666 | 0.7454 | 1.8124 | Heterogenic |
| Beverages | 6 | 0.3712 | 0.6708 | -0.6202 | 1.4000 | 1.8070 | Heterogenic |
| Paper & Forest Products | 7 | 0.2032 | 0.3551 | -0.3783 | 0.6318 | 1.7470 | Heterogenic |
| Health Care Providers & Services | 11 | 0.3908 | 0.6322 | -0.8950 | 1.6765 | 1.6179 | Heterogenic |
| Capital Markets | 12 | 0.2772 | 0.4464 | -0.4488 | 1.0465 | 1.6107 | Heterogenic |
| Interactive Media & Services | 3 | 0.3327 | 0.5053 | -0.2389 | 0.7197 | 1.5188 | Heterogenic |
| Insurance | 18 | 0.3449 | 0.5176 | -0.6430 | 1.5366 | 1.5006 | Heterogenic |
| Energy Equipment & Services | 8 | 0.3458 | 0.4968 | -0.5500 | 1.1174 | 1.4365 | Heterogenic |
| Distributors | 5 | 0.2188 | 0.3062 | -0.1393 | 0.5471 | 1.3994 | Heterogenic |
| Machinery | 5 | 0.3599 | 0.4824 | -0.3513 | 0.9111 | 1.3402 | Heterogenic |
| Real Estate Management & Development | 64 | 0.3103 | 0.4149 | -0.7661 | 1.4739 | 1.3373 | Heterogenic |
| Food Products | 49 | 0.3083 | 0.4098 | -0.7320 | 1.0510 | 1.3290 | Heterogenic |
| Trading Companies & Distributors | 12 | 0.2976 | 0.3907 | -0.3262 | 1.0919 | 1.3128 | Heterogenic |
| Construction & Engineering | 26 | 0.5153 | 0.6426 | -0.4943 | 1.7479 | 1.2472 | Heterogenic |
| Consumer Finance | 13 | 0.2631 | 0.3276 | -0.3411 | 0.9855 | 1.2449 | Heterogenic |
| Diversified Telecommunication Services | 14 | 0.3610 | 0.4367 | -0.5641 | 0.9130 | 1.2095 | Heterogenic |
| Tobacco | 4 | 0.6962 | 0.7677 | 0.1150 | 1.7765 | 1.1027 | Heterogenic |
| Transportation Infrastructure | 9 | 0.2959 | 0.3237 | -0.0940 | 0.9064 | 1.0941 | Heterogenic |
| Consumer Staples Distribution & Retail | 9 | 0.4020 | 0.4339 | -0.1826 | 1.0719 | 1.0793 | Heterogenic |
| Chemicals | 15 | 0.3202 | 0.3449 | -0.5659 | 0.8594 | 1.0771 | Heterogenic |
| IT Services | 3 | -0.1477 | 0.1558 | -0.3104 | 0.0000 | 1.0547 | Heterogenic |
| Ground Transportation | 11 | 0.4833 | 0.4898 | -0.3811 | 1.3829 | 1.0135 | Heterogenic |
| Industrial Conglomerates | 2 | 0.4741 | 0.4785 | 0.1357 | 0.8125 | 1.0093 | Heterogenic |
| Oil, Gas & Consumable Fuels | 33 | 0.4372 | 0.4146 | -0.6237 | 1.3883 | 0.9482 | Heterogenic |
| Commercial Services & Supplies | 8 | 0.2188 | 0.2049 | -0.1123 | 0.4979 | 0.9365 | Heterogenic |
| Banks | 44 | 0.6219 | 0.5680 | -0.1619 | 1.9031 | 0.9133 | Heterogenic |
| Metals & Mining | 24 | 0.5661 | 0.4959 | -0.3852 | 1.3515 | 0.8760 | Heterogenic |
| Pharmaceuticals | 9 | 0.3758 | 0.3247 | -0.0480 | 0.8538 | 0.8640 | Heterogenic |
| Specialty Retail | 16 | 0.4744 | 0.4065 | -0.0371 | 1.3177 | 0.8568 | Heterogenic |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Media | 13 | 0.5926 | 0.4999 | -0.5481 | 1.2815 | 0.8437 | Heterogenic |
| Broadline Retail | 4 | 0.4258 | 0.3527 | 0.0792 | 0.8715 | 0.8283 | Heterogenic |
| Automobile Components | 7 | 0.5464 | 0.4355 | 0.0636 | 1.2874 | 0.7970 | Heterogenic |
| Marine Transportation | 12 | 0.4510 | 0.3437 | 0.0070 | 1.0973 | 0.7620 | Heterogenic |
| Wireless Telecommunication Services | 2 | 0.5495 | 0.4136 | 0.2570 | 0.8419 | 0.7528 | Heterogenic |
| Household Durables | 4 | 0.4258 | 0.3138 | 0.1168 | 0.7789 | 0.7369 | Heterogenic |
| Technology Hardware, Storage & Peripherals | 2 | 0.1733 | 0.0990 | 0.1034 | 0.2433 | 0.5709 | Heterogenic |
| Construction Materials | 6 | 0.7286 | 0.3655 | 0.2039 | 1.1955 | 0.5016 | Heterogenic |
| Personal Care Products | 4 | 0.2217 | 0.1083 | 0.0666 | 0.3183 | 0.4882 | Heterogenic |
| Household Products | 2 | 0.2050 | 0.0568 | 0.1649 | 0.2452 | 0.2769 | Heterogenic |
| Gas Utilities | 2 | 0.7409 | 0.0000 | 0.7409 | 0.7409 | 0.0000 | Homogenic |
| Aerospace & Defense | 1 | 0.8117 | | 0.8117 | 0.8117 | | Homogenic |
| Communications Equipment | 1 | -0.0731 | | -0.0731 | -0.0731 | | Homogenic |
| Diversified Consumer Services | 1 | 1.8042 | | 1.8042 | 1.8042 | | Homogenic |
| Professional Services | 1 | -0.3155 | | -0.3155 | -0.3155 | | Homogenic |
| **Total Market** | **601** | **0.3718** | **0.4831** | **-1.1792** | **1.9461** | **1.2994** | **Heterogenic** |

Shifting from sectoral to industry-level formal testing enhances the main insights of $H_2$, while introducing significant statistical nuance. Following the process, the Shapiro-Wilk test shows significance ($p < 0.001$), validating that any underlying Beta distribution is not normal but heavy-tailed. The results indicate that, unlike conventional measures, the Coefficient of Variation (CV) is the relevant metric for measuring heterogeneity, contrary to traditional parametric assumptions, which are argued to be invalid. The Levene's Test ($p = 0.2362$) and the Kruskal-Wallis Test ($p = 0.1838$), which are crucial across industries, also provide a nonintuitive but significant insight for this study. As shown in Table 10, the study rejects the null hypothesis in both tests, indicated by the extreme within-industry dispersion (CV > 1.0). Agree with the previous observation, this finding reiterates that heterogeneity is a systemic constant, not a group-level phenomenon.

The results show that moving from general sectors to a more granular industry classification does not solve the problem of risk dispersion. A firm's exposure to market risk is not limited to its sector — the variance of systematic risk within industries. This injection suggests the acceptance of $H_2$: Beta is firm-specific. The traditional notion, which is commonly called the industry-average beta as a proxy for firm-level risk, is fundamentally flawed, given that constituent firms generally have significant and unique systematic risk profiles that differ from those captured by their individual averages.

Table 10. Beta Heterogeneity Test for the Entire Market from Industrial Level Perspective

| Statistical Test | Scope | Statistic | p-value | Decision (α=0.05) |
|---|---|---|---|---|
| Shapiro-Wilk Test | Market-Wide Beta | 0.9828 | < 0.001* | Reject Null (Non-Normal) |
| Levene's Test | Across GICS Industries | 1.1811 | 0.2362 | Fail to Reject (Homogeneous Variance) |
| Kruskal-Wallis H-Test | Across GICS Industries | 36.7752 | 0.1838 | Fail to Reject (Equal Medians) |

*Significant at the 0.01 level.

### 4.5. Examining $H_3$: A Higher Beta Dispersion Exhibit Higher Alpha Spread

*4.5.1 Inter-Industry Beta Heterogeneity at Sectoral Level*

In Table 11, the sectoral correlation data show that, overall, there is a large disparity between system risk dispersion and the performance of different industries. Therefore, we may now sort GICS industries into distinct classes. The only exception is Health Care, which shows both lower dispersion amongst alphas ($\Delta_\alpha$= 0.004055) and risk far superior to that for betas ($\Delta_\beta$ = 0.504799). The results hint at differences in sensitivity to market movements and in the generation of excess returns among health-care companies, as well as a lack of internality among Health Care stocks. Conversely, enterprises such as Information Technology and Real Estate fall into the Idiosyncratic Alpha cluster: their high Alpha Spreads (0.003774 and 0.003498) are accompanied by lower Beta Dispersion. In the Information Technology sector, its Beta is relatively low (0.368539%), meaning that market movements push performance higher. However, the share's performance is more influenced by factors other than the markets themselves.

In contrast, the study notes that the Financials sector is risk-fragmented with a Beta Dispersion of 0.555304, ranking first among sectors. This degree of heterogeneity in market sensitivity is due to the presence of both defensive and aggressive high-leverage institutions within this sector. These exceptions notwithstanding, the Alpha Spread is still relatively low at 0.002472. That means, although the structural risk profile of financial companies is relatively dispersed, compared with high-tech firms which show a narrower distribution in performance, it is efficiently priced by the market. Utilities, on the other hand, represent the market's stable anchor, with an Alpha Spread of only 0.001378 and minimal risk divergences. The figures that follow homogeneity are a byproduct of the industry's core traits, such as stable cash flows and mass-market business models.

Table 11. Alpha spread and beta dispersion at industry level

| GICS Sector Name | N$j$ | Alpha Spread Delta | Beta Dispersion Delta |
|---|---|---|---|
| Communication Services | 36 | 0.002053065 | 0.491636343 |
| Consumer Discretionary | 79 | 0.003549651 | 0.516735212 |
| Consumer Staples | 74 | 0.00332815 | 0.442783302 |
| Energy | 41 | 0.001916604 | 0.426630608 |
| Financials | 90 | 0.002472331 | 0.555304251 |
| Health Care | 20 | 0.004054659 | 0.50479909 |
| Industrials | 106 | 0.002657374 | 0.486592924 |
| Information Technology | 16 | 0.003774256 | 0.368538708 |
| Materials | 67 | 0.003010295 | 0.477355506 |
| Real Estate | 64 | 0.003498177 | 0.414900661 |
| Utilities | 8 | 0.001378435 | 0.442042958 |

The study employed a correlation analysis at the sectoral level, using both Pearson Correlation (r) and Spearman Rank, to study the relationship between risk dispersion and performance heterogeneity. The table analyses how Beta Dispersion relates to Alpha Spread across all 11 GICS Sectors. The results of this sector-level analysis are presented in Table 12, which shows the association between Intra-Industry Alpha Spread and Beta Dispersion. The findings suggest that there is no linear or monotonic relationship between systemic risk dispersion and performance heterogeneity. In addition, these two variables are not correlated (Pearson test: r = −0.08, p = 0.81; Spearman rank correlation: rho = 0.027, p = 0.94).

These results have important implications for market risk, particularly regarding which firms are more sensitive to the global market. While differences in systematic risk, likely due to varying firm behaviours across trading strategies, were observed, performance in terms of excess returns (Alpha) did not correlate with systematic risk. For example, the IT industry shows the greatest range of Alpha values (Mean = 0.0037), whereas the financial sector has the largest spread in Beta = 0.555. These findings suggest that, although firms in these sectors respond differently to overall market conditions, their excess returns tend to follow a similar, independent pattern. Therefore, the study does not support Hypothesis $H_{3a}$, the following can be seen in the table 12.

Table 12. Correlation of alpha spread and beta dispersion at sectoral level

| Metric | Coefficient | p-value | Interpretation |
|---|---|---|---|
| Pearson Correlation (r) | -0.080421465 | 0.81416796 | Not Significant |
| Spearman Rank (rho) | 0.027272727 | 0.936558448 | Not Significant |

*4.5.2 Inter-Industry Beta Heterogeneity at Industry Level*

The study observes similar findings at the GICS Industry level, supporting the suggestion that non-uniform exposure to systematic risk does not match non-uniform performance. Table 13 provides observed Peason Correlation coefficient of 0.12, as well as the insignificant p-value in the regression model (p = 0.483), show that the industry has failed to convert its risk, as reflected in Beta, into a performance measure represented by Alpha spread. The result strengthens the overall conclusion that Alpha fragmentation is an idiosyncratic issue. Thus, the study supports the rejection of Hypothesis $H_{3b}$, the following can be seen in the table 13.

Table 13. Correlation of alpha spread and beta dispersion at industry level

| Metric | Coefficient | p-value | Significance |
|---|---|---|---|
| Pearson Correlation (r) | 0.1207 | 0.4831 | Not Significant |
| Spearman Rank (rho) | 0.0324 | 0.8527 | Not Significant |

This empirical result, i.e., that Beta and Alpha are essentially unrelated, motivates revisiting the modern portfolio theory and industrial organization questions at a more fundamental level. In a classic risk pricing model like the CAPM (Capital Asset Pricing Model), Beta is recognized as driving expected return, and Alpha represents market inefficiency within a segment of the marketplace. This relatively low correlation (r = 0.12) observed in this study indicates that the drivers of market sensitivity differ from those driving excess returns (e.g., innovation, managerial talent, or proprietary technology).

The negligible effect size (p = 0.483) further confirms the predominance of the Resource-Based View (RBV) over the Structure-Conduct-Performance (SCP) approach. Within SCP, industry structure is the most important factor affecting performance. The findings, however, imply that the industry effect is not a homogeneous cross-sectional transmission mechanism for risk premiums. On the contrary, Alpha fragmentation seems to be a purely firm-specific mechanism, since competitive differences arise at the single-firm level through idiosyncratic resource characteristics, irrespective of the more general systematic industry risk profile. As a result, investors and analysts cannot leverage industry risk attributes to clarify variation in performance, since the determinants of greater or lesser exposure to market risk are conceptually distinct from the strategic components that give rise to excess returns after controlling for industry risk.

## 5. Conclusions

### *5.1 Conclusion*

This study offers an interesting empirical counter to the assumption of homogeneity, which has been used to justify the Capital Asset Pricing Model (CAPM) and sector-specific indexing. Applying a Market Model approach and using nonparametric statistical analysis (Kruskal-Wallis H and Levene's tests) to test whether risk-return profiles differ across GICS classification groups, the study examines company performance by type. It is a landscape of striking structural and performance heterogeneity, as this analysis shows. Although broad industry classifications are used as simple proxies for systematic risk, they often hide the volatility clusters and idiosyncratic features that govern modern-day investing. The study finds significant heterogeneity in Alpha across sectors and industries.

The null hypothesis that the differences between Alpha medians and variances were not significant was rejected. The study findings suggest that industry membership alone cannot be the overriding determinant of risk-adjusted excess returns. Therefore, stock performances are mainly determined by firm-specific strategic choices and sustainable competitive advantages. On the other hand, systematic risk exposure, as measured by Beta, exhibits substantial sectoral commonality. However, the findings indicate that while actual firm performance widely differs within a sector or industry, they all exhibit similar market sensitivities at a high level of classification, and suggest that systematic risk is more about individual firms than the collective traits found in sector and industry groups.

This study uncovers a structurally significant decoupling between the systematic risk and performance diversity. The results show that Intra-Industry Alpha Spread does not relate to Intra-Industry Beta Dispersion. This finding suggests the determinants of market sensitivity are quite distinct from those that determine strategic sources of excess returns. The result challenges the traditional concepts by suggesting firms with higher gains do not necessarily pose a higher risk. From a theoretical perspective, the Resource-Based View (RBV) implies it may be more successful than the Structure-Conduct-Performance (SCP) framework, as the latter neglects a systematic stream of risk premia. One of the study's main contributions is moving from a predictive analytics framework to an industry-specific diagnostic framework. The study argues that portfolio managers who search for statistical outliers should find the conclusions fascinating, because variation within and between industries is just too similar, highlighting those differences are often greater than systematic across sectors. The study views these findings as a statistically defensible caution against the risk of homogeneity and therefore recommends that investors and analysts focus on firm-level market model metrics rather than on increasingly biased signals generated by traditional sector classifications.

### *5.2 Research Limitation*

This study assesses firms' risk and returns profiles based only on internal factors. It does not consider external factors that influence market risk. Macroeconomic and geopolitical conditions are also excluded from this research.

### *5.3 Suggestion and Direction for Further Research*

In relation to the conditions mentioned earlier, this study suggests conducting research to assess firms' risk and return profiles, including external factors such as macroeconomic and geopolitical factors that are not covered in this study.

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## Author Contributions

RN worked on conceptualisation, data gathering and analysis, study design, and drafting and revising the manuscript. RLKM improved the writing and proofread the text. Each author made important contributions to the quality and integrity of the research.

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