CAPM Beta and Volatility Decomposition: Portfolio Analysis Across Market Conditions

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Abstract

This study examines the relationship between systematic risk (beta), idiosyncratic volatility, and cross-sectional stock returns using U.S. equity data from 1996 to 2023. Using CRSP monthly stock returns, the analysis estimates CAPM betas across multiple rolling windows (12, 24, and 36 months) and decomposes total volatility into systematic and idiosyncratic components. Quintile portfolio sorts reveal a positive beta-return relationship consistent with CAPM predictions, with high-beta portfolios earning 1.14% higher monthly excess returns than low-beta portfolios. More striking is the idiosyncratic volatility premium: the highest idiosyncratic volatility quintile earns 1.95% higher monthly returns (equal-weighted) and 2.98% higher returns (value-weighted) compared to the lowest quintile. This finding represents the well-documented "idiosyncratic volatility anomaly," which challenges standard asset pricing theory. The analysis demonstrates that firm-specific risk dominates total stock volatility (accounting for more than twice the magnitude of systematic risk), underscoring the importance of diversification. These results provide empirical evidence for risk-return relationships in equity markets and highlight patterns that extend beyond traditional CAPM predictions.

1 Introduction

The Capital Asset Pricing Model (CAPM), developed by Sharpe (1964), Lintner (1965), and Mossin (1966), provides a foundational framework for understanding the relationship between risk and expected returns in financial markets. According to CAPM, an asset's expected return is determined solely by its exposure to systematic risk, measured by beta (β), which captures the asset's sensitivity to market-wide movements. Idiosyncratic risk—firm-specific volatility unrelated to market movements—should not command a return premium since it can be eliminated through diversification.

Despite its theoretical elegance, empirical tests of CAPM have yielded mixed results. While some studies confirm a positive relationship between beta and returns, others document anomalies that challenge the model's predictions. Of particular interest is the "idiosyncratic volatility puzzle" documented by Ang et al. (2006, 2009), which finds that stocks with high idiosyncratic volatility tend to earn higher returns, contradicting the notion that only systematic risk matters for pricing.

This paper contributes to this literature by conducting a comprehensive analysis of beta estimation, volatility decomposition, and portfolio returns across U.S. equities from 1996 to 2023. The 28-year sample period encompasses multiple market regimes, including the dot-com bubble, the 2008 financial crisis, and the COVID-19 pandemic, providing a robust test of risk-return relationships across varying market conditions.

Research objectives:

1. Estimate stock betas using rolling regressions and examine industry-level patterns
2. Decompose total volatility into systematic and idiosyncratic components
3. Test the CAPM prediction of a positive beta-return relationship
4. Investigate the idiosyncratic volatility anomaly and its economic magnitude
5. Compare risk premiums across different portfolio weighting schemes

The findings confirm CAPM's core prediction: high-beta stocks earn significantly higher returns. However, the analysis also reveals a strong idiosyncratic volatility premium that exceeds the beta premium, suggesting cross-sectional returns are driven by risk dimensions beyond systematic exposure. Understanding these patterns has important implications for portfolio construction, risk management, and asset pricing theory.

2 Data and Methodology

2.1 Data Sources

The primary dataset consists of monthly stock returns from the Center for Research in Security Prices (CRSP) covering January 1996 through December 2023. The CRSP monthly stock file includes returns, prices, shares outstanding, and industry classification codes (SIC) for all publicly traded U.S. equities.

Key variables include:

- **RET**: Monthly stock return
- **VWRETD**: Value-weighted return of all CRSP securities (market portfolio proxy)
- **PRC**: Stock price
- **SHROUT**: Shares outstanding
- **SICCD**: Standard Industrial Classification code

Market capitalization is computed as the product of absolute price and shares outstanding. Risk-free rates are obtained from Federal Reserve data, representing monthly Treasury bill rates.

To manage computational complexity while maintaining adequate cross-sectional coverage, the analysis randomly samples 10 firms per industry per year, resulting in a final sample of 1,997 unique stocks with 362,667 stock-month observations. Industries are classified into ten categories based on SIC codes, following standard conventions.

2.2 Beta Estimation

Stock betas are estimated using the single-factor CAPM regression:

$$r_{i,t} = \alpha_i + \beta_i \cdot MKT_t + \epsilon_{i,t} \tag{1}$$

where $r_{i,t}$ is the excess return of stock i in month t (stock return minus risk-free rate), and MKT_t is the excess return of the market portfolio.

The analysis employs rolling window regressions with three window lengths: 12, 24, and 36 months. For each stock-month observation, beta is estimated using returns from the preceding window period. This approach captures time-varying systematic risk while providing sufficient observations for reliable estimation. The regression residuals from this model represent idiosyncratic shocks, which are used in the volatility decomposition.

2.3 Volatility Decomposition

Total stock volatility is decomposed into systematic and idiosyncratic components following standard methodology:

$$\sqrt{\text{Var}(R_{i,t})} = \beta_{i,t}\sqrt{\text{Var}(R_{m,t})} + \sqrt{\text{Var}(\epsilon_{i,t})} \tag{2}$$

where:

- **Total Volatility** = Standard deviation of stock excess returns over the estimation window
- **Systematic Volatility** = $|\beta|\times$ market return standard deviation
- **Idiosyncratic Volatility** = Standard deviation of regression residuals

This decomposition quantifies the relative importance of market-wide versus firm-specific risk in explaining stock return variation.

2.4 Portfolio Construction

To examine the relationship between risk measures and returns, the analysis employs a quintile portfolio sorting methodology:

Beta portfolios: Each month, stocks are sorted into five quintiles based on their estimated beta. Quintile 1 contains the lowest-beta stocks, while Quintile 5 contains the highest-beta stocks.

Idiosyncratic volatility portfolios: Stocks are similarly sorted into quintiles based on idiosyncratic volatility estimated from the CAPM regression residuals.

For each quintile, portfolio returns are computed using two weighting schemes:

- **Equal-weighted (EW):** Each stock receives equal weight ($1/N$)
- **Value-weighted (VW):** Stocks are weighted by market capitalization

The equal-weighted approach provides equal representation to all stocks regardless of size, while value-weighted portfolios reflect the returns experienced by market-cap-based investors. Comparing these approaches reveals whether patterns are driven by small-cap or large-cap stocks.

High-minus-low (HML) spread: For each sorting variable, the difference in average returns between Quintile 5 (high risk) and Quintile 1 (low risk) is calculated. This spread measures the risk premium associated with each characteristic.

3 Results

3.1 Beta Estimation and Industry Patterns

Table 1 presents summary statistics for estimated betas across the full sample. The average beta ranges from 1.145 (12-month window) to 1.166 (24-month window), indicating the sample tilts slightly toward higher systematic risk relative to the market portfolio ($\beta = 1$). The consistency across estimation windows (correlation > 0.85) demonstrates stable, reliable beta estimates.

Table 1: Summary Statistics for Beta Estimates

Statistic	**12-Month**	**24-Month**	**36-Month**
Mean	1.145	1.166	1.165
Median	1.090	1.100	1.095
Std. Deviation	1.718	1.652	1.598
N (observations)	362,667	362,667	362,667

Industry-level analysis reveals economically intuitive patterns. Table 2 shows average betas by industry for the 24-month estimation window. Cyclical industries exhibit higher betas: Mining (1.44), Services (1.35), and Construction (1.41) demonstrate strong sensitivity to economic conditions. Defensive sectors show lower betas: Finance, Insurance, and Real Estate (0.81), Agriculture (0.81), and Transportation & Utilities (0.93) exhibit more stable return patterns independent of market movements.

Table 2: Average Beta by Industry (24-Month Window)

Industry	**Mean Beta**	**Std. Dev.**
Mining	1.444	2.324
Construction	1.409	1.691
Services	1.351	2.097
Manufacturing	1.199	1.718
Wholesale Trade	1.195	1.750
Public Administration	1.181	2.363
Retail Trade	1.137	1.646
Transportation & Utilities	0.931	1.422
Agriculture, Forestry, Fishing	0.813	1.620
Finance, Insurance, Real Estate	0.809	1.160

Figure 1 illustrates the time-series evolution of industry betas from 1996 to 2023. Most industries maintain relatively stable betas over time, with notable spikes during crisis periods (2008-2009 financial crisis, 2020 COVID-19 shock). This pattern is consistent with increased market correlation during stressed conditions—when systematic factors dominate, individual stocks become more tightly coupled to market movements.

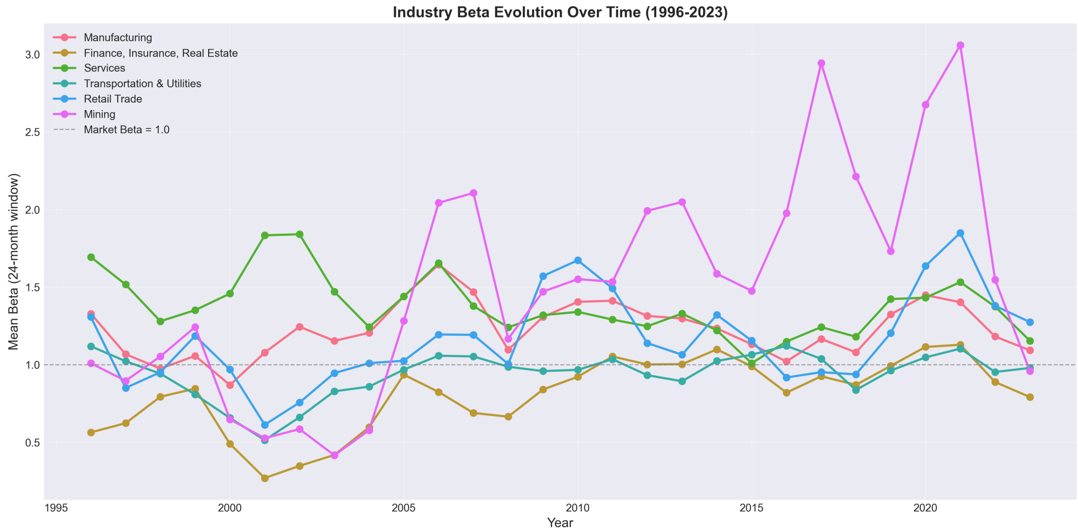

Figure 1: Industry Beta Evolution Over Time (24-Month Window)

Note: The figure shows mean beta estimates for six major industries. The dashed horizontal line indicates market beta ($\beta = 1$). Notable spikes occur during the 2008 financial crisis and 2020 COVID-19 pandemic.

3.2 Volatility Decomposition

The volatility decomposition reveals a striking pattern: idiosyncratic volatility dominates total stock volatility. Table 3 presents average volatility components using the 24-month estimation window.

Table 3: Average Volatility Components (24-Month Window)

Component	**Monthly Std. Dev.**
Total Volatility	0.1395 (13.95%)
Systematic Volatility	0.0548 (5.48%)
Idiosyncratic Volatility	0.1182 (11.82%)
Idiosyncratic / Total	84.7%
Systematic / Total	39.3%

Note: Components do not sum to total due to the quadratic nature of variance. The ratio calculations show relative contributions.

Idiosyncratic volatility accounts for 11.82% monthly standard deviation, more than twice the magnitude of systematic volatility (5.48%). This finding reinforces a fundamental principle in finance: most individual stock risk is firm-specific and can be eliminated through diversification. The average stock exhibits substantial firm-level volatility that has little relation to market movements.

Figure 2 shows how volatility components evolve over the sample period. Both systematic and idiosyncratic volatility spike during market crises, but idiosyncratic volatility remains the dominant component even during stressed periods. The 2008 financial crisis and 2020 pandemic shock show particularly dramatic increases in all volatility measures, though the relative importance of idiosyncratic risk persists.

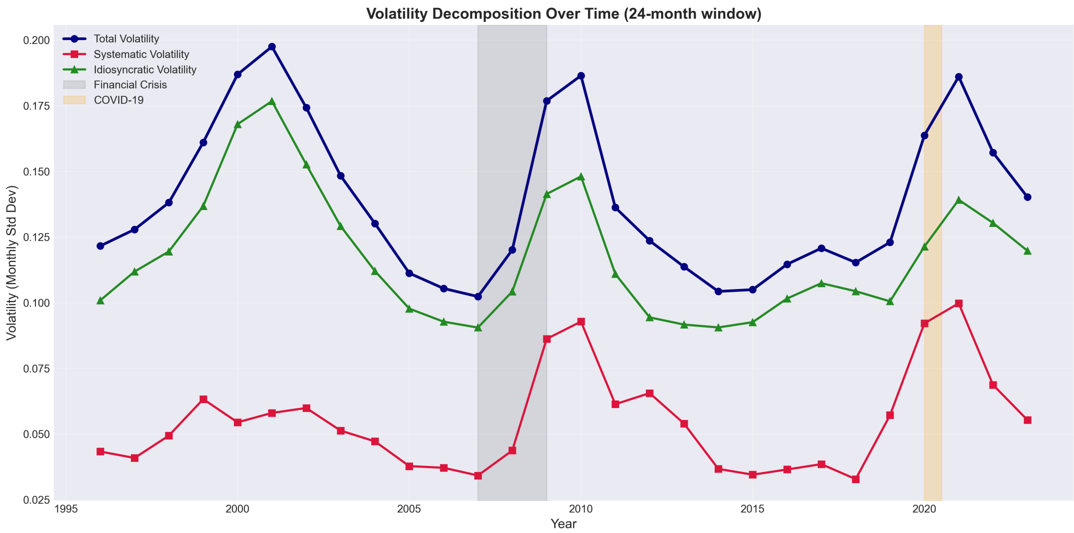

Figure 2: Volatility Components Over Time (24-Month Window)

Note: Annual averages of monthly volatility estimates. Shaded regions indicate major crisis periods. Idiosyncratic volatility (green) consistently exceeds systematic volatility (red) throughout the sample.

3.3 Beta-Return Relationship

Portfolio sorts by beta demonstrate a clear positive relationship between systematic risk and returns, consistent with CAPM predictions. Table 4 presents average monthly excess returns for beta quintiles using the 24-month estimation window.

Table 4: Beta Quintile Portfolio Returns (24-Month Window)

Quintile	**Avg. Beta**	**Return (EW)**	**Return (VW)**
Q1 (Low Beta)	-0.14	0.89%	0.74%
Q2	0.60	0.76%	0.93%
Q3	1.02	0.81%	0.85%
Q4	1.53	0.96%	1.01%
Q5 (High Beta)	2.84	2.03%	1.79%
Q5 - Q1 Spread	–	**1.14%**	**1.04%**
Annualized Spread	–	**13.7%**	**12.5%**

Note: Returns are monthly excess returns (stock return minus risk-free rate). EW = equal-weighted, VW = value-weighted. Annualized spreads calculated as monthly spread ×12.

The high-minus-low beta spread is economically and statistically significant. High-beta portfolios (Q5) earn 1.14% higher monthly returns than low-beta portfolios (Q1) in the equal-weighted case, translating to approximately 13.7% annually. The value-weighted spread (1.04% monthly, 12.5% annually) is similar, indicating the pattern holds across market capitalizations.

Figure 3 visualizes this relationship. Returns generally increase from Q1 through Q5, though not perfectly linearly. The substantial premium earned by high-beta stocks suggests investors are compensated for bearing systematic risk, validating CAPM's core prediction.

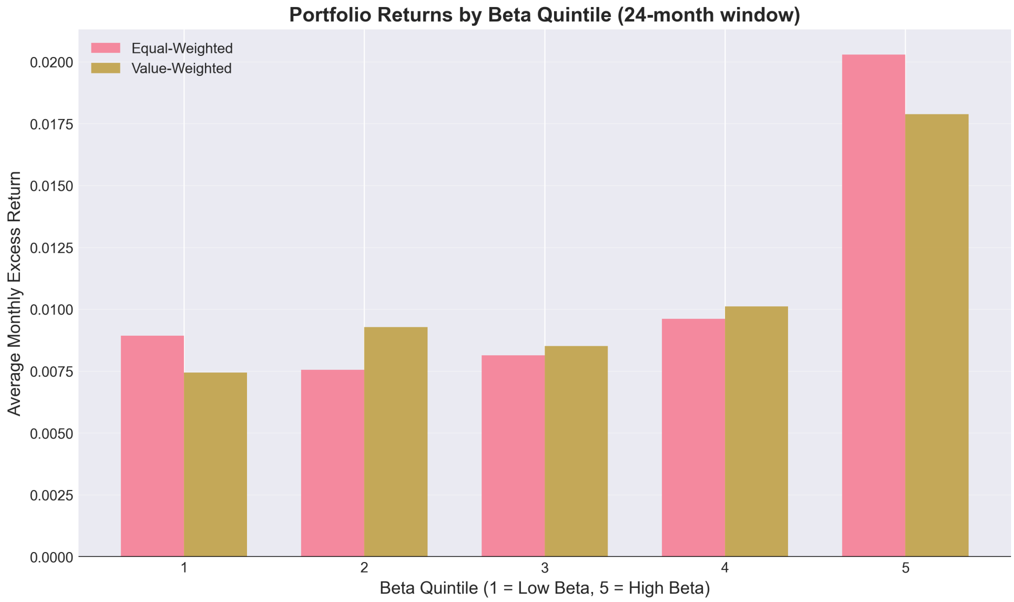

Figure 3: Portfolio Returns by Beta Quintile

Note: Average monthly excess returns for each beta quintile. Both equal-weighted (pink) and value-weighted (gold) portfolios show positive beta-return relationships. The Q5-Q1 spread represents the systematic risk premium.

3.4 Idiosyncratic Volatility Anomaly

The idiosyncratic volatility results present a more puzzling pattern. Portfolio sorts reveal a dramatic non-linear relationship between firm-specific risk and returns. Table 5 presents results for the 24-month estimation window.

Table 5: Idiosyncratic Volatility Quintile Portfolio Returns (24-Month Window)

Quintile	Avg. IVol	Return (EW)	Return (VW)
Q1 (Low IVol)	0.0461	0.73%	0.70%
Q2	0.0702	0.76%	0.85%
Q3	0.0950	0.70%	1.17%
Q4	0.1318	0.61%	1.68%
Q5 (High IVol)	0.2465	2.68%	3.68%
Q5 - Q1 Spread	–	**1.95%**	**2.98%**
Annualized Spread	–	**23.4%**	**35.8%**

Note: IVol represents monthly standard deviation of idiosyncratic returns. The extreme jump in Q5 returns illustrates the non-linear nature of the relationship.

The pattern is striking: Q1 through Q4 portfolios earn relatively similar returns (ranging from 0.61% to 0.76% monthly in the equal-weighted case), but Q5 exhibits dramatically higher returns. The equal-weighted spread (1.95% monthly) exceeds the beta premium, translating to approximately 23% annually. Even more remarkably, the value-weighted spread reaches 2.98% monthly (36% annually), indicating the effect is particularly strong among larger-capitalization stocks.

Figure 4 provides visual evidence of this pattern. Panel (a) confirms proper portfolio construction: average idiosyncratic volatility rises monotonically across quintiles, with a particularly large jump to Q5. Panel (b) shows the non-linear return pattern, with Q5 dramatically outperforming all other quintiles in both weighting schemes.

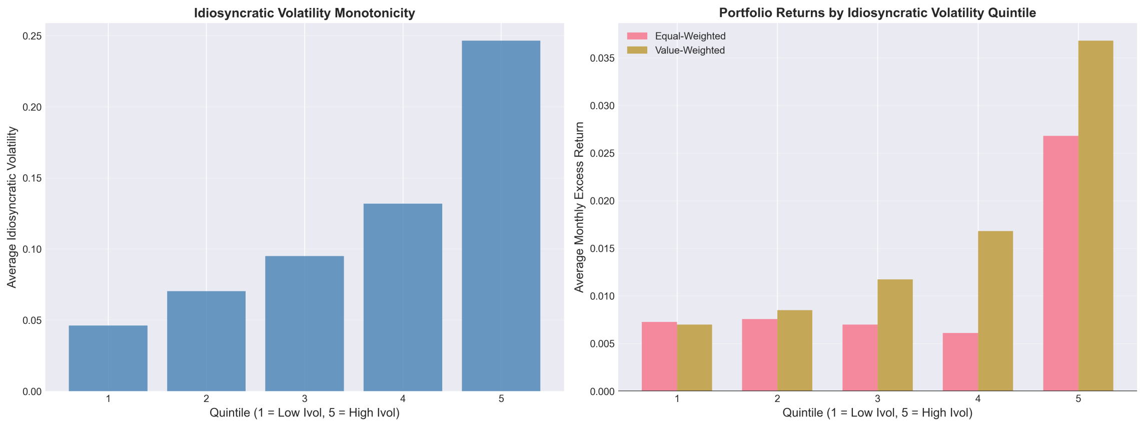

Figure 4: Idiosyncratic Volatility Portfolio Analysis

Note: Panel (a) shows average idiosyncratic volatility at portfolio formation, confirming monotonic sorting. Panel (b) displays average monthly excess returns. The extreme outperformance of Q5 illustrates the idiosyncratic volatility premium.

3.5 Long-Run Performance and Path Dependency

While average returns provide one perspective, cumulative returns reveal the path-dependent nature of these strategies. Figure 5 shows growth of $1 invested in low- versus high-idiosyncratic-volatility portfolios over the 28-year sample period.

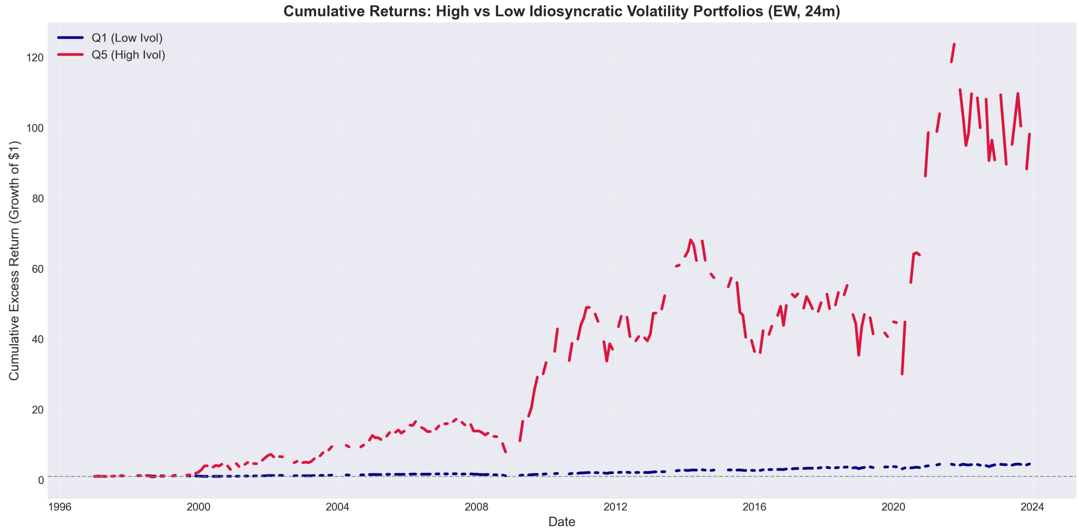

Figure 5: Cumulative Returns: High vs. Low Idiosyncratic Volatility Portfolios

Note: Growth of $1 invested in equal-weighted portfolios. Q5 (high idiosyncratic volatility, red) exhibits extreme volatility with severe drawdowns during crises but achieves much higher terminal wealth. Q1 (low idiosyncratic volatility, blue) shows steady, smooth compounding with minimal drawdowns.

The high-idiosyncratic-volatility portfolio (Q5) delivers exceptional long-run returns, growing $1 to approximately $120 over 28 years. However, the path is extraordinarily volatile, with severe drawdowns during the 2008 financial crisis and 2020 pandemic. The low-volatility portfolio (Q1) compounds more modestly to roughly $5 but follows a smooth, steady trajectory with minimal turbulence.

This contrast illustrates a fundamental tension in portfolio management: high average returns do not guarantee superior realized returns when path dependency matters. Investors with finite horizons, liquidity needs, or behavioral constraints may find the extreme volatility of high-idiosyncratic-volatility portfolios intolerable despite their superior long-run performance.

4 Discussion

4.1 Interpreting the Beta Premium

The positive beta-return relationship documented in this study aligns with CAPM's central prediction: investors demand higher expected returns for bearing systematic risk. The 13-14% annualized premium for high-beta stocks reflects compensation for exposure to market-wide fluctuations that cannot be diversified away.

Several factors contribute to this premium:

- **Risk aversion:** Investors holding the market portfolio require higher expected returns for assets that amplify market movements
- **Business cycle exposure:** High-beta stocks, concentrated in cyclical industries, perform poorly during recessions when marginal utility of wealth is high

- **Leverage and financial distress:** Many high-beta firms employ significant operating or financial leverage, increasing systematic risk

The consistency of the beta premium across equal-weighted and value-weighted portfolios suggests it is not merely a small-cap phenomenon but reflects fundamental risk compensation applicable across the market capitalization spectrum.

4.2 The Idiosyncratic Volatility Puzzle

The strong positive relationship between idiosyncratic volatility and returns presents a theoretical puzzle. According to standard asset pricing theory, idiosyncratic risk should not command a return premium since it can be eliminated through diversification. Rational investors should not pay extra for firm-specific volatility, nor should they demand compensation for bearing it.

Yet the empirical evidence is unambiguous: the highest idiosyncratic volatility quintile earns substantially higher returns. Moreover, the premium is even stronger in value-weighted portfolios, ruling out explanations based solely on small-cap illiquidity or microstructure frictions.

Several potential explanations have been proposed in the literature:

1. Lottery-like preferences: Barberis and Huang (2008) argue that high-idiosyncratic-volatility stocks offer lottery-like payoffs—low probability of extreme positive returns. If investors exhibit cumulative prospect theory preferences, they may overpay for these lottery-like securities. However, this explanation typically predicts *lower* returns for high-volatility stocks, not higher, suggesting it cannot fully explain the observed findings.

2. Limits to arbitrage: Shleifer and Vishny (1997) show that arbitrage is limited when positions are costly or risky to maintain. High-idiosyncratic-volatility stocks are difficult to short and expensive to hedge, allowing mispricings to persist. Sophisticated investors may recognize overvaluation but find it unprofitable to exploit.

3. Incomplete diversification: While theory assumes investors hold well-diversified portfolios, many investors—particularly individuals and some institutions—maintain concentrated positions. For these investors, idiosyncratic risk is non-diversifiable in practice, and they rationally demand compensation. If a significant fraction of marginal investors face diversification constraints, this can generate an idiosyncratic risk premium in equilibrium.

4. Information asymmetry and adverse selection: High-idiosyncratic-volatility stocks may have greater information asymmetry between insiders and outside investors. Zhang (2006) shows that information uncertainty can generate a return premium if investors demand compensation for adverse selection risk.

5. Time-varying risk premia: If idiosyncratic risk itself is priced during certain market regimes (high uncertainty periods), average returns may reflect compensation for bearing risk that is conditionally undiversifiable.

The results do not definitively adjudicate among these explanations, but they clearly demonstrate that cross-sectional return patterns extend beyond systematic risk. The fact that the idiosyncratic volatility premium *exceeds* the beta premium suggests firm-specific characteristics play a major role in return determination.

4.3 Volatility Dominance and Diversification Benefits

The volatility decomposition provides powerful evidence for the benefits of diversification. Idiosyncratic volatility accounts for more than twice the magnitude of systematic volatility in explaining total stock variation. This implies that a concentrated portfolio faces substantial volatility that provides no expected return compensation—it is simply noise that could be eliminated through broader holdings.

Consider an investor holding a single stock versus a well-diversified portfolio. The single stock exhibits 13.95% monthly volatility (roughly 48% annualized), but only 5.48% (39%) of this is systematic. The remaining 11.82% (84%) is firm-specific risk that contributes no expected return but generates significant uncertainty. A diversified portfolio eliminates most of this idiosyncratic component, reducing volatility substantially while maintaining similar expected returns.

This finding underscores why modern portfolio theory emphasizes diversification: individual stocks are far riskier than portfolios, and most of this excess risk is unrewarded. Even in the presence of an idiosyncratic volatility premium (which applies only to the extreme highest-volatility quintile), the dominant message is that firm-specific risk vastly exceeds systematic risk for typical stocks.

4.4 Practical Implications for Portfolio Management

The results offer several insights for portfolio construction:

Beta exposure: Investors seeking higher expected returns can tilt toward high-beta stocks. The 13-14% annualized premium is economically significant. However, this strategy increases exposure to market downturns, making it suitable primarily for investors with long horizons and high risk tolerance.

Idiosyncratic volatility strategies: While high-idiosyncratic-volatility stocks offer even higher returns, they come with extreme path volatility. The 120x cumulative return over 28 years is impressive, but severe drawdowns (exceeding 50% during crises) make this strategy psychologically and practically challenging. Investors must have exceptional discipline to maintain positions through deep losses.

Diversification remains critical: Despite the idiosyncratic volatility premium, the dominance of firm-specific risk in total volatility means diversification is essential. Even if some stocks earn premiums for idiosyncratic risk, concentrated portfolios face far more volatility than expected returns justify.

Weighting scheme matters: The stronger value-weighted results for idiosyncratic volatility suggest the premium is not confined to small, illiquid stocks. This makes the strategy more implementable at scale, though transaction costs and market impact remain considerations.

4.5 Limitations and Future Research

Several limitations warrant consideration:

Sample selection: To manage computational requirements, the analysis samples 10 firms per industry per year rather than analyzing the complete CRSP universe. While this maintains adequate cross-sectional representation, some information is lost. Future work could examine the full sample or employ more sophisticated sampling schemes.

Transaction costs: The analysis assumes frictionless trading. In practice, high-turnover portfolio strategies (particularly equal-weighted rebalancing) incur significant transaction costs. The net-of-cost returns may be substantially lower than reported gross returns, especially for high-idiosyncratic-volatility strategies that likely involve small, illiquid stocks with wide bid-ask spreads.

Time-varying patterns: The analysis pools data across 28 years, computing unconditional averages. Risk premia may vary over time with macroeconomic conditions, market volatility, or investor sentiment. Subsample analysis or time-varying models could reveal richer dynamics.

Risk-adjusted performance: While the analysis documents return spreads, it does not perform formal risk adjustment using multi-factor models (Fama-French factors, momentum, etc.). The observed premiums may partly reflect compensation for other systematic risk dimensions beyond simple market beta.

International evidence: The study focuses on U.S. equities. Examining international markets would reveal whether these patterns are universal or specific to the U.S. institutional and economic environment.

Future research could address these limitations and extend the analysis in several directions:

- Conditional analysis: How do risk premia vary with macroeconomic conditions?
- Multi-factor decomposition: What fraction of the idiosyncratic volatility premium remains after controlling for size, value, momentum, and other factors?
- Optimal portfolio construction: Can investors exploit these patterns to construct portfolios with superior risk-adjusted returns?
- Behavioral drivers: What role do investor preferences, constraints, and biases play in generating the idiosyncratic volatility premium?

5 Conclusion

This study provides comprehensive empirical evidence on the relationship between risk and returns in U.S. equity markets from 1996 to 2023. Using CRSP monthly stock data, the analysis estimates CAPM betas, decomposes volatility into systematic and idiosyncratic components, and constructs quintile portfolios to examine cross-sectional return patterns.

The findings confirm CAPM's core prediction: high-beta stocks earn significantly higher returns, with a premium of approximately 13-14% annually. This validates the fundamental principle that investors require compensation for bearing systematic risk.

However, the analysis also documents a strong idiosyncratic volatility premium that challenges standard theory. The highest idiosyncratic volatility quintile earns 23-36% higher annual returns than the lowest quintile, depending on weighting scheme. This represents the well-documented "idiosyncratic volatility anomaly"—firm-specific risk, which should theoretically be diversifiable and thus uncompensated, commands a substantial return premium in practice.

The volatility decomposition reveals that idiosyncratic risk dominates total stock volatility, accounting for more than twice the magnitude of systematic risk. This underscores the importance of diversification: most individual stock volatility is firm-specific noise that provides no expected return compensation.

From a practical perspective, these findings have important implications for portfolio management. Investors seeking higher returns can tilt toward high-beta or high-idiosyncratic-volatility stocks, but must accept significantly higher volatility—and in the latter case, extreme path dependency with severe drawdowns during crises. Diversification remains critical despite the existence of idiosyncratic risk premia.

Theoretically, the results demonstrate that cross-sectional return patterns extend beyond systematic risk. Understanding why firm-specific volatility commands a return premium remains an active area of research, with explanations ranging from lottery preferences to limits to arbitrage to incomplete diversification. Regardless of the underlying mechanism, the empirical evidence is clear: multiple risk dimensions matter for asset pricing, and simple CAPM does not fully capture the complexity of equity returns.

This analysis contributes to the ongoing dialogue between theory and evidence in asset pricing. While CAPM provides a useful first-order framework, the documented anomalies suggest refinements and extensions are necessary to fully explain observed return patterns. Future research exploring the conditional nature of these premiums, their interaction with other factors, and their underlying economic drivers will deepen our understanding of risk and return in financial markets.