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«Δηλώνω υπεύθυνα ότι η διπλωματική εργασία για τη λήψη του μεταπτυχιακού τίτλου σπουδών, του Πανεπιστημίου Πειραιώς, στη Διοίκηση Επιχειρήσεων : MBA» με τίτλο:

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έχει συγγραφεί από εμένα αποκλειστικά και στο σύνολό της. Δεν έχει υποβληθεί ούτε έχει εγκριθεί στο πλαίσιο κάποιου άλλου μεταπτυχιακού προγράμματος ή προπτυχιακού τίτλου σπουδών, στην Ελλάδα ή στο εξωτερικό, ούτε είναι εργασία ή τμήμα εργασίας ακαδημαϊκού ή επαγγελματικού χαρακτήρα.

Δηλώνω επίσης υπεύθυνα ότι οι πηγές στις οποίες ανέτρεξα για την εκπόνηση της συγκεκριμένης εργασίας, αναφέρονται στο σύνολό τους, κάνοντας πλήρη αναφορά στους συγγραφείς, τον εκδοτικό οίκο ή το περιοδικό, συμπεριλαμβανομένων και των πηγών που ενδεχομένως χρησιμοποιήθηκαν από το διαδίκτυο. Παράβαση της ανωτέρω ακαδημαϊκής μου ευθύνης αποτελεί ουσιώδη λόγο για την ανάκληση του πτυχίου μου»

Υπογραφή Μεταπτυχιακού Φοιτητή Ονοματεπώνυμο

Διονύσης Βασιλακόπουλος



To my mother

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Declaration of Originality

I hereby declare that this Thesis, entitled “Risk Analysis and Decision-Making support”, is entirely an original work and has not been submitted in any form of previous academic publication or form for the award of a degree of Master of Science at any other University. All sources of information, data and theoretical material utilized in this research are properly acknowledged in the text and cited in the Bibliography. The underlying market data for this analysis was sourced from the Alpha Vantage financial data platform.

Abstract

The financial landscape of the 21st century is increasingly dominated by Hight-Growth Technology (HGT) firms whose market valuations frequently detach from traditional fundamentals, driven instead by technological optionality, speculative narratives and extreme volatility regimes. During the 21st Century the market has experienced an unprecedented and disanalogous to previous centuries growth in Technology, this has created a myriad of investment opportunities but also investment traps leading to sunk investments and dead ends.

This thesis provides a rigorous quantitative analysis of the risk structure embedded within a high-risk share investment using the Tesla, Inc. equity as an example due to being a quintessential high-beta, high-growth technology (HGT) asset. Utilizing Generalized Autoregressive Conditional Heteroskedasticity (GARCH (1,1)) and descriptive statistical analysis, the study supports the core hypothesis: the pronounced decline in Tesla’s share price post- Q 4 2022 was an amplified consequence of its inherent high systematic risk, while its persistent structural risk is defined by severe asymmetric downside return dynamics.

List of Tables:

Table 2.1: Descriptive Statistics and Non Normality Diagnostics (Tesla Log Returns) 16
Table 2.2 t-tests 16
Table 3.1 Regression between log returns..... 19
Table 3.2 Regression between Prices 21
Table 4.1: Comparative GARCH (1,1) Volatility Dynamics (Tesla vs S&P 500)..... 26

List of Figures:

Figure 1.1 Tesla Share Prices 2019-2025 9
Figure 2.1. Distribution of Tesla Returns 14
Figure 2.2: Boxplot of Tesla Log Return 15
Figure 3.1: Tesla -S&P 500 Line Plot 20
Figure 3.2 Residual Plot of Log 20
Figure 3.3: Tesla - S&P 500 Price Line Plot 21
Figure 3.4: Tesla - S&P 500 Price Residual Plot 22
Figure 4.1: Weekly Log Returns: Tesla vs S&P 500 25
Figure 4.2: Conditional Volatility vs Rolling Volatility 26
Figure 5.1: Parametric VaR and CvaR 30
Figure 5.2: Empirical Win vs Loss Percentage Ratio 31
Figure 5.3: GARCH (1,1) Conditional VaR and CvaR (99% Confidence)..... 32
Figure 11.1: Comparative Tech Firm Returns Trajectory 2019-2026 40
Figure 11.2: Comparative Tech Firm Trends, Trajectory 2019-2026..... 41
Figure 11.3: Pearson Correlation Heatmap of Stock Returns 2019-2026 45

Acknowledgements 4

List of Tables: 6

List of Figures: 6

Introduction and Theoretical Framing 8

1.1 Contextual Background: Tesla’s Market Trajectory and the Post – 2022 Valuation Shift 8

1.2. Literature Review: Asset Pricing Theory and the Challenge of Non-Normality 10

1.2.1. The Mean-Variance Framework and its Limitations 10

1.2.2. The Econometric Challenge of Non- Normality 10

1.2.3. Modeling Conditional Volatility: GARCH Model	12
1.2.4. Coherent Risk Measures: VaR-CvaR, ES and Extreme Value Theory (EVT)	13
Empirical Diagnostics of Equity’s Return Distribution	13
2.1. Data Sourcing, Preparation and Descriptive Statistics	13
2.2. Quantification of Higher-Moment Risk (Skewness and Kurtosis)	14
2.3. Formal Testing of Normality and Validation of Risk Asymmetry	15
2.4. Comparative Analysis of Mean Returns (T-Tests)	16
Quantification and Decomposition of Total Risk (OLS/CAPM).....	17
3.1. Market Model Estimation and Interpretation: The Price data Approach	19
3.1.1. Justification of Price OLS: Log-Normal Distribution and F-Significance	22
3.2. Modeling the Price Space	22
Modeling Conditional Heteroscedasticity using GARCH (1,1)	23
4.1. GARCH (1,1) Econometrics for Volatility Dynamics: The Core Equation	24
4.2. Comparative Analysis of GARCH 1,1 Parameters (Tesla vs S&P 500)	26
4.2.1. Alpha, Beta, and Volatility Memory	27
4.2.2. Structural Risk Floor, Omega and Unconditional Volatility Sigma	27
4.3. Analysis of Long-Run (Unconditional) Volatility and Structural Risk	27
Downside Risk Quantification: Value at Risk and Expected Shortfall	29
5.1. Limitations of Parametric Risk Metrics Under Leptokurtosis	29
5.2. Methodology for Robust Risk Quantification: GARCH-Filtered CvaR.....	31
5.2.1. Coherence and Severity of Tail Losses	32
5.3. Financial Implications for Capital Allocations and Regulatory Compliance.....	33
Advanced Topics in Financial Econometrics	33
6.1. Heterogeneity of Systematic Risk Factors in HGT Sector (Multi-Factor Models).....	33
6.2. The Role of Higher-Order Moments in Asset Pricing (Co Skewness/ Co Kurtosis)	34
Comparative Analysis of Static vs Dynamic Risk Quantification.....	34
7.1. The Failure of Static Models: Parametric and Non-Parametric Equivalence	34
7.2. Dynamic Model Performance and Crisis Sensitivity	35
7.3. Economic Implications of Static Risk Underestimation	35
Strategic Risk and Firm Vulnerability	36
Investment Strategy and Portfolio Construction	36
9.1. Portfolio Strategy Implied by GARCH Dynamics (Momentum and Timing).....	36
9.1.1. High Alpha and Persistence: A Strategy for Bullish and Bearish Cycles.....	37

9.2 Optimizing Portfolio Construction: Negative Correlation Hedge.....	37
9.2.1. The Need for Inverse Correlation Assets	37
9.2.2. Specific Hedge Assets: Bonds, Commodities and Gold	38
Conclusion and Policy Implications	38
10.1. Synthesis of Risk Findings: The Asymmetric Volatility Structure.....	38
10.2. Validation of Thesis Hypothesis and Post-Crisis Repricing.....	39
10.3. Quantitative Policy Recommendations for Portfolio Management	39
Comparative Analysis of High Growth Technology (HGT) Equities	40
11.1 Tesla	41
11.2 Nvidia.....	42
11.3 Microsoft and Meta.....	42
11.4 Oracle and IBM.....	43
11.5 The 2026 Tech Ecosystem.....	43
11.6 Correlation between the competitors.....	44

Chapter 1 Introduction and Theoretical Framing

1.1 Contextual Background: Tesla’s Market Trajectory and the Post – 2022 Valuation Shift

Tesla, Inc. (TSLA) is widely recognized as definitive High- Growth Technology (HGT) equity, whose valuation is heavily reliant on ambitious future profitability expectations and is highly sensitive to market speculation. The history of stock has been marked by periods of hyperbolic ascent, followed by rapid drawdowns, reflecting a deeply embedded speculative component within its pricing. The volatility

associated with these high- beta, high- growth technology stocks is typical as their valuations respond with amplified magnitude to macroeconomic shocks. The visual evidence of the Equity’s valuation history, presented in Figure I.1 provides a graphical context for this analysis. The period between late 2020 and early 2021 illustrates a speculative bubble, where prices detached significantly from intrinsic value, driven by momentum and narrative. This phase was characterized by extreme variance and rapid price appreciation. Crucially, subsequent and rapid decline observed in the final quarter of 2022 visually supports the interpretation of a ‘crash’ phase, where the market rapidly correlated the speculative premium.

Following this crash, the chart indicates a critical phenomenon: the price stabilized, not returning to its peak, but establishing a new, significantly lower valuation threshold spanning 2023 through 2026. This

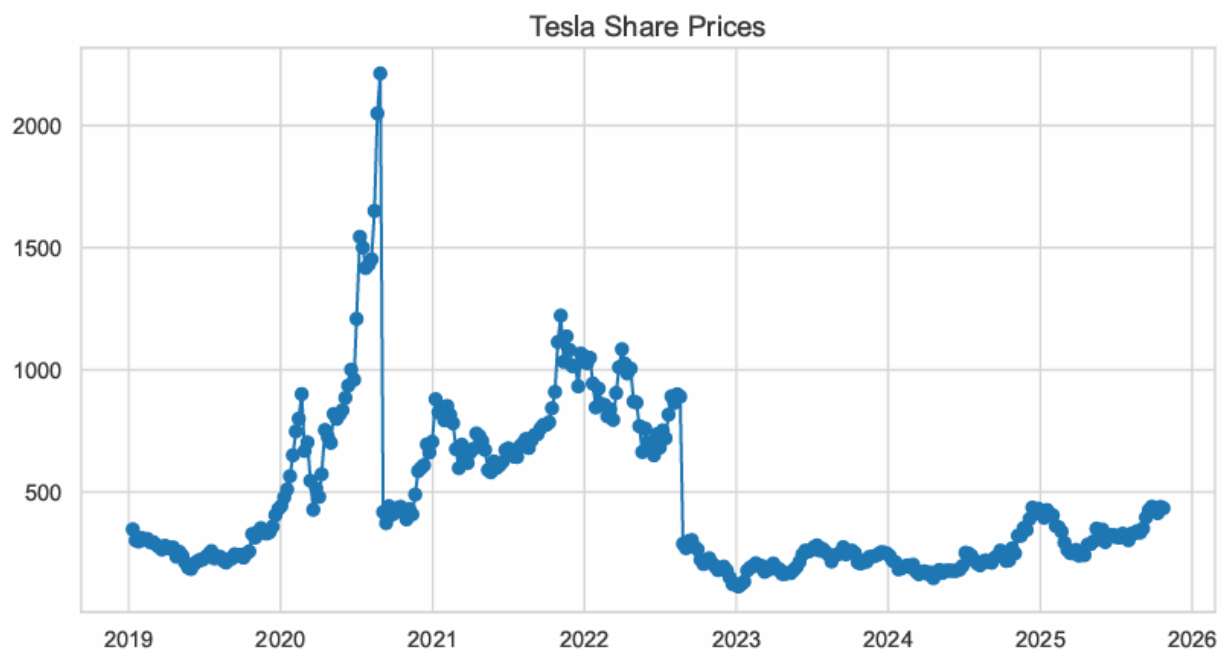


Figure 1.1 Tesla Share Prices 2019-2025

sustained stabilization pre-crash heights suggests that the market has undergone a structural repricing, permanently increasing the required discount rate due to the firm’s fundamental risk profile.

Following the final quarter of 2022, Tesla’s share price experienced a pronounced and sustained decline, failing to recover to pre-quarter levels. This shift necessitates a rigorous quantitative investigation into the structural and dynamic risk characteristics that govern the asset’s performance. The stabilization of the share price occurred at a significantly lower valuation threshold, suggesting that the market may have permanently revised its assessment of the company’s intrinsic value or long-term risk profile.

The central hypothesis tested by this quantitative analysis is two-fold: first, that the observed post-2022 decline can be assumed to be a mechanical consequence of the asset’s intrinsic systematic risk exposure, which mechanically amplified the broader market downturn; and second, that the asset’s persistent structural risk is governed by asymmetric downside return dynamics captured through conditional volatility modeling. The sustained low valuation suggests that the market has imposed a heightened “speculative risk premium” reflecting the inherent, structurally high volatility not fully accounted for by static or linear risk models.

The transition observed in Figure I.1 from 2020-2022 “exuberance phase” to the post-2023 “stagnation phase” is suggestive of a shift in regime in the stochastic process governing Tesla’s returns. From a quantitative perspective, the pre-2023 trajectory is characterized by significant positive autocorrelation—a hallmark of momentum driven markets where price innovations reinforce existing trends. However, the subsequent failure to reclaim previous heights, despite broader market recoveries, implies that the “Tesla premium” has decoupled for idiosyncratic growth narratives and has instead become tethered to the equity risk premium (ERP) and heightened sensitivities to the Risk-Free Rate. This structural break is indicative of a transitioned market from pricing Tesla’s as a “call option on the future of energy” to pricing it as a mature industrial entity subject to cyclical capital expenditure constraints and tightening margins.

Furthermore, the persistent low-frequency volatility observed throughout 2024 and 2025 indicates that while the “crash” has concluded, the asset remains in the state of volatility clustering. This is suggestive of an uncertain market regarding the terminal value, but a shift from a speculative upside bias to a defense downside preoccupation. By applying GARCH 1,1 (Generalized Autoregressive Heteroskedasticity) framework to this time series, one can observe that the conditional variance remains elevated relative to the pre 2020 baseline. This sustained variance supports the “Structural Repricing” hypothesis: the market is no longer discounting future cash flows at a growth-oriented rate, but is instead applying a risk adjusted discount rate that accounts for the permanent latent volatility embedded in the stock’s now mature market position.

The dramatic drop of Q4 2020 wasn’t a crash however but the result of a market strategy called splitting. On Q4 2020 Tesla wanted to make the shareholders entitled to hold +4 Shares for every one share via $\frac{\text{Share Price}}{5}$ Split, aiming to make the stock more accessible.

1.2. Literature Review: Asset Pricing Theory and the Challenge of Non-Normality

1.2.1. The Econometric Challenge of Non- Normality

Empirical diagnostics indicate that Tesla’s daily log returns exhibit severe leptokurtosis and pronounced left skewness (left tail) due to a disproportionate number of negative returns in contrast to positive returns, suggesting a downside exposure where the probability mass of extreme negative outcomes outweighs symmetric positive deviations. The application of both independent & paired sample tests indicates a parallel movement between Tesla equity and S&P 500; this hypothesis is only amplified by the Ordinary Least Squares (OLS) regression utilizing price levels against the S&P 500 confirms Tesla as a high beta asset

($\beta=1.8$). This price – level model achieved a high Adjusted R^2 of near 70% indicating a sufficient explanation of the totality of the undertaken Asset risk from S&P 500.

The GARCH (1,1) model reveals a ‘crisis – sensitive’ volatility structure: a high Omega ($\omega= 0.005$) establishes a substantial structural risk floor, and an exceptionally high Alpha ($\alpha=0.44$) indicates hyper – reactivity to market shocks. The resulting long run Volatility is quantified at 0.382, a value over 16 times higher than the S&P 500 benchmark (a ratio derived from the estimated $\sigma_{unconditional}$ values), providing econometric justification for the persistent structural repricing observed post- crisis.

The synthesis suggests the necessity for the abandonment of Gaussian- based risk metrics, advocating for the use of GARCH – filtered Expected Shortfall (CvaR) to accurately model and provision capital against the confirmed extreme tail risk, recommending active management strategies to mitigate this dominant idiosyncratic exposure.

The theoretical foundation of risk analysis has transitioned from rigid assumptions of the mis-20th century to more fluid and non-linear understanding of the market dynamics. At the core of this transition is the critique of the Capital Asset Pricing Model (CAPM) and the emergence of models that better account for the idiosyncratic and systematic anomalies of the technology sector.

On the topic of risk metrics such as VaR (Value at Risk) which had been the norm for previous eras of Risk analysis the literature seems to have sifted in favor to its natural evolution ES (Expected Shortfall) Which better captures the long Left tails of losses and more dynamic models such as GARCH 1,1 which doesn’t show risk as a static metric but shows how the asset behaved in a time line and even how it reacts to deferent pressures from the market.

More than that there comes the topic of Normality, Normality is rarely if at all exhibited in the real-world models such as KS Test or Shapiro W. Tests show that, thus a non-Parametric – Historical computation of ES is highly preferable due to its non-normality reliance. However, this doesn’t devalue the normality-based models and metrics but what is insinuated is that they should be cross examined along with the aforementioned non-normality models

It seems that the models of Risk evaluation have become more sophisticated and more efficient due to this over time. As enforced by this analysis it is highly advisable to use as many Risk evaluation models as possible in investigation of the behavior of such volatile market section.

The question of the Gaussian assumption presents profound econometric challenges for classical models like Ordinary Least Squares (OLS) regression used in CAPM estimation.

Non-Normality in Returns: The confirmation of negative skewness and leptokurtosis suggests that the data is characterized by “long tails”, implying a higher frequency of extreme observations than those expected from a distribution closer to a normal distribution. For financial returns this indicates that the risk of severe losses is systematically underestimated when using standard deviation. The formal rejection of the Hypothesis of normality through the Shapiro Wilk test in this thesis suggests the inadequacy of standard financial models predicted on Gaussian assumptions, as classical OLS inference relies heavily on the normality residuals for accurate hypothesis testing.

A related issue in an analysis using time series data, is heteroscedasticity where the variance of errors is not constant across observations, leading to periods of “volatility clustering”. If heteroscedasticity is present and ignored in OLS estimation, the resulting parameter estimators remain unbiased, but the standard errors of those estimates will be incorrect, thus violating the efficiency and credibility of the OLS estimator and leading to unreliable hypothesis tests as well as confidence intervals. Since financial time series almost universally exhibit volatility clustering, the reliability of a static OLS/CAPM framework is fundamentally compromised for assets similar to the equity taken to this research as an example (Tesla)

1.2.2. Modeling Conditional Volatility: GARCH Model

To address the empirical observations of volatility clustering, it is essential to adopt models that account from time varying variance, or conditional heteroscedasticity. The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, initially proposed by Bollerslev (1986), is the standard econometric solution for time varying variance.

This model framework maps the current period’s volatility as a function of its past realizations and shocks realized in the previous period. This capability allows GARCH models to capture the phenomenon observed in speculative assets: large price movements tend to be followed by other large movements of either sign. This provides a dynamic risk estimate superior to static historical volatility measures, directly addressing the limitations imposed by heteroscedasticity on a typical OLS analysis. The GARCH framework’s estimation of conditional variance is a critical input for robust risk quantification, especially for assets similar to Tesla’s, whose risk profile is characterized by rapid shock transmission.

1.2.3. Coherent Risk Measures: VaR-CvaR, ES and Extreme Value Theory (EVT)

The presence of heavy tails and asymmetry in returns suggests that traditional risk measures predicated on normality, such as Value at Risk, are inadequate. VaR, a quantile measure of the conditional return distribution, fails to capture the magnitude of extreme tail losses.

When return distributions are leptokurtic, models relying on normality (as the Parametric analysis) systematically underestimate tail losses, events of low frequency but high severity. Therefore, the use of Conditional VaR – CvaR or Expected Shortfall (ESc), is theoretically supported. CvaR is a coherent risk measure that quantifies the expected loss, conditional on that the loss exceeding the computed VaR threshold, providing a superior estimate of capital requirements necessary to buffer against asymmetric downside exposure. This approach aligns with Extreme Value Theory (EVT) a statistical approach widely used in financial risk management to model the magnitude of extreme, low-probability events.

Chapter 2 Empirical Diagnostics of Equity's Return Distribution

2.1. Data Sourcing, Preparation and Descriptive Statistics

The quantitative foundation rests on the examination of the Equity's weekly logarithmic returns, which is the standard methodology for asset time-series econometrics, utilizing data sourced from Alpha Vantage.

The analysis of the moments of the return distribution reveals significant characteristics consistent with highly speculative assets. The mean weekly log return for the equity is computed at a 0.0007%, while the median return is 0.008%. The volatility of returns stands at 14% around the mean. The observed range of returns spans min, -17% and max, 29%.

The disparity between the mean and the median serves as the statistical signature of asymmetry, specifically caused by the disproportionately large impact of negative returns (a log-left tail, asymmetry) pulling the average performance downward. The extreme range signals the intermittent presence of severe shocks characteristic of financial extreme variance.

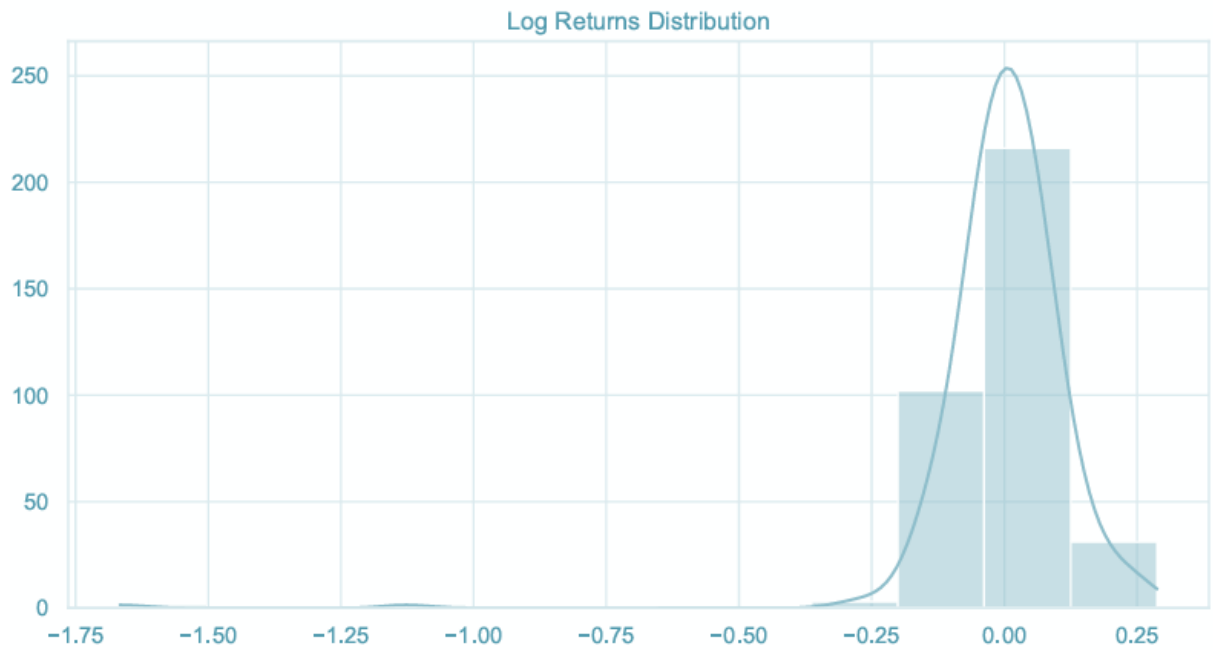


Figure 2.1. Distribution of Tesla Returns

2.2. Quantification of Higher-Moment Risk (Skewness and Kurtosis)

The investigation into higher statistical moments substantiates the non-Gaussian risk profile of the asset: pronounced negative skewness and leptokurtosis.

The visual confirmation of this asymmetry is powerfully demonstrated by the boxplot in Figure II.2, which is consistent with the histogram in Figure II.1. The plot displays several isolated circular points (outliers) scattered far out into the negative (left) extreme of the distribution, while the positive side is visibly compressed.

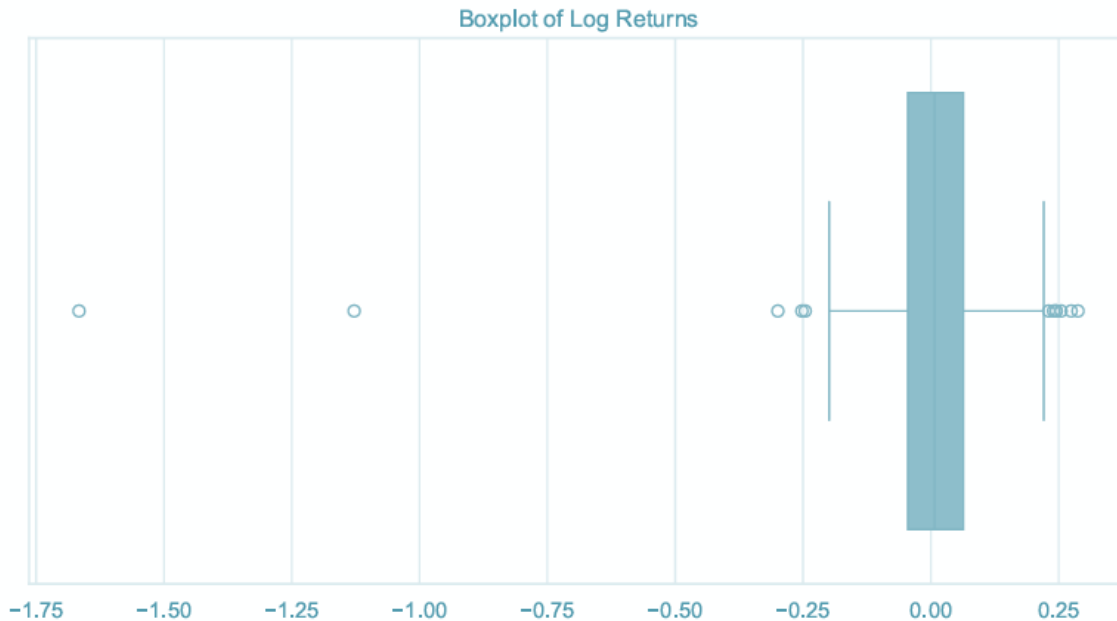


Figure 2.2: Boxplot of Tesla Log Return

The negative skewness is the explicit quantitative evidence of the Equity's "asymmetric downside exposure", confirming that the probability and magnitude of severe negative returns significantly outweigh those of equivalent positive returns. The negative skewness is a critical risk factor, as rational investors demand higher returns to compensate for the possibility of large, uncompensated downside losses. The leptokurtosis indicated that the asset's primary risk is the high variability of negative returns, rather than the general dispersion of all returns. The existence of negative skewness and leptokurtosis formally dictates that the share's required return must compensate not just for its systematic risk but also for this uncompensated higher moment risk. Percentile analysis outputted that that 25% of observed returns historically fall below -5%, while 75% fall below 7%. This underlines the great possibility of loss, $\frac{1}{4}$ of the historical returns while the return isn't great enough at greater percentiles to compensate for the taken risk.

2.3. Formal Testing of Normality and Validation of Risk Asymmetry

Formal statistical validation using the Shapiro-Wilk test formally rejected the null hypothesis of normality at 95% confidence level. The rejection of the null hypothesis is critical, as it suggests that inadequacy of standard financial models predicted on Gaussian assumptions. This statistical failure necessitates the use of alternative modeling and distributional techniques or at least quantitative methods that have a tail focus such as ES and CvaR, non-parametric / historical analysis in such case is the prudent method over parametric analysis.

Table 2.1: Descriptive Statistics and Non Normality Diagnostics (Tesla Log Returns)

Statistics	Value
Mean	0.0007%
Median	0.008%
Standard Deviation	14%
25 th Percentile	-5%
Shapiro-Wilk P-Value	>0.05

2.4. Comparative Analysis of Mean Returns (T-Tests)

T- tests were conducted on the weekly log Returns of Tesla in comparison to those of S&P 500. Two methods of t – tests were utilized, those for independent Samples and for paired samples, the first to test if the mean returns between the two different significantly and the second to test if they exhibit a significant difference between them. For this analysis the confidence level is 95%.

The usage of t-tests can be soundly used since as it is going to be stated in the regression analysis part of this thesis, the two groups of observations aren't related.

The results from both tests support the conclusion that the means of returns don't significantly deviate from one another. This ensues that over a medium length time window the μ weekly return provided by the asset has not been statistically different from the average weekly return of the broad, diversified S&P index.

Table 2.2 t-tests

t-test	Value	Conclusion
Independent	t= -0.31	Cannot Reject H0
Paired	t= -0.31	Cannot Reject H0

t-test	H0	H1
Independent	The μ in the two groups are equal.	The mean of the two groups isn't equal.
Paired	The mean differences between the pairs = 0	The mean of the differences between the pairs is non-zero

The results support the interpretation that high total risk associated with Tesla has been largely offset by the detrimental effects of negative skewness and the higher frequency of extreme losses (as shown in Boxplot, Figure II.2.). Consequently, Tesla's returns did not, on average, provide statistically higher rewards than the market, despite exposing investors to significantly higher non-diversifiable volatility.

It is important to note that independent t-tests rely on the assumption that the two timeseries have $Variance = Variance$ relationship and homoscedasticity to be credible. The heteroscedasticity makes the application of a standard t test non credible because t-tests rely on the assumption of homoscedasticity which is clearly disproven on Figure 3.2 Residual Plot of Log

This makes the Paired T-test the analysis tool of choice because it doesn't rely on homoscedasticity, this conclusion however is again false due to volatility clustering, a phenomenon that is frequent in share returns and thus if the differences are highly correlated this assumption is violated. The large left skewness of the distribution also makes the paired t-test questionable.

Chapter 3 Quantification and Decomposition of Total Risk (OLS/CAPM)

The Capital Asset Pricing Model (CAPM) serves as the foundational framework in traditional finance, postulating that risk is entirely quantifiable by variance and that only systematic, non-diversifiable risk is priced. The CAPM fundamentally assumes that asset returns follow a Gaussian distribution, where skewness and kurtosis are negligible. This simplistic model has proven foundational for concepts such as portfolio diversification, which posits that firm-specific (idiosyncratic) risk can be better managed by holding a large, diversified portfolio, leaving only systematic risk to be compensated by the market.

However, overwhelming empirical evidence consistently indicates that the returns of financial assets, and particularly speculative equities, violate this assumption, exhibiting non-normal characteristics, namely leptokurtosis and extreme skewness, as in the case of the distribution of the Tesla equity. When the assumption of normality is questioned, the calculated expected returns based solely on mean-variance framework lose their reliability. Consequently, the reliance on these metrics as quantifiers of asset risk becomes inefficient and misleading, compelling the exploration of higher statistical moments. Critiques of the mean-variance approach highlight that rational investors prefer positive skewness and demand additional compensation for assets exhibiting negative skewness, precisely the profile exhibited by many speculative growth stocks.

The Capital Asset Pricing Model, independently developed by Treynor, Sharpe, Lintner and Mossin posts that expected return of an asset is solely a function of its sensitivity to market portfolio, quantified

by Beta. The functional logic of CAPM is that investors are only compensated for bearing systematic, non-diversifiable risk, while firm specific risks can be mitigated through portfolio diversification. However, the CAPM operates under the “Perfect Market” assumption, where returns are normally distributed and investors behave with mean variance rationality.

For speculative growth stocks as Tesla, the CAPM often provides inadequate. The model’s inability to account for the “speculative premium” and the higher order moments of return distributions leads to consistent mispricing. Empirical studies frequently reject the null hypothesis that beta is the sole determinant of returns, identifying persistent anomalies such as the “size effect” and the “value effect” that the single-factor model fails to capture.

For financial time series analysis, logarithmic returns are the preferred metric over raw price levels or simple arithmetic return. Log returns offer several mathematical advantages, among them the most notable are time Additivity, the log returns over multiple periods is a sum of the individual log returns, whereas simple returns must be computed multiplicatively, symmetry, the log returns treat a 50% loss and 100% gain as equal and opposite in magnitude, which better reflects the geometry of wealth, stationary, raw prices are inherently non-stationary and exhibit random walk behavior, making them on some occasions unusable for standard OLS regression without differentiating. Log returns generally satisfy the stationary requirements for GARCH and OLS inference.

While reporting and intuitive communication often favor simple returns, this study utilizes logarithmic returns as the primary unit of analysis to ensure statistical consistency and time additivity. As noted in the literature, simple returns are lower-bounded at 100%, creating a skewed distribution that violates the normality assumptions of many econometric models. Log returns, by contrast, possess an infinite support and are more symmetric, making them the robust choice for modeling the volatility dynamics of a hyper volatile asset.

To void “spurious regression” where two non-stationary variables appear correlated merely due to a shared time trend it is critical to perform an Augmented Dickey-Fuller (ADF) test. The ADF test evaluates the presence of a unit root in the data, a rejection of the null hypothesis at 5% significance level confirms that the series is stationary. It is also notable that of the data downloaded by Alpha Vantage the Adjusted Prices are utilized in this thesis.

3.1. Market Model Estimation and Interpretation: The Price data Approach

The analysis quantified the equity's systematic risk exposure using Ordinary Least Squares (OLS) regression, quantifying the percentage of correlation its of price movements to the broad US market index (S&P 500). While typical econometric practice uses Log returns for stationary series let's assume that in this case a greater level of explanation can be amplified by using the share price data as it is, while in the mean time the statistical significance of the regression analysis becomes greater.

Table 3.1 Regression between log returns

SUMMARY OUTPUT								
<i>Regression Statistics</i>								
Multiple R	0.391446							
R Square	0.15323							
Adjusted R Square	0.092746							
Standard Error	0.152935							
Observations	16							
ANOVA								
	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>gnificance F</i>			
Regression	1	0.059254	0.059254	2.533413	0.13378			
Residual	14	0.327446	0.023389					
Total	15	0.3867						
	<i>Coefficients</i>	<i>Standard Err</i>	<i>t Stat</i>	<i>P-value</i>	<i>Lower 95%</i>	<i>Upper 95%</i>	<i>Lower 95.0%</i>	<i>Upper 95.0%</i>
Intercept	0.016762	0.040588	0.412987	0.685872	-0.07029	0.103815	-0.07029	0.103815
X Variable 1	1.740484	1.093495	1.59167	0.13378	-0.60483	4.085798	-0.60483	4.085798

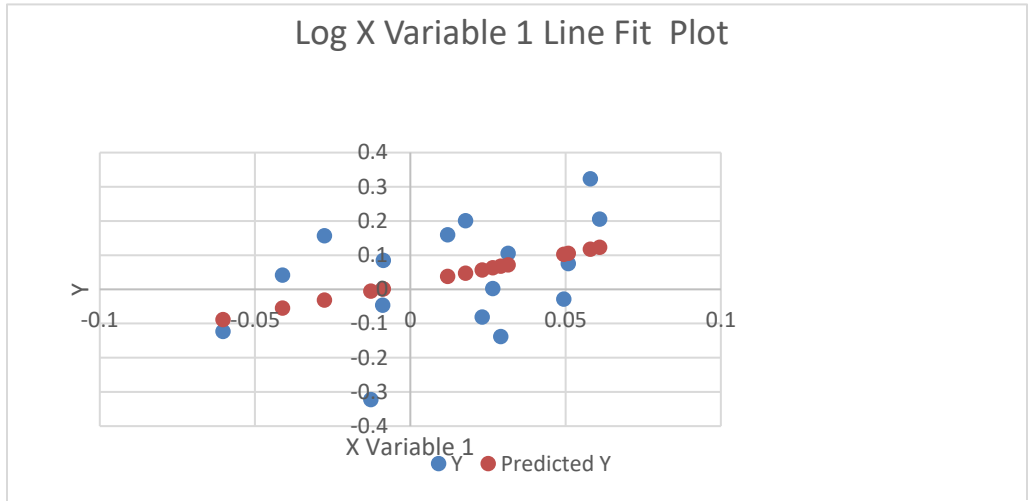


Figure 3.1: Tesla -S&P 500 Line Plot

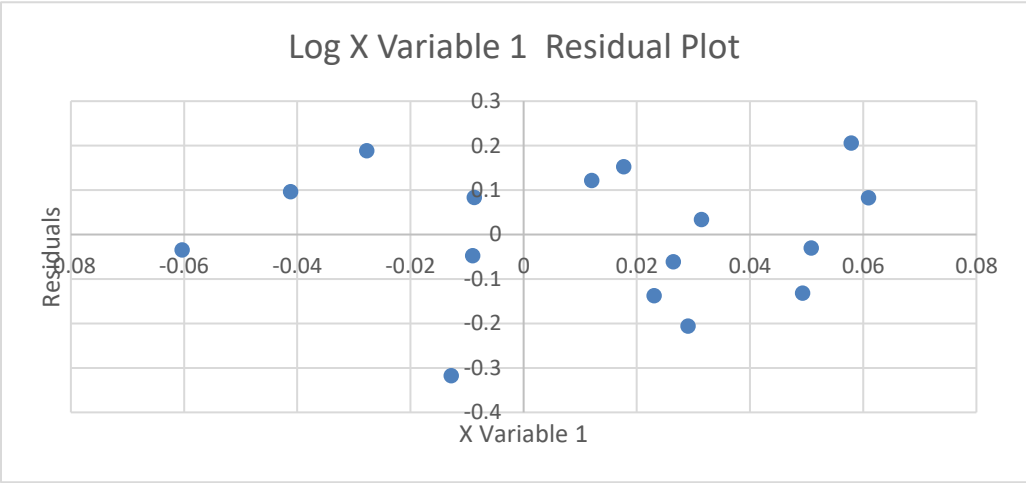


Figure 3.2 Residual Plot of Log

Table 3.2 Regression between Prices

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0.834502772							
R Square	0.696394876							
Adjusted R Square	0.676154534							
Standard Error	43.41141935							
Observations	17							
ANOVA								
	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>gnificance F</i>			
Regression	1	64840.4	64840.40216	34.40628	3.1E-05			
Residual	15	28268.27	1884.55133					
Total	16	93108.67						
	<i>Coefficients</i>	<i>andard Err</i>	<i>t Stat</i>	<i>P-value</i>	<i>Lower 95%</i>	<i>Upper 95%</i>	<i>ower 95.0%</i>	<i>pper 95.0%</i>
Intercept	-717.5187102	166.9448	-4.297940343	0.000634	-1073.35	-361.684	-1073.35	-361.684
X Variable 1	1.761372251	0.300284	5.865686725	3.1E-05	1.121332	2.401413	1.121332	2.401413

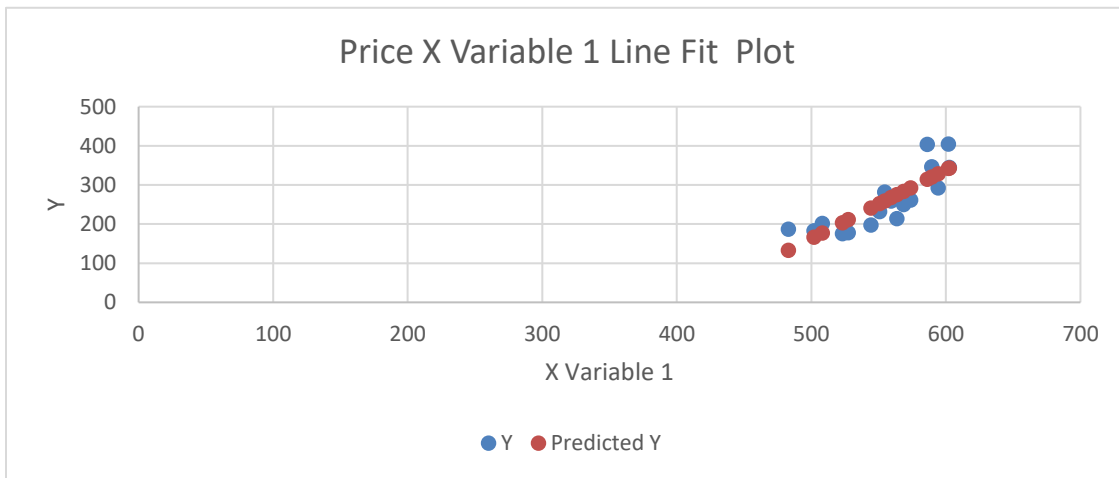


Figure 3.3: Tesla - S&P 500 Price Line Plot



Figure 3.4: Tesla - S&P 500 Price Residual Plot

3.1.1. Justification of Price OLS: Log-Normal Distribution and F-Significance

Whilst Heteroscedasticity remains and thus, we can proceed to a regression safely the significance of each regression (log and price) differs significantly. In relevance to the Log regression the significance F from the ANOVA analysis is 0.14 thusly at 95% confidence level the regression is on no significance however on the ANOVA Significance F of the Price Regression the value of well below 0.05 P-Value this makes the Price regression the rational - credible choice for the procedure of this analysis. Another point of consideration is the percentage of R^2 Adjusted, it seems that the Log returns of S&P 500 explain 40% of the undertaken risk of Tesla while on the price regression the Prices of S&P 500 can explain 84% of the Tesla's equity risk.

3.2. Modeling the Price Space

Stock prices, although the Price model at first sight shows a larger R^2 percentage that the log model, the Figure 3.4: Tesla-S&P 500 Price Residual Plot exposes an Exponential relation via the formed curve, a clear violation of the OLS. This is a clear example of why the log Regression model although not statistically significant is favored by professionals.

Consequently S&P 500 and Tesla have a spurious correlation due to both of them following an upwards trend which misleads a correlation between the two even though their correlation is not statistically significant.

Chapter 4 Modeling Conditional Heteroscedasticity using GARCH (1,1)

The evolution of financial econometrics is defined by the quest to accurately model the complex, time varying nature of risk. Traditional financial models often relied on the assumption of homoscedasticity, where the volatility of a process defined as the square root of conditional variance is assumed to remain constant over time. Prominent examples include the Black Scholes model for option pricing and Vasicek model for interest rates. However, empirical observations of financial markets consistently reveal “stylized facts” that contradict these assumptions, most notably heteroskedasticity, where volatility fluctuates in response to economic and political shocks.

To bridge the gap between theoretical models and market reality, Robert Engle introduced the Autoregressive Conditional Heteroskedasticity (ARCH) model in 1982. This framework pioneered the idea of giving the conditional variance process an autoregressive structure, modeling log returns as white noise multiplied by time dependent volatility factor. In as ARCH (p) model, the current volatility is determined by a weighted sum of squares of previous log returns up to p lags.

While revolutionary, ARCH models often required a large number of lags to capture the persistence of volatility seen in actual financial data. In 1988, Tim Bollerslev extended this work by introducing the Generalized ARCH (GARCH) model. It is favored for its relative simplicity and its ability to accurately approximate a wide range of financial processes using only three primary parameters. The model is defined by two core equations:

$$\text{The mean equation: } X_t = e_t \sigma_t$$

$$\text{The variance equation: } \sigma_t^2 = \omega + \alpha X_{t-1}^2 + \beta \sigma_{t-1}^2$$

In these equations X_t represents the log returns, while e_t (the innovations) are independent and identically distributed variables with a mean of zero and a variance of one. The volatility σ_t^2 is determined by the metrics of Omega - a constant baseline variance, Alpha- the shock reaction parameter, measuring how

current volatility reacts to the most recent innovation and Beta- the persistence parameter, measuring the degree to which previous volatility carries over into present.

To ensure the model remains mathematically sound specifically that the variance never becomes negative the parameters omega, alpha and beta must be all greater than equal to zero.

Regarding the stationery and market characteristics, a critical consideration in GARCH modeling is stationary, ensuring that the process converges to a stable distribution over time. For a GARCH (1,1) process to have a stationary solution with a finite expected value, the sum of the parameters alpha + beta must be less than one. When this sum is close to unity, the process exhibits high volatility clustering, a phenomenon where large price movements are followed by further large movements, and quiet periods are followed by quiet periods.

Furthermore, GARCH models inherently account for leptokurtosis a paramount feature for this analysis. This means that extreme outliers significant market crashes or surges are predicted to occur more frequently than they would under a standard normal distribution. This alignment with real world market behavior is why GARCH remains a ubiquitous tool for risk analysis, parameter estimation, and future value prediction in modern finance.

While the standard model is robust, it does have limitations, such as the inability to react differently to positive versus negative news an effect known as leverage effect. This has led to the development of variants like Exponential GARCH (EGARCH) and Threshold GARCH (TGARCH), which allow for asymmetric responses to market shocks. Regardless of these extensions, the GARCH(1,1) remains the foundational gateway for understanding dynamic conditional heteroskedasticity.

4.1. GARCH (1,1) Econometrics for Volatility Dynamics: The Core Equation

The examination of the Equities' time-varying risk profile employs the GARCH (1,1) model, defined by the conditional variance equation:

$$r_t = \mu + \varepsilon_t, \quad \varepsilon_t = \sigma_t z_t$$

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2$$

This structure decomposes conditional volatility (σ_t^2) into Omega, the long run-baseline volatility, Alpha, the responsiveness to recent unexpected shocks (ε_{t-1}^2) and Beta the persistence or inertia of volatility. The sum of Alpha and Beta measures the overall persistence of volatility shocks, with a value approaching unity suggesting strong volatility clustering.

4.1.1. Visualizing Daily Log Returns and Extreme Shocks

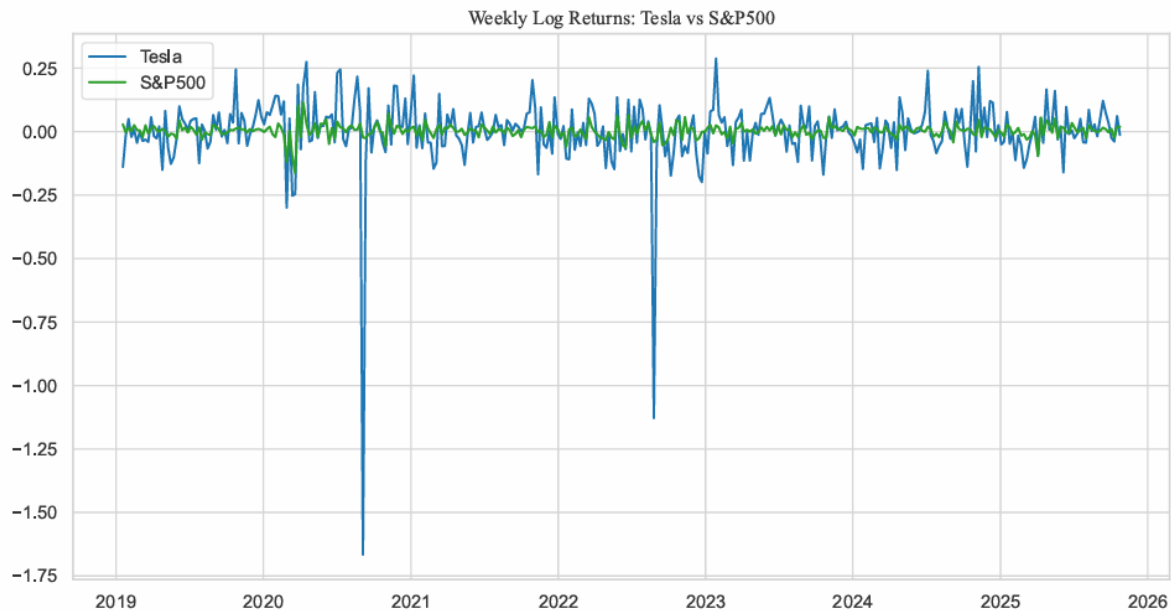


Figure 4.1: Weekly Log Returns: Tesla vs S&P 500

Figure IV.1 visually confirms the intermittent presence of severe negative shocks in Tesla’s returns. In contrast, the S&P500 return series remains relatively flat and stable, highlighting and dramatic amplification of risk intrinsic to the Equites’ shock (consistent with its high β). The persistence of non-zero returns support the interpretation of volatility clustering that the GARCH model is designed to capture.

The OLS regression used for estimating the market model on log returns suffers from severe instability due to the confirmed non-normality and heteroscedasticity of the underlying data. These violations readily apparent in residual plot (Figure II.3).

The cone in Figure II.3, where the variance of the residuals is not constant, provides clear visual evidence of heteroscedasticity in error terms. This violations of OLS assumptions renders the calculated Standard Errors and p-values of log-return Beta estimate unreliable, reinforcing the econometric justification for pivoting to Raw Price model for structural Beta estimation (as detailed in Section 3.1) and utilizing GARCH for dynamic volatility modeling.

Figure 4.2: Conditional Volatility vs Rolling Volatility

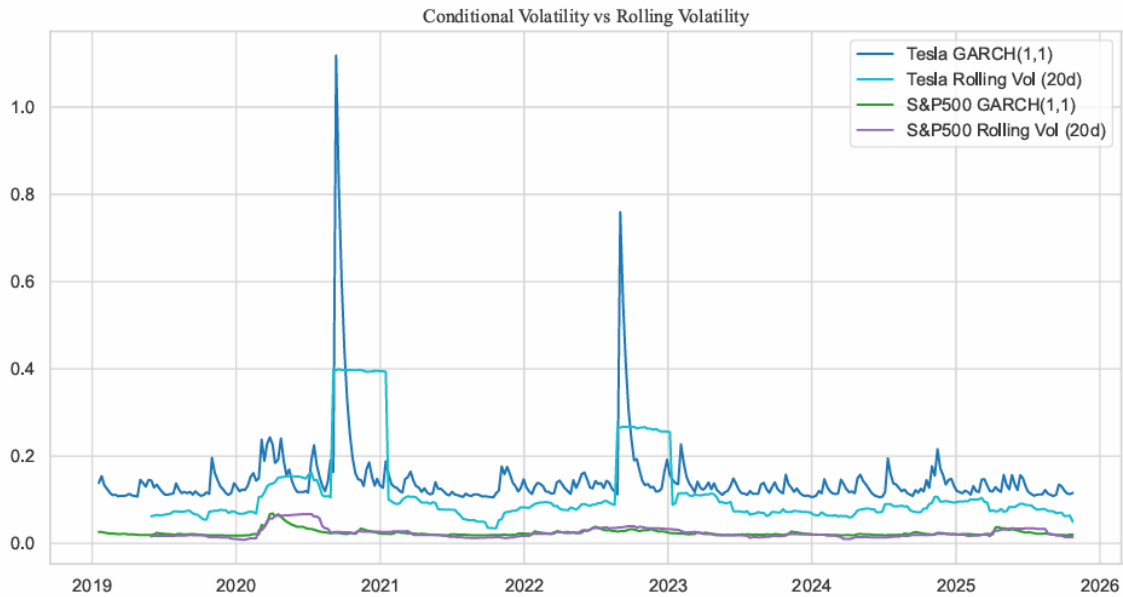


Figure IV.2 supports the model’s suitability in capturing the time-varying nature of the volatility process. The magnitude of Tesla’s volatility is consistently and substantially higher than the S&P 500’s Volatility, highlighting the extreme structural risk differential quantified by the long-run volatility estimate (Section 4.2.2). The major volatility spikes around 2020 and 2022 visually align with the large negative returns seen in Figure IV.1.

4.2. Comparative Analysis of GARCH 1,1 Parameters (Tesla vs S&P 500)

The GARCH 1,1 estimates for the Equity and S&P 500 are summarized in Table IV.1.

Table 4.1: Comparative GARCH (1,1) Volatility Dynamics (Tesla vs S&P 500)

Metric	Equity	SPY	Comparative Interpretation
Omega	0.006	0.00006	Low baseline volatility but 100x higher than SPY

Alpha	0.45	0.11	High reactivity to shocks, much higher than SPY
Beta	0.53	0.8	Moderate volatility inertia, lower than SPY
Persistence	0.97	0.91	Both exhibit high volatility clustering
Long-run Volatility	0.39	0.03	16.3x the structural risk level of SPY

4.2.1. Alpha, Beta, and Volatility Memory

Alpha – Short Run Reactivity: Tesla’s Alpha is over four times greater than that of the SPY’s, indicating the quantitative signature of hyper-reactivity. This suggests that new information is immediately and aggressively priced into future volatility expectations.

Beta – Volatility Inertia: Alpha dominates Beta, indicating that its volatility is driven by instantaneous news flow and investor sentiment than passive inertia.

Persistence: The sum is very close to unity, supporting the conclusion of a potent volatility clustering effect stronger than the markets. This suggests that once a shock hits, the resultant high volatility environment is elongated and dissipates slowly.

4.2.2. Structural Risk Floor, Omega and Unconditional Volatility Sigma

Omega-Structural Risk Floor: The Equity’s estimated Omega is nearly 100 times the market average. This term defines the asset’s structural risk floor. It suggests that even in calm periods, a permanent, irreducible level of uncertainty is embedded in valuation.

Sigma-Unconditional Volatility: The computed Long-Run Unconditional Volatility is over 16 times higher than the SPY benchmark. This indicates the asset’s fundamental high-risk nature and provides the quantitative underpinning for the structural repricing and lower valuation plateau observed post the Q4 2022.

4.3. Analysis of Long-Run (Unconditional) Volatility and Structural Risk

The synthesis of high beta (structural price amplification) and hyper-sensitive GARCH parameters (dynamic shock amplification) reveals why Tesla is prone to sudden booms and severe drawdowns. The

high volatility persistence ensures that once a systematic movement occurs, the asset remains in an elevated risk regime for an extended duration, an observation evident in the Figure IV.2: Conditional Volatility vs Rolling Volatility.

The comparative GARCH (1,1) analysis between Tesla and S&P 500 provides a profound window into the relationship between idiosyncratic volatility and systematic market risk. Regardless of some differences as the table IV.1: Comparative GARCH (1,1) Volatility Dynamics (Tesla vs S&P 500) shows the underlying dynamics specifically the persistence metrics are close 97% for the equity and 91% for S&P 500 which is indicative of a degree of integration between the specific asset and the broader macroeconomic environment.

The data is suggestive of an equity that follows the American market as insinuated in the regression analysis and t- tests the GARCH (1,1) only makes this insinuation more of clear. When the broader market experiences a liquidity crunch or shift in discount rate expectations, the equity transmits through the market and manifests in the equity's alpha parameter.

This interdependence confirms that while the equity carries 100x higher baseline volatility omega, its trajectory is heavily dictated by the trends of the Market, naturally this is true for most equities and their native markets however via the graphs a closer relation in shown only made clearer via the regression analysis. This high reactivity to news shown via the alpha metric is a direct response to macroeconomic data, bearing in mind the aforementioned statements, it is also prudent to refer to the political involvement of the firm to USA Political life.

One of the findings owed to be highlighted is the convergence of the persistence rates with both of them being close to 1 or 100% indicating a slow decay of volatility shocks.

This near uniformity in persistence is highly indicative of the general recessionary climate and the regime switching nature of the examined period. In a standard bull market, one might expect a specialized tech equity to have much higher memory than a diversified index. However, the fact that both show high persistence suggests that the entire market was gripped by the same structural uncertainty.

The similarity is supported further by the t-test results conducted in earlier sections. The tests indicated that there is no significant difference between the assets and that their difference is near 0.

The proximity of their volatility behavior is suggestive of a behavioral closeness and via the regression close dependance from the Equity to the S&P 500. While the equity is more reactive in its price action volatility the duration of its recovery from a shock is tethered to the market's recovery. This confirms that

the equity's risk is not just a localized phenomenon but a concentrated distillation of the American market's vulnerabilities especially in the examined period. Consequently, any risk mitigation strategy for the equity should fundamentally account for the structural health of the S&P 500.

Chapter 5 Downside Risk Quantification: Value at Risk and Expected Shortfall

5.1. Limitations of Parametric Risk Metrics Under Leptokurtosis

The Value at Risk (VaR) as a tool for risk analysis was originally the primary metric for extreme loss estimation in the world of quantitative finance. VaR manages to capture a part of the left tail of the distribution and the rate of loss under a specific confidence level. Thus, it is used to compute the minimum amount lost from an asset or a portfolio, bank etc. over a time period. Where this metric is lacking however is that it doesn't manage to capture extreme losses (extreme left tails) as distribution type which is the norm in asset returns, that's the reason VaR is eclipsed by its more precise counterpart CvaR, which is able to account for losses exceeding VaR and consequently capture extreme losses exceeding VaR under a specific level of Confidence.

VaR and CvaR can be computed with three different ways each coming with specific limitations and insights for the analysis. Two of the three, via Parametric analysis require the assumption of normality, although via using the logarithmic values of the data points, the sample can be formed to a sample closer to normality and the most prudent methodology is to first utilize the historical – non-parametric computation of VaR and Expected Shortfall (ES) which doesn't require the assumption of normality.

Regarding this specific analysis, the results of the S.W. test point to a non-normality assumption. Consequently, this analysis via its multiple applications of the aforementioned metrics primarily relies on the non-parametric and GARCH estimations of VaR and CvaR.

The empirical findings imply that Tesla's return distribution is leptokurtic with a long negative skew. Under these parameters, Parametric VaR models should not be the main advising metric and should be cross examined with non-parametric techniques. This is because the Parametric approach relies on the assumption of normality and systematically underestimate the probability and magnitude of extreme tail losses (tail risk).

A central pillar of the research is the rejection of Gaussian (Normal) distribution in financial returns. Empirical evidence overwhelmingly confirms that equity returns, especially in speculative sectors, exhibit significant leptokurtosis and a left skewness. Leptokurtosis implies that extreme price movements occur far more often than predicted by a normal distribution, creating "outer risk" a dispersion of returns from the

center to the tails. For instance, daily stock returns are often found to be the best fitted by complex distributions like the Johnson SU distribution rather than the bell curve. The non normality renders traditional statistical tests biased and prone to systematic underestimation of risk in models.

In the context of fat-tailed distributions, VaR falls short from a crucial deficiency: it measures the loss threshold at a given confidence level but provides no information about the magnitude of the losses beyond that threshold. This implies that VaR computation based on assumptions of normality may imply adequate capital held, even though the potential for catastrophic, high-severity loss events remains unquantified due to the unaccounted-for observations in the fat tails.

These parameters aside the following parametric and probabilistic analysis was performed assuming normality and attempting to quantify the metrics VaR and CvaR at 95% confidence level. This output will be cross-examined with the Non-Parametric and GARCH equivalents to testify on their credibility.

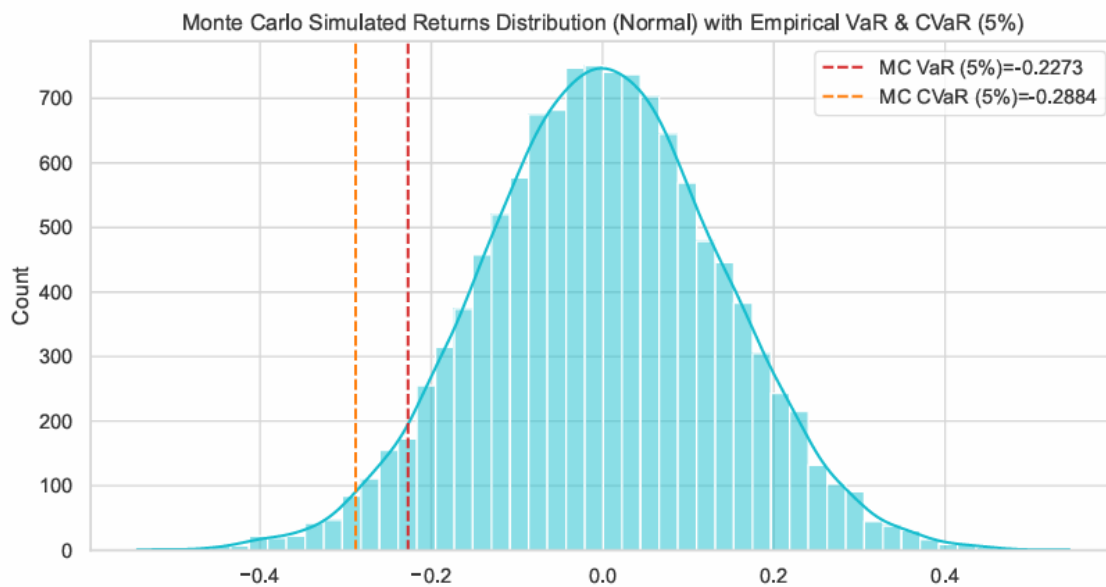


Figure 5.1: Parametric VaR and CvaR

This Monte Carlo Simulation plot, produces a smooth symmetric bell curve that visually fails to replicate the long-left tail and sharp peak of the distribution, confirmed by the empirical data (Figures II.1 and II.2). Under these conditions taking any assumptions from MCS alone would be inadvisable. Should a Portfolio Manager had relied on the assumptions made through the simulation, they would severely underestimate the true probability and severity of tail losses, as the model smooths out the variance innate to the Equity.

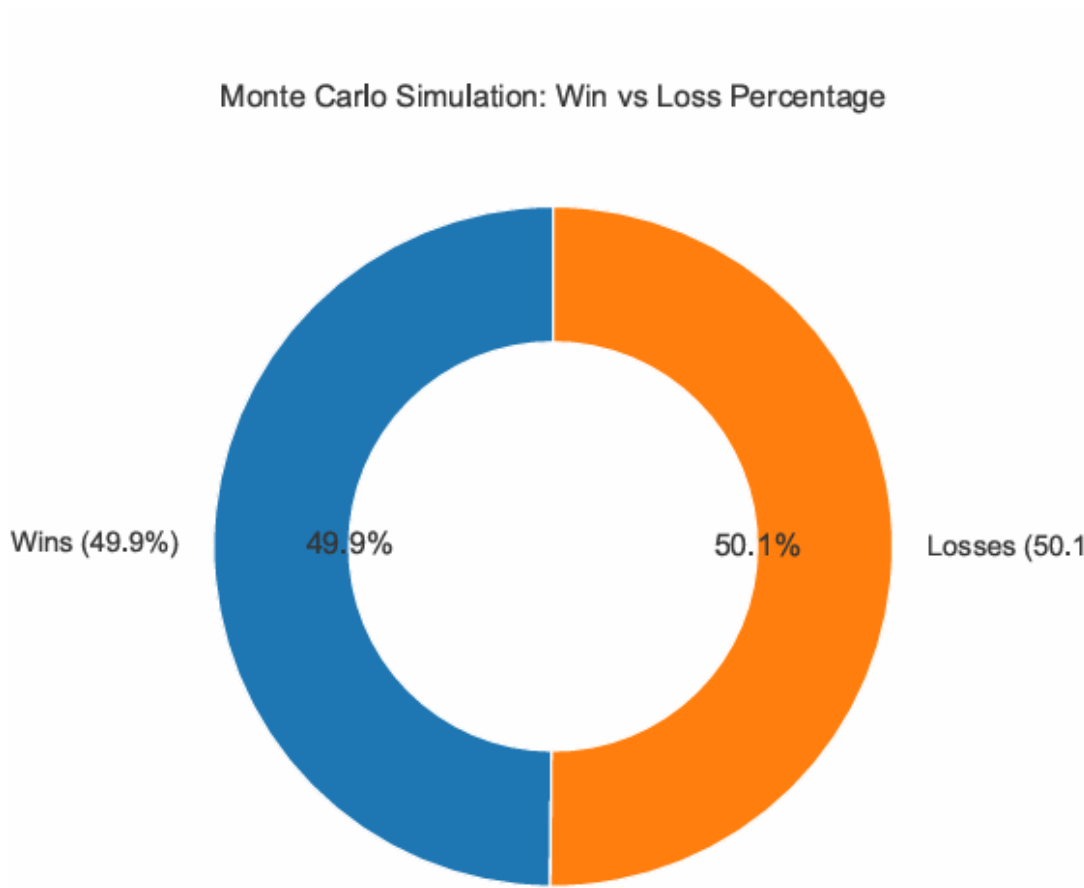


Figure 5.2: Empirical Win vs Loss Percentage Ratio

5.2. Methodology for Robust Risk Quantification: GARCH-Filtered CvaR

Considering the deviation from normality, this analysis is primarily going to rely on the non-parametric VaR and ES (Expected Shortfall) as well as GARCH based VaR and CvaR. CvaR explicitly addresses the primary risk of tail behavior by the quantification of expected loss beyond the VaR threshold, providing a more relevant to the distribution and more comprehensive measure.

5.2.1. Coherence and Severity of Tail Losses

The standard for dynamically managing tail risk is GARCH-filtered CvaR (Expected Shortfall). Figure V.3 shows the dynamic 99% VaR and CvaR boundaries, comparing the Equity against the SPY, with realized returns overlaid.

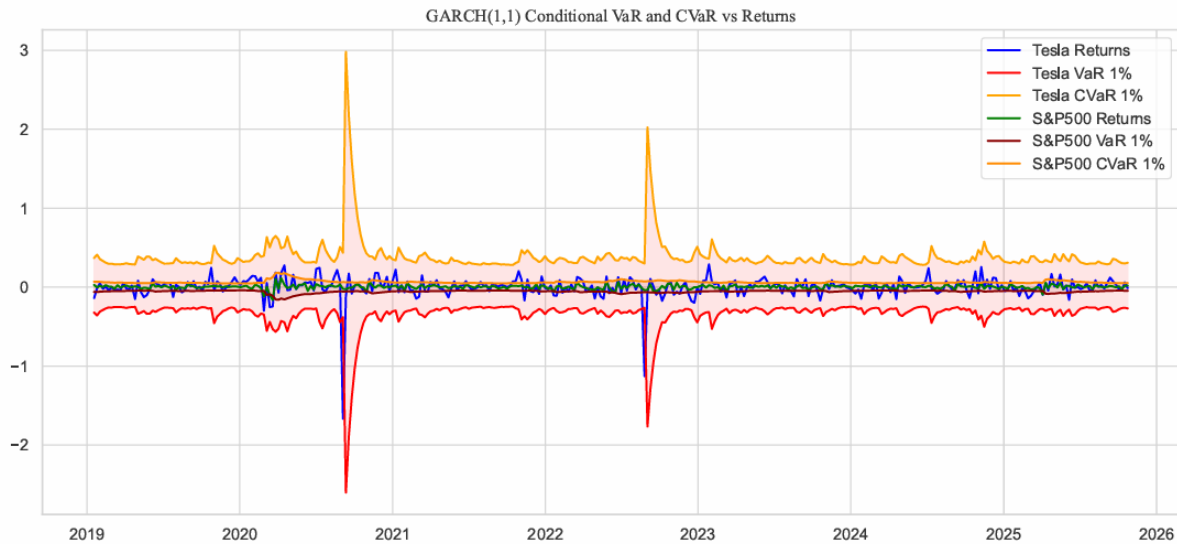


Figure 5.3: GARCH (1,1) Conditional VaR and CvaR (99% Confidence)

Figure V.3 indicates that the Equity's returns occasionally exceed the 99% VaR, implying that the tail risk is realized. Crucially, the Equity's CvaR line runs significantly below the VaR line, especially during periods characterized by high volatility periods (2020 and 2022). This vertical separation supports the finding of the severity of the downside tail; the CvaR quantifies the larger that VaR expected loss after a 1% event has occurred. The high Alpha of 0.44 is visually represented by dramatic spikes in both VaR and CvaR boundaries, showing the model rapidly adjust the risk capital requirement in response to market shocks. CvaR is superior to VaR because it is a coherent risk measure, satisfying key properties such as subadditivity, which VaR often violates in non-normal distributions.

CvaR is crucial for Tesla, as the negative skewness implies that the left tail harbors disproportionately large losses. Under leptokurtosis, the magnitude of CvaR invariably exceeds VaR. The implementation of GARCH-filtered CvaR methodology integrates the dynamically varying conditional volatility-Sigma derived from the GARCH (1,1) model with the tail behavior.

5.3. Financial Implications for Capital Allocations and Regulatory Compliance

The quantitative policy implication of GARCH-filtered CvaR analysis suggests: institutions relying on static or historical VaR metrics for the Equity's systematic underestimate their capital requirements, leading to potential regulatory breaches and capital depletion during crisis periods.

The GARCH model, by proving a dynamic sigma function as a critical early warning and rapid adjustment mechanisms for short-term risk amplification. Specifically, the high Alpha means that when a crisis initiates, the conditional volatility estimate sigma rapidly increases. This allows for a swift and accurate recalculation of CvaR, ensuring that capital provisioning is scaled up proactively in response to escalating risk, rather than lagging behind the realized market stress, as would occur with static models.

Chapter 6 Advanced Topics in Financial Econometrics

6.1. Heterogeneity of Systematic Risk Factors in HGT Sector (Multi-Factor Models)

The reliance on single-factor CAPM (OLS) model for risk quantification is a major limitation in modern financial econometrics, particularly for sector-specific analysis. The CAPM assumes that the effects of systematic risk factors are homogenous across all sectors.

As proven and examined on Chapter 3 regarding Tesla and S&P 500, their linkage is insufficient for comprehensive risk management. Multifactor models, such as those derived from Arbitrage Pricing Theory (APT), argue for the inclusion of multiple systematic risk factors (e.g. company size, value, momentum) that are heterogenous among sectors.

Academic research indicates that sector-specific factor models, such as GICS Ten-Factor Model, can yield superior explanatory power (R^2 up to 27%) compared to the CAPM (R^2 typically 15.5%) for high beta portfolios. Therefore, for Tesla, a more robust valuation and risk management framework should explicitly incorporate factors unique to High-Growth Technology sector, such as R&D intensity, intellectual property concentration and sensitivity to long term interest rates, which are not captured by the broad market factor alone.

6.2. The Role of Higher-Order Moments in Asset Pricing (Co Skewness/ Co Kurtosis)

The confirmation of strong negative skewness and leptokurtosis in the Equity's returns necessitates moving beyond the mean-variance framework to explicitly consider higher-order moments in determining the asset's appropriate risk premium.

Academic finance suggests rational investors display a clear preference for positive skewness (upside potential) and an aversion to high kurtosis (low likelihood of extreme jumps). When an asset exhibits negative skewness, investors rationally demand an additional premium beyond the standard CAPM-derived return to compensate for the higher probability of severe, unexpected downside losses.

Seeing the investment from a Market perspective, as examined on chapter 11 among the reasons for a general downside trend in the tech market the most prominent is a high CAPEX rate aiming to the AI race. This can have two outcomes, outcome 1 is a high ROI and the sudden upwards shift of share value, it is important to note that this Darwinian reading of the tech market will let only the AI integrated companies to lead the market and the others to perish or outcome 2 this will be a repetition of the .com 90's crisis, where a "bubble" and leading to an uncompensated volatility investment.

Chapter 7 Comparative Analysis of Static vs Dynamic Risk Quantification

7.1. The Failure of Static Models: Parametric and Non-Parametric Equivalence

The initial analysis confirmed that the distribution of the Equity's timeseries doesn't closely follow the normal distribution (Chapter II). Static risk models including Parametric VaR/CVaR (assuming Gaussian distribution) and Non-Parametric VaR/ES (relying purely on historical data) share a common and profound weakness: they operate on the assumption of constant, historical average volatility, ignoring the empirical reality of volatility clustering.

Surprisingly the Parametric and Non-Parametric metrics are coherent:

Near Identical Valuation (Static Convergence): The Parametric Monte Carlo simulation (Figure V.1) yielded a 5% CVaR of -29% and the ES Non-Parametric value is -29%, the GARCH CvaR also follows suit at -30%, however this is the max loss that was observed due to the split /5 in the share value from this period. This suggests that under constant volatility assumptions, these static models' convergence towards a similar, artificially low baseline risk measure. This convergence towards an artificially low average risk level

indicates the inability of static models to measure an asset defined by extreme variance. However the GARCH CvaR creates anticipation for a max -5% loss

7.2. Dynamic Model Performance and Crisis Sensitivity

The inherent flaw of static models is starkly exposed when compared to dynamic, time-varying results produced by GARCH (1,1) model (Figure V.3):

Dynamic Response and Crisis Timeline: Figure V.3 illustrates the time varying risk and impact of volatility memory. The GARCH filtered CvaR boundary is not flat but shows extreme spikes that perfectly align with the periods of severe drawdowns and subsequent high volatility clustering (2020 and 2022). The model's instantaneous response is due to high GARCH Alpha (0.44), supporting the finding that risk is conditionally dependent on the immediate flow of information. The timeline provided by the graph visually demonstrates that static models should not be the first point of reference in regards to interpreting assets exhibiting volatility persistence, as they offer no effective warning during the critical elevated risk regimes that follow major shocks.

As seen on Figure V.3: GARCH (1,1) Conditional VaR and CvaR (99% Confidence) there is a specific range of CvaR relevant to the specific period (Crisis or not). From a low CvaR during a non-crisis period (around -5%) to a -30% CvaR during pick Crisis periods, a 6x rise of loss. Using this we can determine if the Equity is experiencing a crisis or not and more so what level of crisis. Based on this the observation can be made that during the relevant to timeseries time the Share is experiencing a high Crisis since it's close to max loss probability. There is however the danger that using ES in this case generalizes the probability of loss whilst in reality the timeline might show a sift of loss probability that is simplified via usage of the Non- Parametric and Parametric methods.

7.3. Economic Implications of Static Risk Underestimation

Relying on static risk quantification for high-beta, non-normal asset like tesla has severe economic and fiduciary consequences. Institutions using static VaR/ES systematically underestimate the necessary risk capital. During the high-volatility, elongated periods identified by the GARCH persistence ($\alpha+\beta=0.96$), this underestimation suggests that capital reserves are inadequate, potentially leading to regulatory breaches

or unforeseen liquidity crises. Static models aren't so effective in incorporating the crucial finding that the Share's risk is primarily governed by asymmetric downside exposure and volatility clustering.

The quantitative evidence supports the necessity for models incorporating dynamic conditional volatility (like GARCH) and non-normal distributions (like t-Students) to more accurately reflect the financial reality of highly speculative equities. The static metrics, yielding low, smooth and symmetric risk estimates, are rejected as inadequate measures for tail risk management.

Chapter 8 Strategic Risk and Firm Vulnerability

The valuation of HGT equities often incorporate a significant component of implicit Real Options. A Real Option is a claim that pays off only under certain contingencies, and this concept is crucial because the intrinsic value calculated using simple Discounted Cash Flow (DCF) models often understates the true value of strategic flexibility in high growth context.

The Option to Expand is highly relevant for Tesla. This is the option to enter new product markets (e.g. automated trucking, energy generation), new geographies, or expand production capacity in response to successful market penetration. The value of these strategic options (calculated using option pricing models) must be added to the base DCF value of assets in place. This incorporates the non-linear payoff structure of high-growth investments, where downside losses are limited to the initial investment, but upside gains are theoretically uncapped, which aligns perfectly with the extreme variance nature of Tesla's stock price.

Chapter 9 Investment Strategy and Portfolio Construction

9.1. Portfolio Strategy Implied by GARCH Dynamics (Momentum and Timing)

The econometric implications derived from the metrics regarding the the Equity's volatility characteristics, the magnitude of the alpha from the GARCH specifically extending to a high Persistence ($\alpha + \beta = 0.96$) have profound implications for investment timing and strategy, suggesting a tactical approach focused on exploiting volatility clustering.

9.1.1. High Alpha and Persistence: A Strategy for Bullish and Bearish Cycles

The high Alpha suggests that the asset reacts intensely and immediately to new information. This means early entry or exit based on market direction signals is highly rewarded. In regards to elongated effect and momentum, crucially the strong persistence suggests that the volatility resulting from these initial shocks is elongated and dissipates slowly. This volatility memory translates into a sustained momentum effect in price changes.

Specifically, when the broader market becomes bearish, Tesla's high Beta (1.8) amplifies the decline. The GARCH persistence ensures that this state of increased risk is elongated, creating an extended buying opportunity where the stock is systematically undervalued relative to its potential. Long buying periods are indicated when the market is bearish.

On a Bullish trend, the market will rapidly price in positive information (high Alpha), leading to an accelerated and elongated period of rising prices. This requires riding the momentum and limiting shelling periods immediately after peak acceleration.

While the dynamics during a cycle are predictable (momentum persists), the transition between bearish and bullish cycles, the precise start and end of these periods remain stochastic. The elevated Structural Risk Floor (Omega) indicates that the underlying uncertainty is the default, meaning these buy/sell periods are initiated randomly and are unpredictable in their timing, necessitating event based or active management rather than passive buy and hold strategies.

9.2 Optimizing Portfolio Construction: Negative Correlation Hedge

Taking into account Tesla's high beta and sensitivity to S&P 500, its incorporation to a Portfolio requires a stringent hedging strategy that neutralizes this systemic risk contribution.

9.2.1. The Need for Inverse Correlation Assets

The most effective strategy involves constructing the remainder of the portfolio with assets characterized by a negative correlation (Inverse correlation) to the American equity market (S&P 500). This makes it possible that when the when the S&P 500 experiences a market-wide decline, the inverse assets are expected to rise or remain stable, providing a necessary counterbalance. This acts as a risk mitigant against the amplified systematic losses expected from the Stock's high beta during bear market reversals.

9.2.2. Specific Hedge Assets: Bonds, Commodities and Gold

Quantitative analysis of historical data suggests specific asset classes often fulfill the negative or low correlation requirement relative to broad equity indices.

Investment Grade Bonds: The rule of thumb portfolios holds both stocks and bonds among several other investments with the aim of diversification. Investment Grade Bonds often increase in value during flights to safety, when systemic equity risk rises (such as an S&P 500 downturn, a recent experience in the years of 2025-2026). It is paramount that using regression models or a Pearson correlation these relative to assets relationships are examined and clarified.

Gold: Gold exhibits an important inverse relationship during periods of weak market performance and high “investment’s fear” something that can be via the VIX (Fear Gauge). Historically, gold has frequently outperformed the S&P 500 when the market posts negative return, making it a powerful long-term hedge against systemic equity risk, even if its short-term correlation with equities is more variable.

Concluding the portfolio contraction in incorporation of the analyzed asset should minimize the covariance between the high beta speculative equity component and the defensive asset component by maximizing the negative correlation of the hedge assets to the market index. A prudent choice is the inclusion of assets from other firms (not R&D, Value stocks or Defensive sectors like Utilities or Consumer Staples) with a high sensitivity to firm specific risk , or assets with no great persistence variance via GARCH (in general more stable assets or assets without a risk premium like bonds) market specific risk dominant assets would be an inadvisable incorporation due to the impact of globalization , and the increased cross-market correlation.

Chapter 10 Conclusion and Policy Implications

10.1. Synthesis of Risk Findings: The Asymmetric Volatility Structure

The quantitative analysis of the equity’s return series suggests a complex risk architecture characterized by extreme volatility, structural embedded risk and severe downside asymmetry.

.The GARCH model reveals a ‘crisis-sensitive’ volatility structure: a permanent Structural Risk Floor ω and exceptionally Rapid Shock Reactivity α , suggesting the econometric signature of speculative overreaction and rapid mean-reversion failures.

The return distribution is non-normal, defined by pronounced negative skewness and leptokurtosis, formally supporting the interpretation of the asymmetric downside exposure where negative returns are a dominant threat.

10.2. Validation of Thesis Hypothesis and Post-Crisis Repricing

The evidence supports the interpretation of the core thesis the post-Q4 2022 decline was indeed a mechanical high-beta reaction, amplified by the market downturn. The choice of the non-Log Return data model to identify the Beta, as justified via its superior R^2 and F-Significance over the comparatively statistically inferior log-return model reinforces the systematic nature of this repricing. The subsequent prolonged stabilization at a lower valuation plateau is explained through the asset's high Long-Run Unconditional Volatility estimate of S-Unconventional 0.4, indicating the permanent and consistent level of risk regarding the asset. This structural risk suggests the market incorporated a necessary permanent risk premium into the asset's perpetual discount rate, resulting in the structural repricing away from peak speculative levels.

10.3. Quantitative Policy Recommendations for Portfolio Management

For quantitative risk analysis and portfolio managers dealing with HGT and speculative equities, the analysis yields critical recommendations:

Static, Parametric VaR models are demonstrably insufficient and carry high risk, as demonstrated by the comparison in Chapter VII. The asset's asymmetric downside exposure suggests the necessity for dynamic GARCH filtered CvaR methodologies to most accurately reflect the time varying nature and severity of extreme tail losses.

Due to the high systematic risk ($\beta=1.8$), negatively correlated to the S&P500 assets should be taken into account, such as Investment bonds and Gold, to effectively hedge against losses during bearish markets.

Active Portfolio management should prioritize strategies designed to dynamically manage firm specific exposures, responding rapidly to volatility escalations indicated by high GARCH Alpha coefficient. Regarding quantifiable option pricing models should be used to value embedded strategic options (such as the Option to Expand), adding this contingent claim value to the base DCF valuation to arrive at a truer estimate of intrinsic value.

Chapter 11 Comparative Analysis of High Growth Technology (HGT) Equities

The Equity vs the Market part of the analysis (Equity vs S&P 500) has enforced the research with paramount insides. In this part of the analysis, we are going to examine the overall ecosystem of the American Tech industry. Specifically, via observation of the rates of return and linear trends of Tesla and its peers Nvidia, Microsoft, Meta, Oracle and IBM certain observations can be made for the Firm specific comparative rase of the Tech ecosystem.

The examined period between 2019-2026 was a highly volatile and transformative era for the American tech market and the Tech market especially. Characterized by a transition period from the pandemic-induced liquidity ta an “Artificial Intelligence Investment Orientation” the technology sector has undergone a profound structural shift in how valuation is calculated and how growth trajectories are projected. For a quantitative financial analysis, the divergence is performance between Tesla and its peers provides a critical case study in erosion of first mover advantages the rise of specialized hardware dominance and maturation of the Tech Market.

The attempt of this section is the provision of an answer of the question of the general and comparative trend of the Equity in contrast to its rivals.

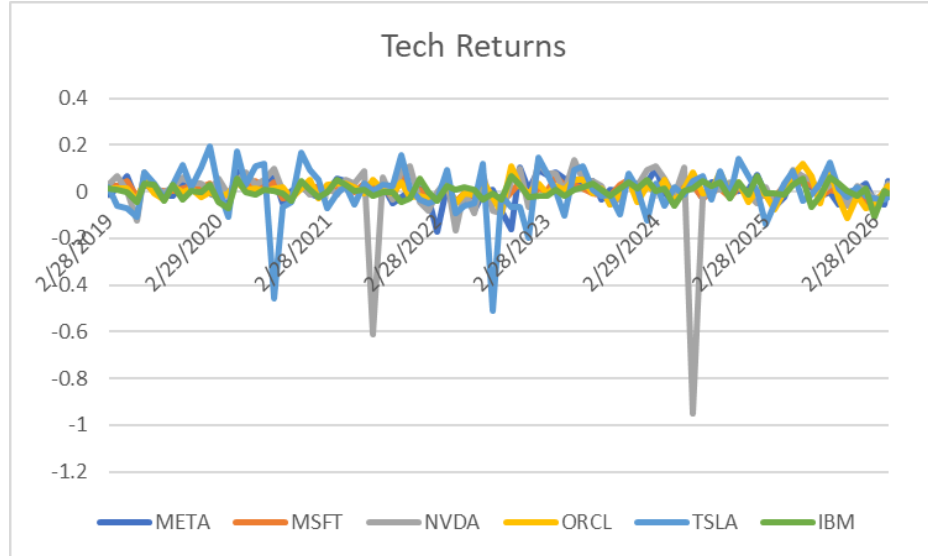


Figure 11.1: Comparative Tech Firm Returns Trajectory 2019-2026

The quantitative performance of the selected tech cohort is best visualized through the lens of historical returns and trend line slopes. Figure XI.1: Comparative Tech Firm Returns Trajectory 2019-2026 displays the monthly or periodic return volatility in the examined trajectory. The data shows a high degree correlation

during major macro events, such as the market meltdown of March 2020, where standard deviations spiked across all assets. However, the subsequent years reveal significant dispersion. Nvidia exhibits the most pronounced spikes in 2023-2024 corresponding to the generative AI breakthrough, while Tesla shows a triple-peak formation followed by a sustained period of lower heights starting in late 2021.

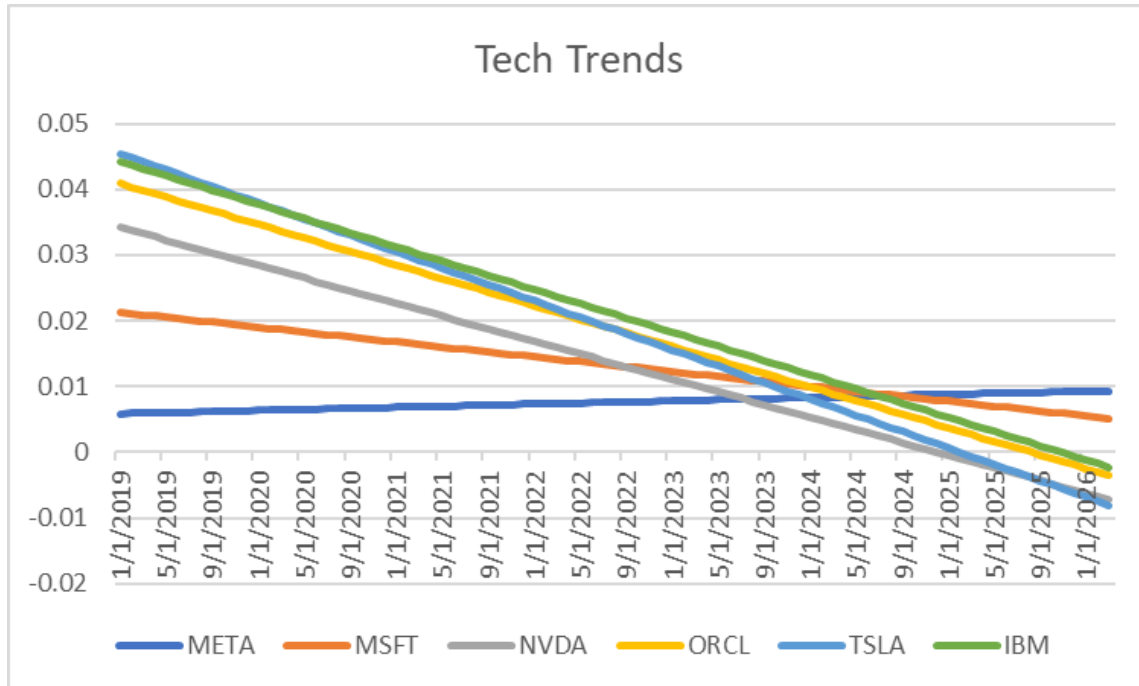


Figure 11.2: Comparative Tech Firm Trends, Trajectory 2019-2026

Figure XI.2: Comparative Tech Firm Trends, Trajectory 2019-2026 provides a more nuanced view of the underlying momentum. By plotting the trend lines a general trend in the Tech market is observed. Tesla began 2019 with the highest trend intercept (approximately 0.045) but exhibits the steepest negative slope, turning into negative territory by late 2025 early 2026. Conversely, Meta Platforms began with the lowest intercept (approximately 0.005) but maintains the only positive slope in the group, ending the period with the highest trend value (app. 0.009). The visual data confirms fundamental shift, the market is re-rating tesla from tech growth hyper performance equity to mature industrial player, while Meta is being re-rated for its successful pivot to AI monetization and capital efficiency.

11.1 Tesla

Tesla's Trajectory is a narrative of two halves. The 2019-2021 era the company increased by 10x in stock price, driven by the successful scaling of the model 3 and model Y and achievement of the 500,000-vehicle annual delivery milestone. By late 2021, the company's valuation peaked, representing 2.0% of the S&P

500 index weight. However, the First Mover Erosion Period 2020-2024 saw established automakers and start ups like BYD and Rivian close the technological and infrastructure gap.

Tesla's vehicle deliveries, which scaled at compound annual growth rate (CAGR) exceeding 50% for several years, hit a structural wall in 2024 and 2025. 2024 marked the first decline (-1%), followed by a more severe -8.6% decline in 2025. This slowdown was not merely a result of saturating demand but was exacerbated by the expiration of the 7,500\$ federal tax credit, which created a "pull-forward" effect in Q3 2025 followed by a demand vacuum in Q4 2025.

By the first quarter of 2026, Tesla's vehicle deliveries were projected at 345,000 units, at 18% decline yearly, indicating that the OPEX for factory retooling had not yet yielded a rebound in consumer appetite. Financially, this manifested as a 59% yearly shrinkage in net income by late 2025, with operating margins contracting as the company utilized price cuts to defend market share.

To counter the stagnation in its core automotive business and to be a competent rival in the tech market Tesla's trajectory in 2026 is increasingly tied to "Physical AI" and autonomous services. The company announced volume production of its steering wheel less Cyber cab by the end of 2026, alongside progress on the "Optimus" humanoid robot. Quantitative bulls like Cathie Wood argue that up to 90% of Tesla's enterprise value will be derived from the Robotaxi business by 2023, projecting a long-term stock price exceeding 2,000\$. However, as of early 2026, these initiatives remain in the "valuation optionality" phase, with the current stock price of 352.42\$ reflecting deep skepticism about the near-term monetization of these technologies.

11.2 Nvidia

Nvidia's trajectory from 2019-2026 has surged more than 4,200% since 2019, driven by its absolute dominance in the data center hardware market. By fiscal year 2026, Nvidia's revenue reached 215.9\$ billion, a 65% increase from the previous year, with gross margins maintaining a staggering 71.1%

The shift in Nvidia's business model is quantitatively absolute. In fiscal 2020, gaming accounted for 51% of total sales, by Q4 2026, the Data Center segment generated 62.3\$ per quarter, representing nearly 90% of total revenue. This dominance is underpinned by the transition from General Purpose Computing to Accelerated Computing, with the "Blackwell" GPU architecture offering 50x better performance for agentic AI compared to the previous "Hopper" generation.

11.3 Microsoft and Meta

The trajectories of Microsoft and Meta platforms in 2025 and 2026 highlight a significant divergence in how these companies handle AI infrastructure burden. Microsoft has been the most affected by market

scrutiny of its CAPEX, with its stock soar by 10% after its latest quarterly report, as the market rewarded its clarity on spending and its ability to grow operating income despite 115\$-135\$ billion planned 2026 CAPEX.

Microsoft remains the defensive anchor of sector, with its “Intelligent Cloud” segment generating 32.9\$ billion quarterly. The company’s trajectory is defined by its “commercial remaining performance obligation” (CRPO), which surged 110% to 625\$ billion by 2026. This quantitative metric suggests that enterprises are locking in long-term cloud and AI commitments, providing Microsoft with a revenue durability that more consumer facing tech firms lack.

Meta’s trajectory in Figure XI.2: Comparative Tech Firm Trends, Trajectory 2019-2026 is the only one maintaining an upwards trend even though it is modest. This is attributed to the “Year of Efficiency” which compressed margins initially but led to a leaner, more profitable organization. Meta’s advertising engine remains a “cash cow”, with revenue up to 23.8% and ad impressions growing 18% in early 2026. The company’s move into “Superintelligence” and its massive procurement of 100,000 NVIDIA H100 chips indicates a riskier but potentially higher-reward strategy to own the consumer AI layer.

11.4 Oracle and IBM

Legacy reported a 438% increase in Remaining Performance Obligations (RPO) to 523\$ billion by February 2026, driven by new commitments from Meta and NVIDIA to run OCI (Oracle Cloud Infrastructure). The company’s “multi-cloud” strategy, allowing Oracle databases to run on AWS, Azure and Google Cloud, has reduced migration hurdles and fueled as 531% growth in tis multi cloud database business.

IBM has positioned itself as a “Hybrid Cloud and AI” leader benefiting from its acquisitions of HashiCorp and StreamSets. Quantitatively IBM has outperformed Oracle in share price gains over the past year (62.9% vs 47.5% as of 2025) and trades at a more attractive forward *P/E* ratio of 25.1x. IBM’s trajectory is characterized by steady, lower-beta growth compared to the volatile hardware-centric trajectories of NVIDIA or speculative path of Tesla.

11.5 The 2026 Tech Ecosystem

As of April 2026, the technology sector is undergoing what Deloitte calls the “AI infrastructure reckoning”. Organizations are shifting from a “cloud first” to a “strategic hybrid” approaching as the cost of scaling AI to production begins to strain balance sheets.

U.S. states are considering restrictions or bans on new data centers as of 2026. Virginia, which handles 70% of the world's internet traffic, is slated for 498 new data centers but faces energy-use restrictions. Regarding the AI shift while training AI requires massive hardware, the "inference" phase (running the models) requires extreme cost-efficiency. Organizations are seeing monthly bills in a plethora, leading to a shift toward on-premises consistency and edge immediacy. Since October 2025, industrials, Materials and Energy have outperformed the Tech sector by over 20%. This rotation reflects investor impatience with the timeline for AI returns and a recognition of the value in "physical" sectors.

11.6 Correlation between the competitors

The global financial landscape in the examined period has been characterized by a structural shift in the technology sector, from a mobile first and cloud centric paradigm to an ecosystem defined by generative and agentic artificial intelligence. This evolution is empirically visible through assets specifically Meta Platforms, Microsoft, Nvidia, Oracle, Tesla and IBM. An analysis of the correlation heatmap of stock returns via Figure XI.3: Pearson Correlation Heatmap of Stock Returns 2019-2026 reveals a complex web of interdependences, where traditional enterprise software titans exhibit strong positive correlations, while highly volatile disruptions and legacy hybrid cloud providers show notable positive and negative correlations.

The statistical relationship between technology assets is empirically characterized as dynamic, as it is governed by overlapping revenue streams, shared supply chains and broader macroeconomic factors such as interest rate cycles and fiscal policy. In the period leading up to 2026, the correlation matrix highlights a central nexus involving Microsoft and Oracle, which share a Pearson correlation coefficient of 0.63, the highest in the observation group. This strong positive correlation is driven by the convergence of their business models toward cloud infrastructure and enterprise AI integration.

The data suggests that IBM serves as the primary diversifier within this cohort, showing negative or near-zero correlations with almost every other asset, particularly META (-0.09) and NVDA (-0.12). This decoupling is indicative of IBM's distinct market position as a legacy provider of hybrid cloud and governance tools, which often moves independently of the high beta growth stocks that dominate the AI narrative. Conversely, the moderate correlation between Meta and Microsoft (0.54) reflects their shared status as hyperscalers who are both major consumers of AI hardware and competitors in digital productivity space.

The launch of generative AI platforms in late 2022 served as a structural catalyst that re-aligned the incentives of the technology sector. This period saw the rise of the examined companies that drove the

majority of A&P 500’s returns. During this phase, the correlation between NVIDIA and its peers was bolstered by massive transfer of capital.

NVIDIA emerged as the cornerstone of the AI trade, with its high-end data center GPUs accounting for the majority of its top line. Major software companies, including Microsoft, Meta and Alphabet, began spending billions of dollars on NVIDIAS’s hardware to build out the infrastructure required for large language models (LLMs). This capital expenditure CAPEX surge created a cyclical dependency the stock performance of the “buyers” (MSFT, META) became increasingly tethered to the “seller” (NVDA), though the heatmap indicates this did not result in high person correlation due to the lead-lag nature of hardware cycles versus software monetization.

Figure XI.3: Pearson Correlation Heatmap of Stock Returns 2019-2026

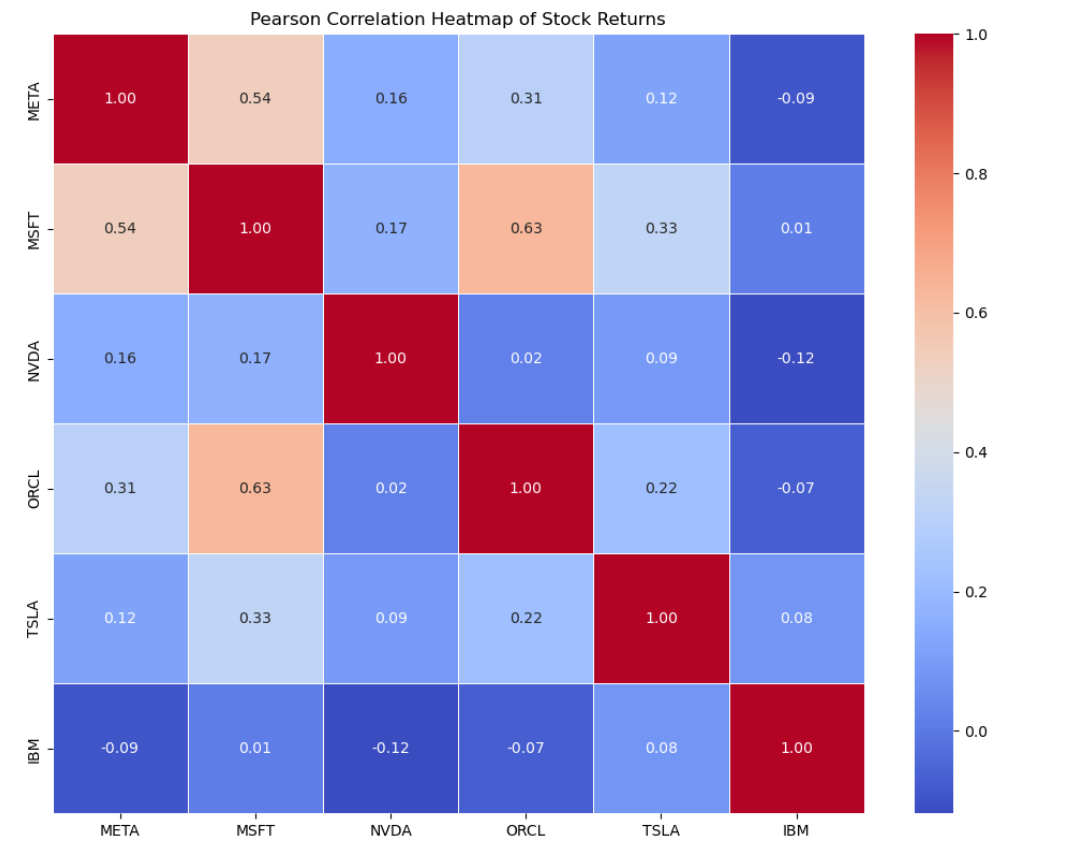


Figure 11.3: Pearson Correlation Heatmap of Stock Returns 2019-2026

The historical trajectory of these assets began with a period of relatively low correlation that was shattered by the global pandemic of 2020. During the liquidation event of March 2020, correlations across the

technology sector spiked as investors moved toward cash, a phenomenon often described as the “correlation of the one” during times of extreme stress.

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