AUREUM ACADEMIC JOURNAL
VOL. 1, NO. 4, Dec 2024
https://doi.org/10.48161/aaj.v1n4a87

An Empirical Analysis of Risk, Return, and Liquidity in Mercedes-Benz Stock: Evidence from 1996-2021

Elvira Fitriyanti[1*], Hanima O. Cosain[2]

[1] Department of Digital Business, Politeknik Siber Cerdika Internasional, Cirebon, West Java, Indonesia;
[2] High School Department, MSU- College of SPEAR, Mindanao State University, Marawi City, Philippines;

* **Corresponding author:** elvirafitriyanti@gmail.com.

ABSTRACT: This study examines the risk, return, and liquidity dynamics of Mercedes-Benz stock using daily market data from 1996 through 2021. The analysis uses open, high, low, close, adjusted close, and trading-volume variables, using adjusted closing prices to measure investment performance and daily returns. The study evaluates long-run performance, annual return variation, volatility, maximum drawdown, and the relationship between trading activity and price movement. The empirical results show that Mercedes-Benz stock generated a total adjusted return of 400.19% and an estimated compound annual growth rate of 6.49%, indicating meaningful long-term value creation. However, this return came with substantial risk, including annualized volatility of 34.71% and a maximum drawdown of -76.50%. Correlation and regression evidence further indicates that trading volume is more closely associated with absolute return and intraday range than with signed daily return. These findings suggest that volume is more informative about the intensity of price movement than about return direction. Overall, the paper supports a risk-return-liquidity interpretation of Mercedes-Benz stock behavior and provides empirical evidence that daily market data can be used to evaluate volatility, downside risk, and liquidity-related dynamics in a major international equity.

Keywords: Mercedes-Benz stock; financial markets; daily returns; volatility; liquidity.

I. INTRODUCTION

Stock-market data provide a practical basis for examining how investors price firm-specific prospects, respond to uncertainty, and adjust trading activity across changing market regimes. For a large cyclical manufacturer such as Mercedes-Benz, daily price and volume observations are especially useful because they capture both long-term valuation changes and short-term reactions to market stress, liquidity conditions, and investor expectations.

This study focuses on Mercedes-Benz stock from 1996 through 2021 and uses the data to assess financial performance, risk exposure, volatility behavior, and liquidity-related trading dynamics. Using adjusted closing prices allows the analysis to better reflect investment performance, while the high-low range and trading volume variables enable examination of whether market activity is more strongly linked to the magnitude of price movement or the direction of daily returns.

This research is grounded in empirical finance literature showing that stock returns, volatility, liquidity, and market microstructure are connected rather than independent phenomena. Prior studies document the importance of liquidity commonality, trading technology, volatility persistence, downside risk, and factor-based return behavior [1]-[34]. These findings justify examining Mercedes-Benz stock not only through price performance, but also through volatility, drawdown risk, intraday range, and trading volume.

The study's contribution is therefore empirical and applied. Instead of treating the dataset as a simple price-prediction exercise, the manuscript evaluates whether Mercedes-Benz stock performance is better

understood through the interaction of return, risk, volatility, drawdown exposure, and liquidity. This framing is consistent with evidence that negative return shocks and volatility persistence are important for interpreting equity-market risk [32].

Research problem

The central research problem is to determine whether the daily Mercedes-Benz stock variables reveal economically meaningful relationships among investment return, downside risk, volatility, and trading activity. In particular, the study asks whether volume and intraday price movement explain return magnitude and market stress better than they predict the direction of daily returns.

1. RESEARCH OBJECTIVES

- Quantify the long-term performance of Mercedes-Benz stock using adjusted closing prices, annual returns, and compound annual growth.
- Measure risk exposure through daily-return volatility, rolling annualized volatility, extreme returns, and maximum drawdown.
- Assess whether trading volume is more closely associated with signed daily return, absolute return, or intraday price range.
- Test the explanatory power of lagged return, volume change, and intraday range in models of daily return behavior and volatility magnitude.
- Interpret the empirical results in relation to prior studies on liquidity, volatility, market microstructure, asset pricing, downside risk, and return predictability [1].

II. LITERATURE REVIEW

The literature review covers all thirty-four studies used in this manuscript. The studies, published between 2012 and 2021, are organized around five themes that are directly relevant to the empirical design: liquidity and market microstructure, volatility and downside risk, factor-based asset pricing, return predictability, and crisis-period market behavior [1].

Liquidity and market microstructure studies show why trading volume, intraday range, and low-frequency liquidity proxies are useful when detailed order-book data are unavailable. International liquidity commonality, high-frequency market making, algorithmic trading, bid-ask spread estimation, and liquidity premia all indicate that trading activity can affect both price discovery and volatility [2].

Asset-pricing studies provide the theoretical background for interpreting stock performance as a risk-return outcome rather than a simple price trend. Evidence on value, momentum, beta, size, quality, investment, profitability, and expected growth factors shows that equity returns are related to systematic risk exposures and firm characteristics [3].

The volatility and downside-risk literature supports the manuscript's use of annualized volatility, rolling volatility, extreme daily returns, and maximum drawdown. Prior research on tail risk, volatility persistence, momentum crashes, downside risk, and crisis-period shocks shows that negative-return periods and volatility spikes are central to assessing equity-market risk [4].

Return-predictability research also supports a conservative interpretation of the regression results. Studies on anomaly attenuation, post-publication decay, multiple testing, machine learning, and nonparametric characteristic selection show that statistically reliable return prediction is difficult and model-dependent [6]. Therefore, the manuscript interprets weak daily return predictability as consistent with broader empirical evidence rather than as a limitation of the dataset alone.

Overall, the reviewed literature supports the study's central design: Mercedes-Benz stock is analyzed through the joint behavior of return, risk, volatility, drawdown, and liquidity. The comparison table below includes all studies [5] and explains how each contributes to the manuscript.

Table 1. Comparison of all studies used in the literature review.

Reference	Study	Main focus and method	Relevance to this manuscript
[1]	Karolyi, Lee, and Van Dijk (2012)	Global liquidity commonality; international equity-market liquidity analysis.	Shows that liquidity can move systematically across markets, supporting the manuscript's liquidity-risk framing.
[2]	Menkveld (2013)	High-frequency trading and market-maker behavior in modern electronic markets.	Explains why trading activity can affect price discovery, liquidity, and short-term volatility.
[3]	Asness, Moskowitz, and Pedersen (2013)	Value and momentum returns across markets and asset classes.	Supports comparing long-run return behavior with broader empirical asset-pricing evidence.
[4]	Kelly and Jiang (2014)	Tail risk and asset prices using systematic downside-risk measures.	Supports using downside risk and an extreme-return interpretation in the Mercedes-Benz analysis.
[5]	Frazzini and Pedersen (2014)	Betting-against-beta factor and leverage-constrained investor behavior.	Links risk exposure and expected returns, helping interpret risk-return trade-offs.
[6]	Chordia, Subrahmanyam, and Tong (2014)	Stock-market anomalies, liquidity, and trading activity over time.	Supports caution in interpreting simple return predictability from daily variables.
[7]	Fama and French (2015)	Five-factor asset-pricing model using profitability and investment factors.	Provides a benchmark for interpreting equity returns as compensation for systematic characteristics.
[8]	Hou, Xue, and Zhang (2015)	q-factor model based on investment, profitability, size, and market factors.	Supports linking firm-level stock behavior to asset-pricing fundamentals.
[9]	Barroso and Santa-Clara (2015)	Momentum risk management and time-varying crash exposure.	Supports the manuscript's emphasis on volatility and drawdown rather than return alone.
[10]	Bollerslev, Todorov, and Xu (2015)	Tail-risk premia and return predictability from high-frequency risk measures.	Connects extreme-risk measurement with return expectations and market stress.
[11]	Harvey, Liu, and Zhu (2016)	Multiple testing and reliability of cross-sectional return predictors.	Supports the manuscript's conservative interpretation of weak daily return predictability.
[12]	McLean and Pontiff (2016)	Whether published return predictors decay after academic discovery.	Provides support for cautious claims about return prediction and model explanatory power.
[13]	Daniel and Moskowitz (2016)	Momentum crashes and time-varying downside risk.	Supports the interpretation of severe drawdowns and crisis-period losses.
[14]	Bollerslev, Li, and Todorov (2016)	Continuous and discontinuous beta components using high-frequency data.	Shows the importance of separating normal volatility from jump-like market movements.
[15]	Green, Hand, and Zhang (2017)	Stock characteristics with independent information for average returns.	Relates firm-level stock variables to broader return-characteristic research.
[16]	Bali, Brown, Murray, and Tang (2017)	Lottery demand and the beta anomaly.	Supports attention to risk preferences and abnormal return behavior beyond simple beta.

Reference	Study	Main focus and method	Relevance to this manuscript
[17]	Fama and French (2018)	Evaluation and selection of asset-pricing factors.	Supports careful factor interpretation and avoidance of overfitted return explanations.
[18]	Asness, Frazzini, Israel, Moskowitz, and Pedersen (2018)	Size effect after controlling for quality-related characteristics.	Highlights the need to interpret raw performance with risk and quality controls.
[19]	Farago and Tedongap (2018)	Downside risks and cross-sectional asset returns.	Directly supports the use of downside-risk measures such as drawdown and negative shocks.
[20]	Kelly, Pruitt, and Su (2019)	Characteristics as covariances using instrumented principal components.	Supports interpreting stock behavior through risk exposures rather than naive prediction.
[21]	Asness, Frazzini, and Pedersen (2019)	Quality-minus-junk factor and firm-quality characteristics.	Links equity performance to quality-related fundamentals and risk-adjusted returns.
[22]	Gu, Kelly, and Xiu (2020)	Machine-learning methods in empirical asset pricing.	Provides a modern benchmark showing that return prediction is difficult and model-dependent.
[23]	Freyberger, Neuhierl, and Weber (2020)	Nonparametric selection of characteristics for expected returns.	Supports the idea that simple linear models may have limited predictive power.
[24]	Zhang, Hu, and Ji (2020)	COVID-19 pandemic effects on global financial-market risk.	Supports interpreting the 2020 Mercedes-Benz volatility spike as part of market-wide stress.
[25]	Baek, Mohanty, and Glambosky (2020)	COVID-19 and stock-market volatility by industry.	Supports the importance of crisis-period volatility and sector sensitivity.
[26]	Boehmer, Fong, and Wu (2021)	Algorithmic trading and market quality using international evidence.	Shows that trading technology can improve liquidity while increasing short-term volatility.
[27]	Hou, Mo, Xue, and Zhang (2021)	Augmented q-factor model with expected growth.	Adds recent factor-model evidence relevant to interpreting equity returns.
[28]	Corwin and Schultz (2012)	Bid-ask spread estimator from daily high and low prices.	Supports using intraday range as a daily-data proxy for market friction and trading intensity.
[29]	Bekaert, Hoerova, and Lo Duca (2013)	Risk, uncertainty, and monetary policy in financial markets.	Justifies the manuscript's focus on volatility as a core measure of market risk.
[30]	Brogaard, Hendershott, and Riordan (2014)	High-frequency trading and price discovery.	Supports the interpretation that trading activity helps incorporate information into prices.
[31]	Amihud, Hameed, Kang, and Zhang (2015)	International evidence on the illiquidity premium.	Links liquidity conditions to expected returns and supports the liquidity-volatility analysis.
[32]	Patton and Sheppard (2015)	Good volatility, bad volatility, signed jumps, and volatility persistence.	Supports separating ordinary price variation from negative-return and stress-related volatility.

Reference	Study	Main focus and method	Relevance to this manuscript
[33]	Fong, Holden, and Trzcinka (2017)	Best low-frequency liquidity proxies for global research.	Provides methodological support for using daily volume and range-based liquidity proxies.
[34]	Cakici and Zaremba (2021)	Liquidity and the cross-section of international stock returns.	Strengthens the international relevance of the liquidity-return framework.

III. RESEARCH QUESTIONS AND HYPOTHESES

The study is guided by the following research questions, which align with the dataset variables and the empirical tests reported in the results section.

- RQ1: What was the long-term financial performance of Mercedes-Benz stock from 1996 through 2021?
- RQ2: How large were the volatility and drawdown risks in the pre-2022 sample?
- RQ3: Is trading volume more closely associated with return direction or with return magnitude?
- RQ4: Do lagged return, volume change, and intraday range meaningfully explain daily return behavior?
- Based on these research questions and the empirical design, the study tests the following hypotheses:
- H1: Mercedes-Benz stock generated positive long-term adjusted performance during 1996-2021.
- H2: The stock was exposed to substantial volatility and downside risk, as measured by annualized volatility and maximum drawdown.
- H3: Trading volume is more strongly associated with absolute return and intraday range than with signed daily return.
- H4: Lagged return, volume change, and intraday range have limited explanatory power for daily return direction, but volume and intraday range have stronger explanatory power for absolute-return magnitude.

IV. PROPOSED METHOD

The study uses the Mercedes_Stock dataset containing daily Mercedes-Benz stock observations from 1996 through 2021. Observations dated 2022-01-01 and later are excluded to keep the empirical period consistent with the pre-2022 research design. The original variables are Date, Open, High, Low, Close, Adj Close, and Volume. Adjusted close is used for return calculations because it reflects corporate actions such as dividends and splits more appropriately than the raw close price.

Table 2. Proposed method.

Stage	Component	Description
1	Dataset	Mercedes_Stock dataset
2	Study Period	Daily Mercedes-Benz stock observations from 1996 through 2021
3	Sample Filtering	Observations outside the study scope are excluded
4	Original Variables	Date, Open, High, Low, Close, Adj Close, and Volume
5	Return Measure	Adjusted close is used for return calculations because it reflects corporate actions such as dividends and stock splits more appropriately than the raw close price

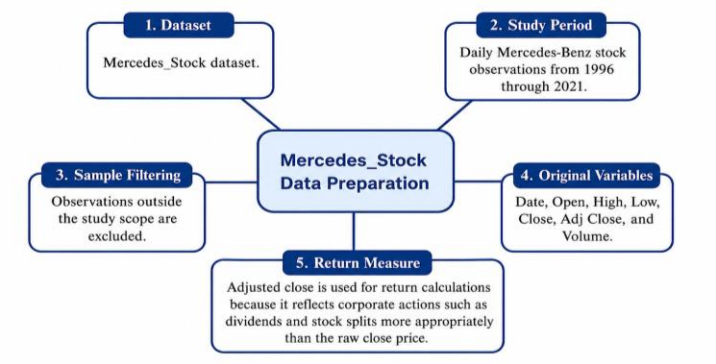


FIGURE 1. Proposed method.

1. METHODOLOGICAL FORMULAS

- Daily return = (Adjusted Close_t / Adjusted Close_{t-1}) - 1.
- Intraday range = (High_t - Low_t) / Open_t.
- Absolute return = |Daily return|; this is used as a simple volatility proxy.
- Annualized volatility = standard deviation of daily returns multiplied by sqrt(252).
- Drawdown = current wealth index / previous peak wealth index - 1.
- Regression standard errors are heteroscedasticity-robust using the HC3 method.

V. RESULTS

1. SUMMARY OF FINANCIAL INDICATORS

Table 3. Summary of main financial indicators.

Headline indicator	Result
Total holding-period return	400.19%
Compound annual growth rate	6.49%
Annualized volatility	34.71%
Maximum drawdown	-76.50%
Best annual return	2013: 57.41%
Worst annual return	2008: -56.74%

The summary table highlights the central empirical message: Mercedes-Benz stock produced strong long-term gains from 1996 through 2021, but those gains were accompanied by high volatility and a severe maximum drawdown.

2. DESCRIPTIVE FINANCIAL RESULTS

Table 4. Key performance and risk indicators.

Metric	Result
Adjusted close at start	9.89
Adjusted close at end	49.46
Total holding-period return	400.19%

Metric	Result
Compound annual growth rate	6.49%
Average daily return	0.0487%
Annualized arithmetic return	12.28%
Annualized volatility	34.71%
Risk-adjusted return, rf=0	0.354
Maximum drawdown	-76.50%
Average daily volume	5,934,487
Median daily volume	5,082,442
Maximum daily volume	73,967,595
Positive return days	3,187
Negative return days	3,102
Best daily return	2020-03-24: 27.28%
Worst daily return	2020-03-12: -18.85%

Table 5. Descriptive statistics.

Variable	N	Mean	Std. dev.	Minimum	Median	Maximum
Open price	6,453	44.51	14.11	14.69	43.08	85.52
High price	6,453	45.06	14.22	15.11	43.62	92.28
Low price	6,453	43.91	14.00	14.31	42.50	84.54
Close price	6,453	44.49	14.09	14.51	43.17	85.05
Adjusted close	6,453	19.63	9.70	5.89	16.25	55.36
Volume	6,453	5,934,487	4,208,946	0	5,082,442	73,967,595
Daily return	6,452	0.049%	2.186%	-18.852%	0.000%	27.277%
Absolute return	6,452	1.499%	1.592%	0.000%	1.056%	27.277%
Intraday range	6,453	2.738%	1.766%	0.000%	2.320%	21.973%
Close-open return	6,453	-0.034%	1.833%	-14.585%	0.000%	18.543%

https://doi.org/10.48161/aaj.v1n4a87

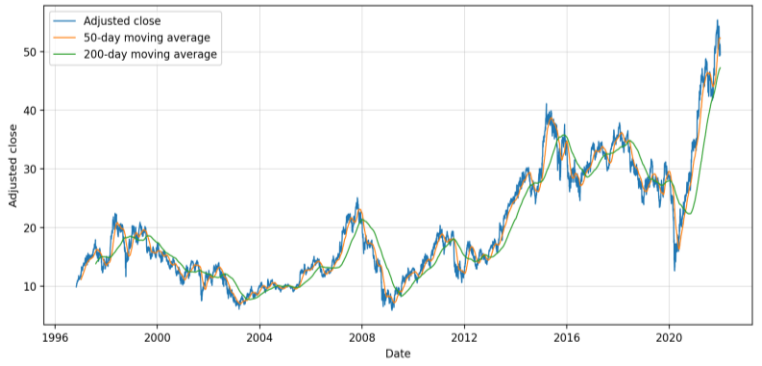


FIGURE 2. Adjusted closing price and moving averages through 2021.

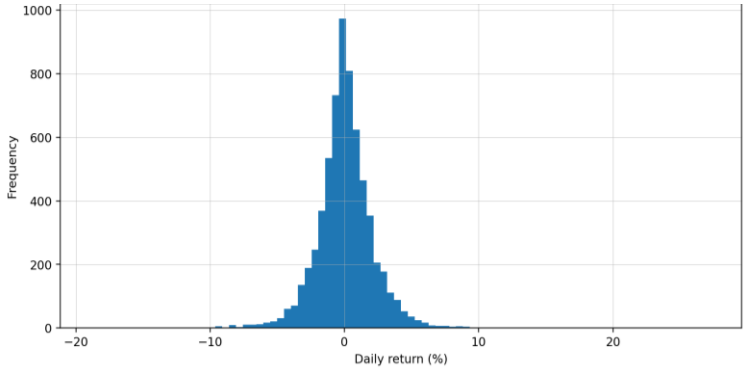


FIGURE 3. Distribution of daily adjusted returns.

The distribution shows that daily returns are concentrated near zero but include extreme positive and negative movements, which is typical of risky equity returns.

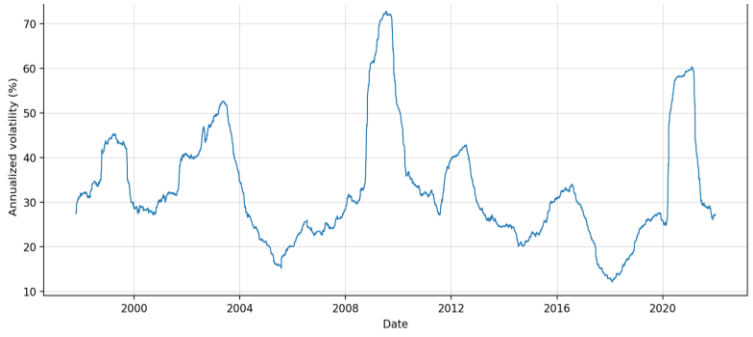


FIGURE 4. Rolling annualized volatility based on a 252-trading-day window.

The volatility chart shows that risk was not constant over time and increased sharply during stress periods, especially around crisis years.

https://doi.org/10.48161/aaj.v1n4a87

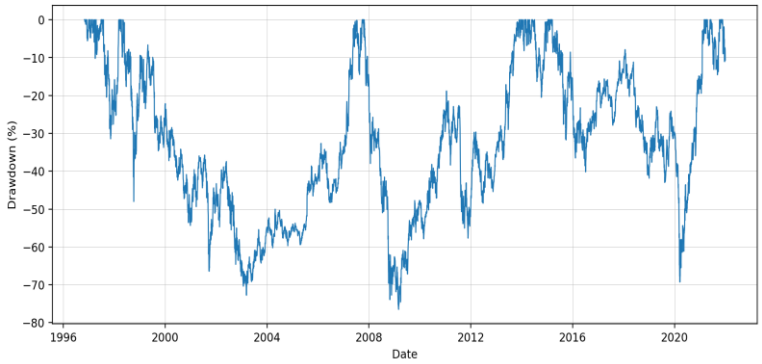


FIGURE 5. Drawdown from the previous wealth-index peak.

3. *RELATIONSHIP ANALYSIS*

The relationship analysis focuses on whether price level, return magnitude, intraday price range, and volume move together. We distinguish between return direction and return magnitude: return direction measures whether the price increased or decreased, while absolute return and intraday range capture volatility or movement intensity.

Table 6. Correlation matrix of selected variables.

Variable	Adj Close	Volume	Daily_Return	Abs_Return	Intraday_Range	Close_Open_Return
Adj Close	1.000	-0.216	0.020	-0.164	-0.264	0.024
Volume	-0.216	1.000	-0.016	0.413	0.526	-0.018
Daily_Return	0.020	-0.016	1.000	0.087	-0.026	0.838
Abs_Return	-0.164	0.413	0.087	1.000	0.665	0.049
Intraday_Range	-0.264	0.526	-0.026	0.665	1.000	-0.034
Close_Open_Return	0.024	-0.018	0.838	0.049	-0.034	1.000

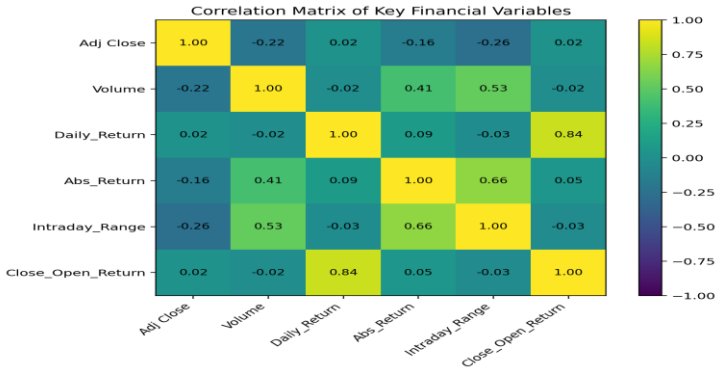


FIGURE 6. Correlation matrix for selected variables.

Table 7. Regression test of daily return predictability.

Model A: dependent variable = daily return	Coefficient	Robust SE	z-statistic	p-value
Constant	0.001644	0.000923	1.781	0.0748
Lagged daily return	0.031089	0.018439	1.686	0.0918
Volume change	-0.000851	0.000759	-1.122	0.2619
Intraday range	-0.041105	0.039904	-1.030	0.3030
Observations	6,258			
R-squared	0.0025			

Table 8. Regression test of liquidity-volatility relationship.

Model B: dependent variable = absolute daily return	Coefficient	Robust SE	z-statistic	p-value
Constant	-0.025891	0.005177	-5.001	0.0000
Log trading volume	0.001628	0.000361	4.505	0.0000
Intraday range	0.575222	0.028821	19.958	0.0000
Observations	6,336			
R-squared	0.4360			

The regression results show a stronger association for volatility: log trading volume and intraday range are statistically significant predictors of absolute daily return.

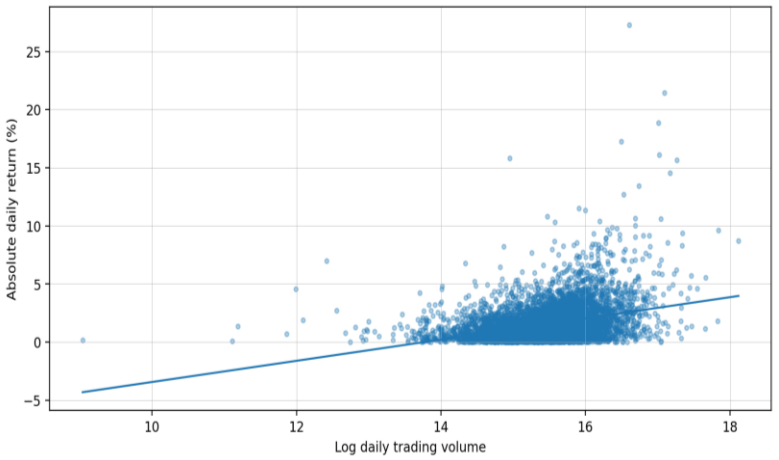


FIGURE 7. Relationship between log trading volume and absolute return.

The scatter plot supports the liquidity-volatility interpretation by showing that larger price movements tend to occur during more active trading days.

4. ANNUAL PERFORMANCE AND MARKET REGIMES

Table 9. Selected annual performance results.

Year	Annual return	Annualized volatility	Average volume	Obs.
2008	-56.74%	61.28%	12,811,232	254
2012	24.19%	29.90%	6,454,793	253
2013	57.41%	24.63%	4,590,346	252
2014	16.34%	22.22%	4,325,756	252
2015	16.66%	30.80%	5,289,629	254
2016	2.44%	27.87%	5,232,705	255
2017	5.14%	12.89%	4,150,944	255
2018	-30.62%	21.53%	4,944,385	252
2019	18.19%	25.81%	5,029,019	251
2020	19.10%	59.38%	6,396,608	254
2021	45.93%	27.13%	3,607,518	255

The annual table shows that the sample contains both severe negative periods and strong recovery years, making the dataset suitable for market-regime analysis.

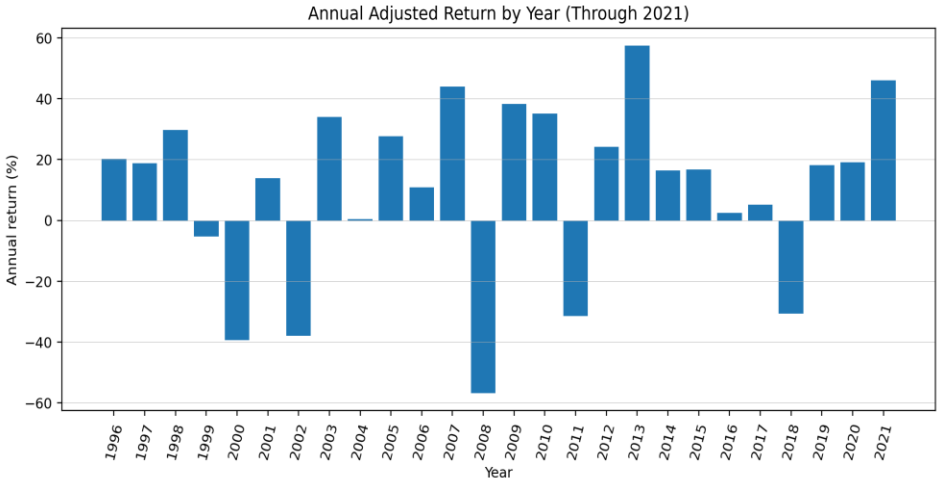


FIGURE 8. Annual adjusted returns through 2021.

The bar chart illustrates year-to-year performance variation and highlights 2008 as the weakest year and 2013 as the strongest year in the selected results.

VI. DISCUSSION

The empirical findings indicate that Mercedes-Benz stock delivered positive long-term adjusted performance from 1996 through 2021, but investors faced considerable volatility and drawdown risk. The adjusted price rose by 400.19% over the sample, while the annualized volatility reached 34.71% and the maximum drawdown reached -76.50%.

The relationship evidence is more supportive of a liquidity-volatility interpretation than a return-prediction interpretation. Trading volume is weakly related to signed daily returns but more strongly related to absolute returns and intraday range. This suggests that volume is more informative about the intensity of market movement than about whether the stock rises or falls on a given day.

The regression evidence reinforces this interpretation. The daily return predictability model has very limited explanatory power, while the absolute-return model has stronger explanatory value. Therefore, the most defensible financial research framing is risk-return-liquidity analysis rather than simple price prediction.

VII. LIMITATIONS AND FUTURE RESEARCH

Several limitations should be considered when interpreting the findings. First, the analysis is based on one stock, so the results should not be generalized to the entire automobile sector or to global equity markets without additional comparative evidence. Second, the study uses daily data rather than intraday order-book data, which limits the ability to measure bid-ask spreads, depth, and transaction-level liquidity directly. Third, the regressions are associational and should not be interpreted as causal evidence that trading volume or intraday range causes returns.

The analysis also omits a market benchmark, risk-free rate series, exchange-rate controls, macroeconomic variables, and firm-level accounting indicators. As a result, the reported risk-adjusted return and volatility measures describe standalone stock behavior rather than fully benchmark-adjusted performance. Future research could extend the study by comparing Mercedes-Benz with BMW, Volkswagen, and major global automobile firms; estimating multifactor asset-pricing models; applying GARCH or jump-volatility models; and using event-study methods around financial crises, earnings announcements, and major corporate actions.

Future work could also strengthen the liquidity analysis by using intraday transaction data, quoted spreads, effective spreads, market depth, and turnover measures. These extensions would help determine whether the liquidity-volatility relationships documented in this manuscript remain robust after controlling for market-wide conditions and sector-specific shocks.

VIII. CONCLUSION

The empirical evidence shows that Mercedes-Benz stock delivered positive long-term adjusted performance from 1996 through 2021, but this return was achieved under conditions of considerable volatility, market uncertainty, and downside exposure. Over the full sample period, the stock generated a total adjusted return of 400.19% and an estimated compound annual growth rate of 6.49%, indicating that long-term investors experienced meaningful capital appreciation. However, the risk measures show this performance was neither smooth nor stable. Annualized volatility reached 34.71%, while the maximum drawdown reached -76.50%, showing that investors faced large fluctuations and severe losses from previous peak values during stressful market periods. These findings confirm that the stock's performance cannot be evaluated solely by its final return; it must also be understood in relation to the risks investors bore throughout the period.

The results therefore support a risk-return-liquidity interpretation rather than a simple price-prediction interpretation. The analysis shows that trading volume is more closely associated with the magnitude of price movement than with the direction of daily returns. In other words, higher trading activity does not necessarily indicate whether the stock price will increase or decrease on a given day, but it is more useful for identifying periods of stronger market movement and greater volatility. This is also supported by the stronger relationship between volume, absolute return, and intraday range compared with the weak relationship between volume and signed daily return. As a result, liquidity-volatility dynamics are central to explaining Mercedes-Benz stock behavior in this dataset. Overall, the study concludes that Mercedes-Benz stock created long-term value before 2022, but this value creation was accompanied by substantial volatility, deep drawdowns, and changing market activity, making the stock more suitable for analysis through a combined framework of return, risk, liquidity, and market stress.

Author Contributions

The author conducted the conceptualization, methodology, data analysis, investigation, writing, review, editing, and final approval of the manuscript.

Funding

This research received no external funding.

Data Availability

The dataset will be available from the author upon reasonable request.

Conflicts of Interest

The author declares no conflict of interest.

REFERENCES

[1]. Karolyi, G. A., Lee, K. H., & Van Dijk, M. A. (2012). Understanding liquidity commonality around the world. Journal of Financial Economics, 105(1), 82-112. https://doi.org/10.1016/j.jfineco.2011.12.008

[2]. Menkveld, A. J. (2013). High frequency trading and the new market makers. Journal of Financial Economics, 110(3), 712-740. https://doi.org/10.1016/j.jfineco.2013.06.006

[3]. Asness, C. S., Moskowitz, T. J., & Pedersen, L. H. (2013). Value and momentum everywhere. The Journal of Finance, 68(3), 929-985. https://doi.org/10.1111/jofi.12021

[4]. Kelly, B., & Jiang, H. (2014). Tail risk and asset prices. The Review of Financial Studies, 27(10), 2841-2871. https://doi.org/10.1093/rfs/hhu039

[5]. Frazzini, A., & Pedersen, L. H. (2014). Betting against beta. Journal of Financial Economics, 111(1), 1-25. https://doi.org/10.1016/j.jfineco.2013.10.005

[6]. Chordia, T., Subrahmanyam, A., & Tong, Q. (2014). Have capital market anomalies attenuated in the recent era of high liquidity and trading activity? Journal of Accounting and Economics, 58(1), 41-58. https://doi.org/10.1016/j.jacceco.2014.06.001

[7]. Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. Journal of Financial Economics, 116(1), 1-22. https://doi.org/10.1016/j.jfineco.2014.10.010

[8]. Hou, K., Xue, C., & Zhang, L. (2015). Digesting anomalies: An investment approach. The Review of Financial Studies, 28(3), 650-705. https://doi.org/10.1093/rfs/hhu068

[9]. Barroso, P., & Santa-Clara, P. (2015). Momentum has its moments. Journal of Financial Economics, 116(1), 111-120. https://doi.org/10.1016/j.jfineco.2014.11.010

[10]. Bollerslev, T., Todorov, V., & Xu, L. (2015). Tail risk premia and return predictability. Journal of Financial Economics, 118(1), 113-134. https://doi.org/10.1016/j.jfineco.2015.06.010

[11]. Harvey, C. R., Liu, Y., & Zhu, H. (2016). ... and the cross-section of expected returns. The Review of Financial Studies, 29(1), 5-68. https://doi.org/10.1093/rfs/hhv059

[12]. McLean, R. D., & Pontiff, J. (2016). Does academic research destroy stock return predictability? The Journal of Finance, 71(1), 5-32. https://doi.org/10.1111/jofi.12365

[13]. Daniel, K., & Moskowitz, T. J. (2016). Momentum crashes. Journal of Financial Economics, 122(2), 221-247. https://doi.org/10.1016/j.jfineco.2015.12.002

[14]. Bollerslev, T., Li, S. Z., & Todorov, V. (2016). Roughing up beta: Continuous versus discontinuous betas and the cross section of expected stock returns. Journal of Financial Economics, 120(3), 464-490. https://doi.org/10.1016/j.jfineco.2016.01.001

[15]. Green, J., Hand, J. R. M., & Zhang, X. F. (2017). The characteristics that provide independent information about average U.S. monthly stock returns. The Review of Financial Studies, 30(12), 4389-4436. https://doi.org/10.1093/rfs/hhx019

[16]. Bali, T. G., Brown, S. J., Murray, S., & Tang, Y. (2017). A lottery-demand-based explanation of the beta anomaly. Journal of Financial and Quantitative Analysis, 52(6), 2369-2397. https://doi.org/10.1017/S0022109017000928

[17]. Fama, E. F., & French, K. R. (2018). Choosing factors. Journal of Financial Economics, 128(2), 234-252. https://doi.org/10.1016/j.jfineco.2018.02.012

[18]. Asness, C. S., Frazzini, A., Israel, R., Moskowitz, T. J., & Pedersen, L. H. (2018). Size matters, if you control your junk. Journal of Financial Economics, 129(3), 479-509. https://doi.org/10.1016/j.jfineco.2018.05.006

[19]. Farago, A., & Tedongap, R. (2018). Downside risks and the cross-section of asset returns. Journal of Financial Economics, 129(1), 69-86. https://doi.org/10.1016/j.jfineco.2018.03.010
[20]. Kelly, B. T., Pruitt, S., & Su, Y. (2019). Characteristics are covariances: A unified model of risk and return. Journal of Financial Economics, 134(3), 501-524. https://doi.org/10.1016/j.jfineco.2019.05.001
[21]. Asness, C. S., Frazzini, A., & Pedersen, L. H. (2019). Quality minus junk. The Review of Financial Studies, 32(1), 34-112. https://doi.org/10.1093/rfs/hhy044
[22]. Gu, S., Kelly, B., & Xiu, D. (2020). Empirical asset pricing via machine learning. The Review of Financial Studies, 33(5), 2223-2273. https://doi.org/10.1093/rfs/hhaa009
[23]. Freyberger, J., Neuhierl, A., & Weber, M. (2020). Dissecting characteristics nonparametrically. The Review of Financial Studies, 33(5), 2326-2377. https://doi.org/10.1093/rfs/hhz123
[24]. Zhang, D., Hu, M., & Ji, Q. (2020). Financial markets under the global pandemic of COVID-19. Finance Research Letters, 36, 101528. https://doi.org/10.1016/j.frl.2020.101528
[25]. Baek, S., Mohanty, S. K., & Glambosky, M. (2020). COVID-19 and stock market volatility: An industry-level analysis. Finance Research Letters, 37, 101748. https://doi.org/10.1016/j.frl.2020.101748
[26]. Boehmer, E., Fong, K. Y. L., & Wu, J. J. (2021). Algorithmic trading and market quality: International evidence. Journal of Financial and Quantitative Analysis, 56(8), 2659-2688. https://doi.org/10.1017/S0022109020000782
[27]. Hou, K., Mo, H., Xue, C., & Zhang, L. (2021). An augmented q-factor model with expected growth. Review of Finance, 25(1), 1-41. https://doi.org/10.1093/rof/rfaa004
[28]. Corwin, S. A., & Schultz, P. (2012). A simple way to estimate bid-ask spreads from daily high and low prices. The Journal of Finance, 67(2), 719-760. https://doi.org/10.1111/j.1540-6261.2012.01729.x
[29]. Bekaert, G., Hoerova, M., & Lo Duca, M. (2013). Risk, uncertainty and monetary policy. Journal of Monetary Economics, 60(7), 771-788. https://doi.org/10.1016/j.jmoneco.2013.06.003
[30]. Brogaard, J., Hendershott, T., & Riordan, R. (2014). High-frequency trading and price discovery. The Review of Financial Studies, 27(8), 2267-2306. https://doi.org/10.1093/rfs/hhu032
[31]. Amihud, Y., Hameed, A., Kang, W., & Zhang, H. (2015). The illiquidity premium: International evidence. Journal of Financial Economics, 117(2), 350-368. https://doi.org/10.1016/j.jfineco.2015.04.005
[32]. Patton, A. J., & Sheppard, K. (2015). Good volatility, bad volatility: Signed jumps and the persistence of volatility. The Review of Economics and Statistics, 97(3), 683-697. https://doi.org/10.1162/REST_a_00503
[33]. Fong, K. Y. L., Holden, C. W., & Trzcinka, C. A. (2017). What are the best liquidity proxies for global research? Review of Finance, 21(4), 1355-1401. https://doi.org/10.1093/rof/rfx003
[34]. Cakici, N., & Zaremba, A. (2021). Liquidity and the cross-section of international stock returns. Journal of Banking & Finance, 127, 106123. https://doi.org/10.1016/j.jbankfin.2021.106123