Stock Price Prediction in the Electric Vehicle Sector: Advanced Forecasting Methodologies and Market Analysis

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Abstract

This report explores advanced methodologies for stock price prediction and portfolio optimization, focusing on the electric vehicle (EV) sector and emerging financial analysis techniques. We evaluate time series models including Chronos, ARIMA, LSTM, and Tiny Time Mixers (TTM), assessing their forecasting accuracy across diverse stock categories. Chronos demonstrates superior probabilistic forecasting capabilities, while TTM excels in few-shot learning for volatile stocks. Our comprehensive approach integrates multiple analytical frameworks. Technical indicators like Relative Strength Index (RSI) and Exponential Moving Averages (EMA) are combined with fundamental metrics, including earnings per share and price-to-earnings ratios, to create a robust prediction framework. Sentiment analysis further enriches the methodology by examining linguistic patterns in earnings calls and corporate communications to capture nuanced market insights.

For portfolio optimization, we synthesize Mean-Variance and Conditional Value-at-Risk methods, enhanced by the Black-Litterman framework, which integrates equilibrium market returns with forward-looking investment strategies. This approach enables precise asset weight determination and adaptive risk management across different market conditions.

Future research will extend this investigation to the S&P 500 Information Technology sector, focusing on comparing Chronos-Bolt and ARIMA in predicting daily stock returns. The study will conduct an in-depth evaluation of model performance using predictive accuracy metrics like Mean Absolute Scaled Error (MASE) and portfolio performance indicators. A key objective will be identifying the most influential technical signals that contribute to prediction accuracy and improved portfolio outcomes.

Code: https://github.com/asdacdsfca/dsc180_b08

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1 Introduction

In the dynamic realm of financial analysis, advanced quantitative methods have become essential tools for understanding market behavior and making informed investment decisions. This report chronicles our comprehensive exploration of sophisticated techniques for stock price forecasting and market analysis, with a specific focus on the electric vehicle (EV) sector as our primary testing ground.

Our research delved into four critical methodological approaches that offer innovative perspectives on financial analysis. Time series analysis emerged as a foundational technique, where we investigated advanced forecasting models by comparing traditional approaches like ARIMA and LSTM with innovative frameworks such as Chronos and Tiny Time Mixers (TTM). These models demonstrate remarkable capabilities in capturing complex market patterns, offering insights that extend beyond linear trend analysis. By examining their performance across various EV stocks, we uncovered nuanced approaches to predicting stock price movements that challenge conventional forecasting methods.

Technical indicators provided another crucial layer of analysis, enabling us to develop a comprehensive approach to understanding market dynamics. We explored both leading and lagging indicators, creating a sophisticated framework that examines metrics like Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), and Exponential Moving Averages (EMA). This approach allowed us to generate dynamic and actionable investment signals by capturing both short-term fluctuations and long-term market trends.

Fundamental analysis complemented our technical approaches by providing a holistic view of company valuation. We distinguished between growth and value investment strategies, analyzing key financial metrics such as Earnings Per Share (EPS), Price-to-Earnings Ratio, and Free Cash Flow. This method enabled us to assess a company's intrinsic value and growth potential, offering insights that go beyond mere price movements and incorporate deeper financial health indicators.

Sentiment analysis emerged as an innovative methodological approach, introducing a unique perspective to market evaluation. By analyzing linguistic patterns in corporate earnings calls, we developed a method for detecting subtle cues of evasiveness and uncertainty in executive communications. This approach allowed us to assess potential market risks and reactions through a linguistic lens, providing an additional layer of predictive insight.

These methodological approaches were rigorously tested within the EV sector, using companies like Tesla, Li Auto, Rivian, and others as comprehensive case studies. Our analysis revealed the strengths and limitations of each approach, providing a nuanced understanding of their predictive capabilities and practical applications in real-world financial environments.

Looking forward to our next quarter, we will build upon these methodological foundations to address a critical research question: How does Chronos-Bolt compare to ARIMA in predicting daily returns for portfolio optimization within the S&P 500 Information Technology sector, and which technical signals most significantly contribute to model performance? This upcoming project will further validate and extend the analytical techniques developed during our initial quarter of research, promising to push the boundaries of our understanding of market prediction and investment strategy.

2 Methods

In this section, we discuss the work we have done in Quarter 1 and methods learned that pave the way for our future project in Quarter 2.

2.1 Time Series Analysis

Traditional time series models, such as ARIMA, have been widely used in financial forecasting due to their simplicity and interpretability, particularly for linear trends (Ariyo, Adewumi and Ayo 2014; Mondal, Shit and Goswami 2014; Khan and Alghulaiakh 2020). However, ARIMA and similar models are often limited in their ability to capture nonlinear patterns and complex dependencies in stock price data, especially in fast-changing sectors such as electric vehicles (EV) (Stevenson 2007; Petrică, Stancu and Tindeche 2016). LSTM models (Istiake Sunny, Maswood and Alharbi 2020; Selvin et al. 2017), which use neural network architectures to capture sequential dependencies, have improved the accuracy of the forecast in some applications; however, they can be computationally intensive and may require significant data preprocessing to effectively handle volatility in the stock market (Bathla 2020).

In contrast, advanced models, such as Chronos and Tiny Time Mixers (TTM), have gained traction in time-series forecasting due to their ability to process long sequences and complex patterns without the limitations of recurrent connections (Ansari et al. 2024; Ekambaram et al. 2024).

2.1.1 Chronos

Chronos framework adapts pretrained language models for time series forecasting. At its core, it transforms continuous time series data into discrete tokens through scaling and quantization techniques, enabling the use of transformer-based models for prediction. The framework's primary goal is to achieve zero-shot learning, allowing it to forecast unseen datasets without requiring retraining.

Unlike traditional time series models, Chronos minimally modifies pretrained language models and generates probabilistic forecasts by sampling from predicted distributions (See Table 1). It enhances its generalization capabilities through data augmentation techniques like TSMixup and KernelSynth. The framework processes data using mean scaling for normalization and quantization for token conversion, while preserving underlying patterns like seasonality and trends.

Table 1: **Comparison of ARIMA, LSTM, Chronos, and TTM**

Feature	**ARIMA**	**LSTM**	**Chronos**	**TTM**
Model Type	Autoregressive, Moving Average	Recurrent Neural Network	Time series framework with ML capabilities	Tensor-based analytical framework
Data Requirements	Stationary and small datasets	Large sequential datasets with diverse features	Structured time-series datasets	Tensor-structured data across dimensions
Interpretability	Clear coefficients and residual analysis	Hidden state dynamics hard to interpret	Semi-transparent depending on ML model	Understandable tensor operations but abstract
Scalability	Small datasets, univariate series	Large-scale, multivariate series	Distributed training, large datasets	Multidimensional tensor computations
Use Case	Stationary time series forecasting	Long-term dependency capture in time series	Integrated time series forecasting and ML pipeline	Tensor decomposition for multidimensional data
Strengths	Simple, interpretable, well-suited for linear trends	Handles non-linear relationships and dependencies	Combines time series and ML tools	Efficient tensor operations and decomposition
Limitations	Poor on non-linear or multivariate data	High computational cost and complexity	Environment compatibility dependency	Requires expertise in tensor mathematics

When running predictions across ten EV firms (Tesla, Rivian, NIO, Xpeng, EVgo, Li Auto, Indie Semiconductor, Chargepoint, Lucid, and Luminar), we find that Chronos generally demonstrates better trend-capturing capabilities compared to ARIMA and LSTM. For example, for Tesla (TSLA), while ARIMA predicted a relatively flat trend and LSTM showed modest growth, Chronos better captured the stock's upward momentum during September 2024, though still underestimating the actual magnitude of the rise (Figure 1). Similarly, for NIO, Chronos successfully tracked the gradual price increase while both ARIMA and LSTM predicted relatively flat trajectories (Figure 2).

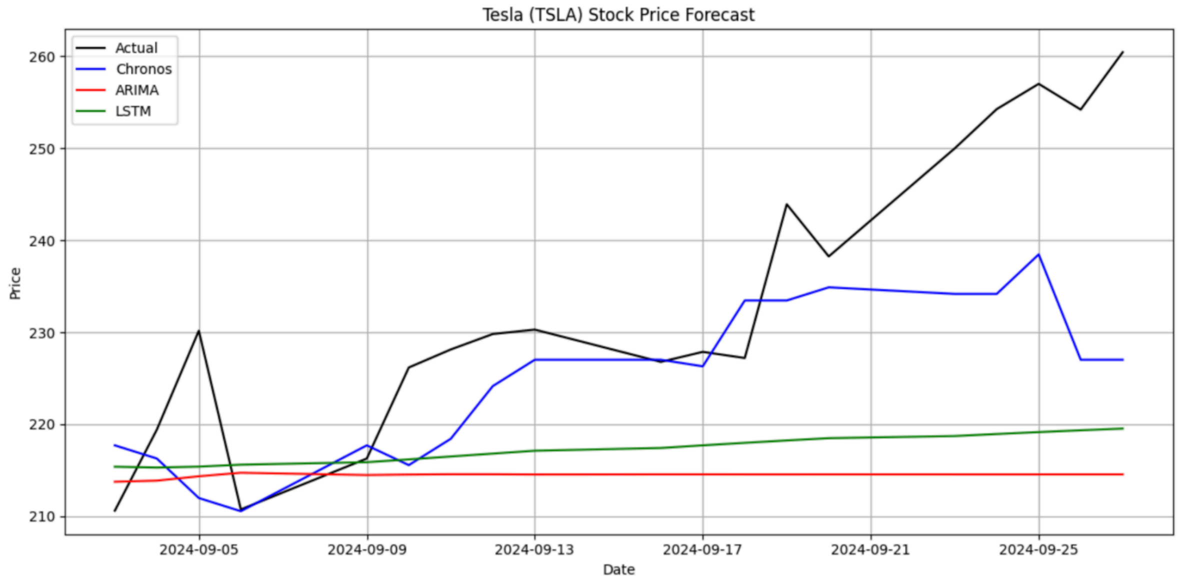

Figure 1

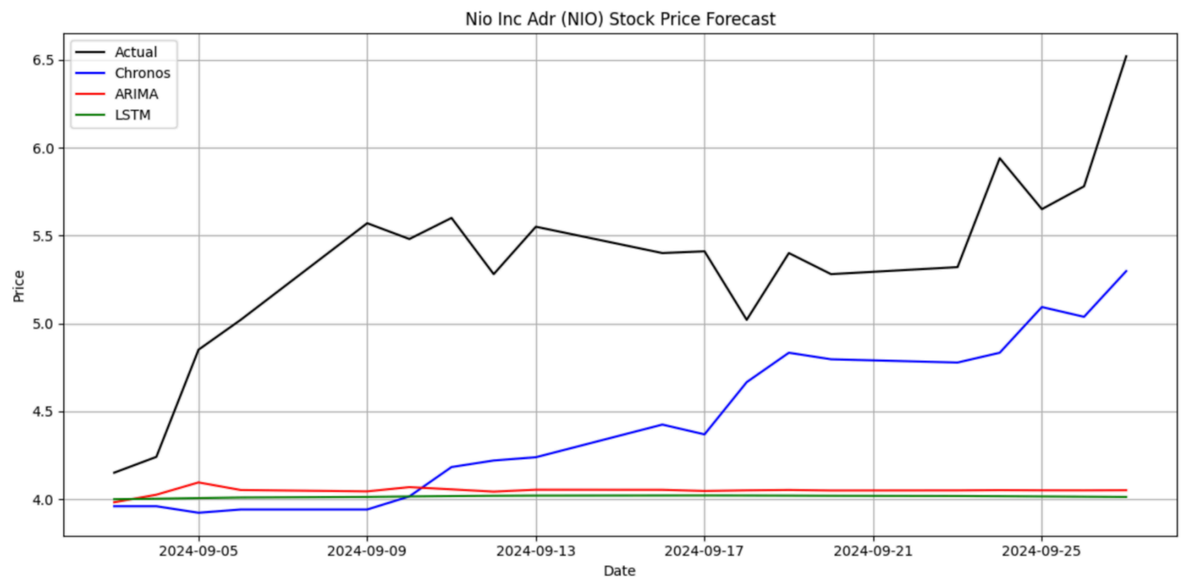

Figure 2

Table 2: Chronos vs Traditional Forecasting Models for EV Stock Price Prediction. We found that Chronos generally outperforms ARIMA and LSTM.

Company	Chronos MASE	Chronos WQL	ARIMA MASE	ARIMA WQL	LSTM MASE	LSTM WQL
Rivian Automotive	5.67	1.02	3.78	0.68	1.75	0.31
Tesla	1.63	5.17	3.17	10.02	2.75	8.72
Nio Inc Adr	3.16	0.45	4.57	0.65	4.69	0.66
Xpeng A Adr	2.26	0.47	3.32	0.70	3.99	0.84
Evgo Inc	2.80	0.18	2.74	0.17	1.16	0.07
Li Auto Adr	1.94	0.71	2.73	0.99	2.75	1.00
Indie Semiconductor Inc Class A	3.31	0.25	2.78	0.21	5.88	0.45
Chargepoint Holdings Inc Class A	9.15	0.26	8.53	0.24	4.16	0.12
Lucid Group Inc	2.07	0.11	3.60	0.19	2.71	0.14
Luminar Technologies A	6.90	0.17	3.22	0.08	10.24	0.26

When comparing performance metrics across all companies (see Table 2), we found that Chronos showed better forecasting accuracy in most cases. Chronos outperformed ARIMA in 7 out of 10 cases for MASE scores and 8 out of 10 cases for WQL scores. Compared to LSTM, Chronos showed better MASE scores in 6 out of 10 stocks and better WQL scores in 9 out of 10 stocks. Notable exceptions included Tesla and NIO, where ARIMA achieved better MASE scores, and Rivian, where LSTM showed lower MASE. EVgo showed one of the best Chronos performances with a MASE of 2.2364 and a notably low WQL of 0.1286, indicating strong probabilistic forecasting ability. Chronos's ability to capture both general trends and probabilistic distributions makes it a versatile tool for stock price prediction.

2.1.2 Tiny Time Mixers

Tiny Time Mixers (TTM) aims to achieve efficient zero/few-shot multivariate forecasting while significantly reducing model size and computational requirements (Ekambaram et al. 2024). At its core, it features head probing, which only fine-tunes the model head while keeping the pre-trained backbone frozen, offering faster training with competitive performance compared to full end-to-end approaches.

A key innovation in TTM is its sophisticated handling of context lengths (FL) through different model variants optimized for specific lengths (TTM-Base: FL=512, TTM-Enhanced: FL=1024, TTM-Advanced: FL=1536). The framework employs two crucial techniques: Adaptive Patching (AP) and Resolution Prefix Tuning (RPT). AP allows different layers to operate at varying patch lengths, improving generalization across datasets with different resolutions and showing a 3% improvement when pre-training data is limited. RPT enhances model performance by explicitly incorporating resolution information, demonstrating an 8% improvement for short context lengths (Ekambaram et al. 2024).

Table 3: MASE Comparison of Forecasting Models for EV Stocks: Mixed Performance Across Different Approaches

Company	TTM MASE	Chronos MASE	ARIMA MASE	LSTM MASE
Rivian Automotive	5.61	5.67	3.78	1.75
Tesla	3.56	1.63	3.17	2.75
Nio Inc Adr	1.05	3.16	4.57	4.69
Xpeng A Adr	4.92	2.26	3.32	3.99
Evgo Inc	0.13	2.80	2.74	1.16
Li Auto Adr	2.89	1.94	2.73	2.75
Indie Semiconductor Inc Class A	0.47	3.31	2.78	5.88
Chargepoint Holdings Inc Class A	0.01	9.15	8.53	4.16
Lucid Group Inc	4.87	2.07	3.60	2.71
Luminar Technologies A	2.79	6.90	3.22	10.24

When comparing MASE scores across different forecasting approaches for EV stocks, we observe mixed performance with each model showing distinct strengths. TTM demonstrates exceptional accuracy in certain cases, achieving remarkably low MASE scores for Chargepoint (0.01), EVGO (0.13), and Indie Semiconductor (0.47), while struggling with stocks like Rivian (5.61) and Xpeng (4.92). Chronos performs best with established companies like Tesla (1.63) and Li Auto (1.94), but shows weakness with volatile stocks like Chargepoint (9.15). Traditional models show more consistent but generally higher error rates - LSTM excels with Rivian (1.75) but struggles with Luminar (10.24), while ARIMA maintains moderate performance across most stocks. The varied performance suggests that model selection should be stock-specific, with TTM particularly suited for volatile stocks, Chronos for established companies, and traditional models for stocks with clear trends.

2.2 Technical Indicators and Fundamental Analysis

Integrating technical indicators with fundamental analysis metrics can significantly enhance the predictive accuracy of stock price models. This dual approach enables a more comprehensive understanding of market dynamics, combining historical data patterns with intrinsic company values.

2.2.1 Technical indicators

Technical indicators are mathematical constructs derived from historical price, volume, and other market data. These indicators provide insights into market trends, momentum, volatility, and potential reversals. They are often classified into two categories based on their utility:

- **Leading Indicators**: These indicators aim to predict future price movements. For instance, the Relative Strength Index (RSI) signals potential overbought or oversold conditions, assisting in generating buy or sell signals. Traders use such indicators to anticipate market changes and act proactively.

- **Lagging Indicators**: These focus on historical price trends to confirm ongoing market behavior. Moving averages, for example, smooth past price data to identify long-term trends but are less responsive to sudden market shifts. Despite their reactive nature, lagging indicators are valuable in validating signals from other sources.

Technical indicators are not only tools for manual analysis but also serve as a foundation for quantitative models and automated trading systems. Their algorithmic structure makes them particularly well-suited for integration into machine learning models, which can dynamically adjust weights and combinations to optimize prediction accuracy. Table A.1 provides a detailed explanation of the technical indicators considered in this study, including Exponential Moving Averages (EMA), Bollinger Bands, and Moving Average Convergence Divergence (MACD), among others.

Example: Tesla in 2024

To illustrate the use of technical indicators, consider the performance of Tesla stock in 2024. By plotting the fluctuations of its Relative Strength Index (RSI) over time, we observed distinct periods of overbought and oversold conditions, highlighted by RSI levels crossing above 70 or below 30, respectively (Figure 3).

Additionally, after calculating a comprehensive suite of indicators—such as oscillators (e.g., RSI, MACD) and moving averages (e.g., Simple Moving Averages, EMA)—we developed a technical analysis dashboard. This dashboard consolidates daily investment decisions by leveraging a majority voting mechanism, where each indicator provides a ”buy,” ”sell,” or ”hold” signal. For Tesla in 2024, this system enabled dynamic and informed decision-making, presenting a clear and actionable investment strategy for each trading day (Table 4).

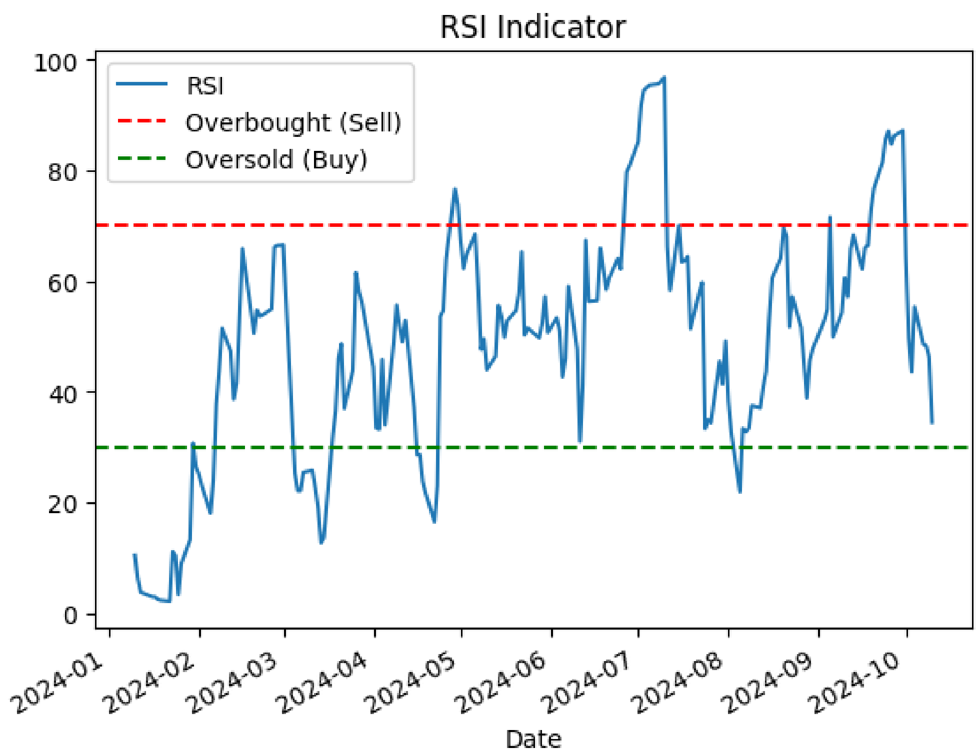

Figure 3: RSI of TSLA in 2024 highlighting overbought and oversold conditions.

Table 4: Daily Summary of Recommending Actions of TSLA Based on Technical Indicators

Index	Date	Total Buy	Total Sell	Total Hold	Final Decision
0	2024-10-01	12	0	1	Buy
1	2024-10-02	10	2	1	Buy
2	2024-10-03	9	3	1	Buy
3	2024-10-04	10	2	1	Buy
4	2024-10-07	8	4	1	Buy
5	2024-10-08	8	4	1	Buy
6	2024-10-09	7	5	1	Buy
7	2024-10-10	5	7	1	Sell

2.2.2 Fundamental Analysis

In addition to technical indicators, this study incorporates fundamental analysis metrics to provide a more holistic view of stock behavior. Fundamental metrics such as Earnings Per Share (EPS), Price-to-Earnings (P/E) Ratio, and Free Cash Flow (FCF) capture the underlying financial health and growth potential of a company. These metrics complement technical indicators by offering insights into intrinsic value and market sentiment, which are often not reflected in price movements alone.

For investors, the application of fundamental metrics is tailored to distinct strategies:

- **Growth Investors** focus on companies with strong revenue growth, positive EBITDA, and favorable operating margins, aiming to capture long-term capital appreciation. Metrics like EPS, Enterprise Value, and Gross Margin play a crucial role in identifying companies with significant growth potential.
- **Value Investors** prioritize undervalued companies based on intrinsic valuation, often relying on low Price-to-Earnings Ratios, low Price-to-Book Ratios, and solid Free Cash Flow generation. Their goal is to identify stocks that are trading below their intrinsic value but have stable financial performance.

Example: Investment Opinions

Using the fundamental data, distinct investment opinions can be formulated:

- **From a Growth Investor's Viewpoint**: Tesla (TSLA) and Li Auto (LI) stand out as top picks for growth investors. Tesla's strong revenue (Table 5), high operating margin (10.7%) (Table 6), and positive EPS make it a clear choice for sustained growth. Similarly, Li Auto's strong Gross Margin (21.5%) and EBITDA indicate robust financial health, supporting its growth trajectory.

Table 5: Financial metrics for growth investors (Part 1).

Ticker	Revenue	EPS (Trailing)	ROE	Enterprise Value
RIVN	4.55×10^9	-5.6	-0.67	1.11×10^{10}
TSLA	9.72×10^{10}	3.66	0.20	1.07×10^{12}
NIO	6.35×10^{10}	-1.5	-1.05	1.10×10^{10}
XPEV	3.62×10^{10}	-1.21	-0.24	1.04×10^{10}
EVGO	2.39×10^8	-0.42	-0.25	1.46×10^9
LI	1.42×10^{11}	1.33	0.17	-4.56×10^{10}
INDI	2.29×10^8	-0.66	-0.28	1.12×10^9
CHPT	4.42×10^8	-0.97	-1.56	5.99×10^8
LCID	7.31×10^8	-1.33	-0.65	6.53×10^9
LAZR	7.50×10^7	-17.4	NaN	4.99×10^9

Table 6: Financial metrics for growth investors (Part 2).

Ticker	Gross Margin	Operating Margin	Net Income	EBITDA
RIVN	-0.43	-1.34	-5.52×10^9	-4.53×10^9
TSLA	0.18	0.11	1.27×10^{10}	1.32×10^{10}
NIO	0.08	-0.30	-2.06×10^{10}	-1.84×10^{10}
XPEV	0.07	-0.20	-7.89×10^9	-6.45×10^9
EVGO	0.28	-0.48	-4.42×10^7	-6.92×10^7
LI	0.21	0.08	1.02×10^{10}	8.25×10^9
INDI	-0.32	-0.84	-1.15×10^8	-1.08×10^8
CHPT	0.11	-0.58	-3.94×10^8	-3.19×10^8
LCID	-1.32	-3.85	-3.08×10^9	-2.73×10^9
LAZR	-0.83	-6.78	-3.77×10^8	-4.68×10^8

- **From a Value Investor's Viewpoint**: Li Auto (LI) emerges as an excellent candidate for value investors with a Price-to-Book Ratio of 0.375 and a positive Free Cash Flow of $13.71 billion, indicating a balance between valuation and financial health. On the other hand, stocks like Tesla (TSLA) and EVgo (EVGO) appear overvalued due to high Price-to-Book Ratios and weaker intrinsic value, making them less attractive for value-focused strategies (Table 7).

Table 7: Financial metrics for value investors.

Ticker	P/E Ratio (Forward)	P/B Ratio	Free Cash Flow	Debt to Equity	Market Cap
RIVN	-4.37	2.00	-3.82×10^9	102.46	1.18×10^{10}
TSLA	103.54	15.51	6.77×10^8	18.08	1.09×10^{12}
NIO	-0.58	0.35	NaN	159.89	9.31×10^9
XPEV	-2.86	0.30	NaN	41.22	1.08×10^{10}
EVGO	-20.28	NaN	-1.19×10^8	18.45	1.97×10^9
LI	1.88	0.33	1.37×10^{10}	23.41	2.31×10^{10}
INDI	-89.21	1.98	-1.07×10^8	39.88	9.11×10^8
CHPT	-6.26	2.15	-8.45×10^7	131.13	4.96×10^8
LCID	-2.36	1.86	-1.92×10^9	64.22	6.43×10^9
LAZR	-1.29	NaN	-1.46×10^8	NaN	2.89×10^8

This combination of growth and value analysis illustrates the importance of tailoring fundamental insights to specific investment objectives, enabling informed and diversified decision-making.

The combination of technical and fundamental factors allows for a more robust predictive framework, capturing both short-term price dynamics and long-term valuation drivers. Table A.1 outlines the fundamental metrics employed, emphasizing their role in understanding financial performance and operational efficiency.

2.3 Sentiment Analysis

Sentiment analysis was utilized to assess market sentiment and identify signals of uncertainty or deception in corporate earnings calls. This method involved analyzing the linguistic patterns of executives to detect evasive behavior, which may indicate potential risks or financial misrepresentation. The analysis was conducted using transcripts of earnings calls, financial news, and social media, allowing for a comprehensive evaluation of investor sentiment and executive communication.

2.3.1 Evasive Detection in Earnings Calls

Building on findings by Larcker and Zakolyukina (2012), which demonstrate that linguistic patterns can reveal deception, we focused on CEO and CFO narratives. Their study found that deceptive CEOs frequently use more extreme positive emotional language while avoiding anxiety-related words, and deceptive CFOs employ more negation and extreme negative terms. Furthermore, CFO linguistic models were observed to produce annualized alphas ranging from -4% to -11%, signifying economic relevance to identifying deception.

To apply these insights, we analyzed earnings call transcripts for NVIDIA (NVDA) FY2025 Q2, Super Micro Computer (SMCI) FY2024 Q1, and Starbucks (SBUX) FY2024 Q2. By prompting a language model to evaluate executive tone and language, we calculated deception scores for both CEOs and CFOs. For example, SMCI's CEO had a relatively low deception score (0.028), while the CFO's score was -0.008, correlating with an extraordinary stock price surge of 109.94% in the following quarter. In contrast, SBUX's CFO exhibited a high deception score of -0.064, corresponding to a stock decline of -14.37% in the subsequent three months (Table 8).

The analysis highlighted key linguistic cues, such as the use of first-person plural pronouns, hesitation markers, and extreme emotional terms, which were consistent with patterns associated with deceptive behavior. For instance, in SBUX's call, the CFO's language included significantly more negations and tentative expressions, aligning with behaviors indicative of uncertainty.

This methodology underscores the value of detecting evasive language as a predictive tool, linking it with stock performance. By comparing sentiment scores with subsequent price movements, we provided empirical evidence of the potential market impact of deceptive communication. These findings enrich the sentiment analysis framework by incorporating advanced linguistic evaluation into investment decision-making processes.

Table 8: Summary Table of Earnings Call Deception Scores and Stock Returns

Company	Quarter	CEO Score	CFO Score	Stock Return (%)
NVDA	FY 2025 Q2	0.053	-0.051	13.04
SMCI	FY 2024 Q1	0.028	-0.008	109.94
SBUX	FY 2024 Q2	0.045	-0.064	-14.37

2.4 Portfolio optimization

Portfolio optimization constructs investment portfolios that maximize returns for a given level of risk. Our approach blends theory, quantitative models, and forward-looking insights to address market complexities and create adaptive, efficient portfolios.

We start by questioning the Efficient Market Hypothesis (EMH), which claims markets fully reflect all available information. While EMH serves as a baseline, evidence like Warren Buffett's consistent outperformance Hagstrom (2024) highlights inefficiencies caused by biases, incomplete information, or mispricing. This inefficiency justifies active portfolio management to exploit undervalued assets and improve returns.

To build a baseline, we use Mean-Variance Optimization, which balances risk and return using historical estimates of means, variances, and correlations Björk, Murgoci and Zhou (2014). This method produces an efficient frontier, identifying optimal portfolios. However, it relies on normal return distributions and stable historical relationships, which fail in turbulent markets or during extreme events. These limitations push us to refine our approach.

We incorporate Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR) to address these shortcomings. VaR estimates the maximum potential loss within a confidence interval, while CVaR measures the average loss beyond this threshold. CVaR's focus on tail risks makes it especially useful for portfolios exposed to extreme market scenarios. These metrics improve risk management by capturing both typical and severe conditions.

To enhance inputs, we combine historical data with forward-looking insights. We estimate expected returns and covariance matrices using maximum likelihood methods while integrating qualitative factors like competitive positioning and operational efficiency. For example, Tesla's profitability and consistent growth justify upward adjustments, while Rivian and Lucid's volatility and scalability issues result in downward revisions. This integration ensures portfolios reflect current trends and future potential (Figure 4).

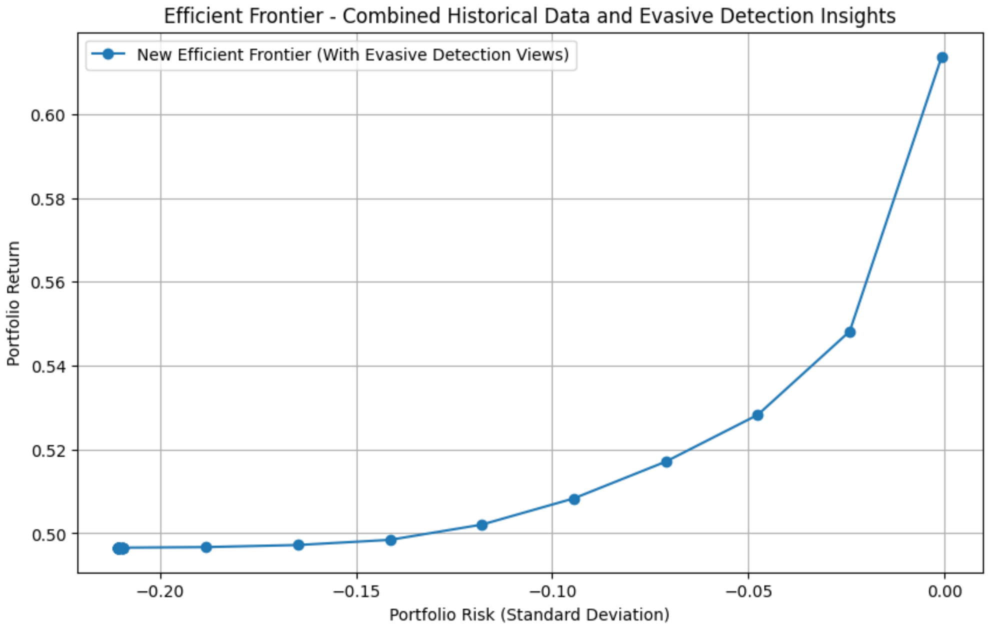

Figure 4

Using these inputs, we construct efficient frontiers with Mean-Variance and CVaR Optimization. The first optimizes traditional risk-return trade-offs, while the second prioritizes robustness against extreme risks. These frontiers highlight the impact of different assumptions but still rely on historical data, requiring further refinement (Figure 5).

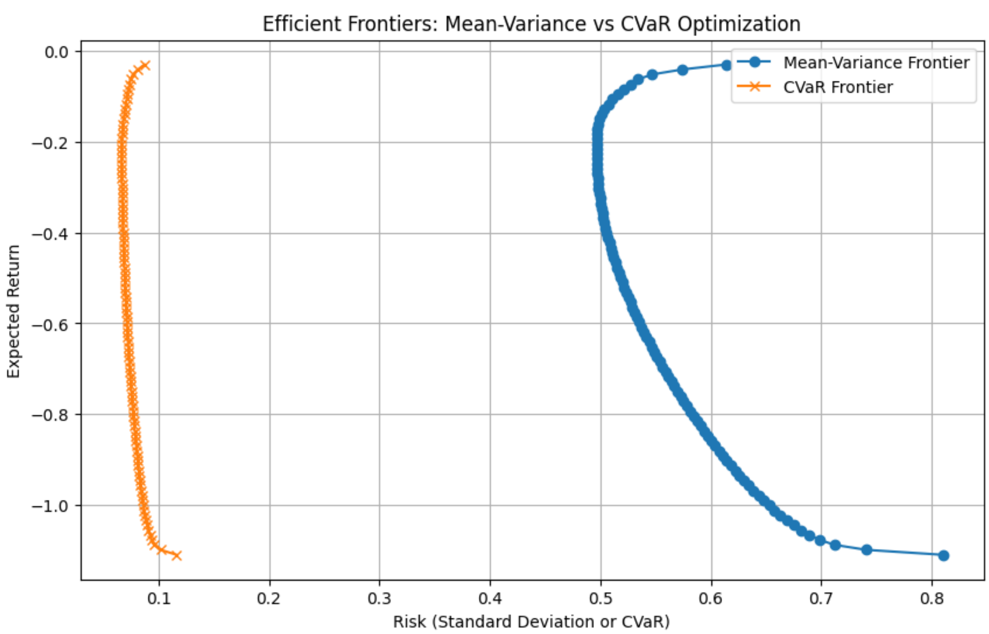

Figure 5

We refine these models using the Black-Litterman framework, which blends equilibrium market returns with subjective views adjusted by confidence levels. This approach integrates both past data and future expectations, allowing precise adjustments. Table 9 outlines the annualized expected returns of the selected stocks, highlighting Tesla's minimal expected loss (-0.03) and Li Auto's relatively better performance (-0.12) compared to others, which justifies our optimistic revisions for these stocks. On the other hand, Rivian and Lucid, with higher expected losses (-0.95 and -1.11, respectively), align with reduced weights due to operational challenges. Additionally, Table **??**'s annualized covariance matrix informs risk assessments and correlations among these assets. The Black-Litterman framework produces a refined efficient frontier with higher returns for the same risk and better-balanced allocations.

Table 9: Annualized Expected Returns

Ticker	Annualized Expected Return
CHPT	-1.07
EVGO	-0.37
INDI	-0.42
LAZR	-1.02
LCID	-1.11
LI	-0.12
NIO	-0.74
RIVN	-0.95
TSLA	-0.03
XPEV	-0.46

Table 10: Annualized Covariance Matrix

Ticker	CHPT	EVGO	INDI	LAZR	LCID	LI	NIO	RIVN	TSLA	XPEV
CHPT	0.72	0.44	0.26	0.40	0.37	0.18	0.29	0.34	0.21	0.26
EVGO	0.44	0.77	0.22	0.32	0.32	0.17	0.26	0.31	0.18	0.21
INDI	0.26	0.22	0.54	0.27	0.22	0.13	0.22	0.26	0.17	0.21
LAZR	0.40	0.32	0.27	0.87	0.35	0.19	0.32	0.35	0.17	0.28
LCID	0.37	0.32	0.22	0.35	0.66	0.18	0.32	0.43	0.24	0.30
LI	0.18	0.17	0.13	0.19	0.18	0.50	0.37	0.20	0.14	0.43
NIO	0.29	0.26	0.22	0.32	0.32	0.37	0.60	0.34	0.22	0.53
RIVN	0.34	0.31	0.26	0.35	0.43	0.20	0.34	0.66	0.25	0.32
TSLA	0.21	0.18	0.17	0.24	0.24	0.14	0.22	0.25	0.38	0.20
XPEV	0.26	0.21	0.21	0.28	0.30	0.43	0.53	0.32	0.20	0.73

3 Discussion and Future Work

The findings from this quarter demonstrate the potential of integrating advanced forecasting methodologies, technical analysis, and portfolio optimization strategies to generate actionable insights. Our current work has primarily focused on a limited subset of companies in the electric vehicle (EV) market, leveraging advanced time-series models like Chrono and traditional ARIMA to explore predictive capabilities. While this has provided valuable initial insights, it also reveals certain limitations. Specifically, the scope of the project was restricted to a small set of EV companies, and the methods were applied independently rather than in an integrated framework that combines the tools we can utilize.

Moving to the next quarter, the next phase of our project will expand the scope to ebroader sector—the S&P 500 Information Technology market. We aim to explore a critical research question that extends beyond our initial focus. Specifically, we aim to evaluate: **How Chronos-Bolt compares to ARIMA in predicting daily returns for portfolio optimization and to identify which technical signals most significantly contribute to model performance.**

By addressing this question, we aim to uncover the comparative strengths of Chronos-Bolt and ARIMA and their practical implications for portfolio optimization strategies.

Context: The S&P 500 Information Technology sector represents a critical and volatile segment of the financial market, where accurate predictions of stock price movements can provide a substantial competitive advantage. Existing predictive models often rely solely on historical price data or focus narrowly on single methodologies. While traditional models like ARIMA excel in analyzing linear patterns, they may fail to capture complex temporal structures that characterize financial time-series data. Conversely, modern models such as Chronos-Bolt, with their ability to analyze patterns across multiple temporal frequencies, offer a promising alternative but require further empirical validation.

Understanding the comparative performance of these models is important for advancing portfolio optimization strategies. By identifying the technical indicators that most significantly contribute to prediction accuracy, we aim to provide actionable insights that bridge the gap between traditional forecasting techniques and the demands of modern financial markets.

Hypothesis: We hypothesize that **Chronos-Bolt will outperform ARIMA** in predicting daily returns for portfolio optimization in the S&P 500 Information Technology sector. This advantage is expected to arise from Chronos-Bolt's ability to analyze complex temporal structures and extract meaningful patterns across multiple frequencies. Chronos-Bolt employs a frequency-domain approach that enables it to capture both short-term fluctuations and long-term trends. This multi-scale analysis is particularly advantageous in the highly volatile S&P 500 Information Technology sector, where market behavior often exhibits intricate patterns across various time horizons.

Furthermore, we anticipate that specific technical signals, such as moving averages, RSI, and MACD, will emerge as key contributors to prediction accuracy due to their established utility in capturing price momentum, relative strength, and trend reversals.

Future Directions: The proposed project will focus on the following steps:

- **Expanded Feature Analysis:** Expand the dataset to include stocks from the S&P 500 Information Technology sector, allowing for a more representative and comprehensive analysis of model performance.
- **Comparative Model Evaluation:** Conduct an in-depth comparison of Chronos-Bolt and ARIMA using predictive accuracy and portfolio performance metrics such as **MASE**.
- **Technical Signal Analysis:** Perform a systematic feature importance analysis to determine which technical indicators drive model performance and how they contribute to portfolio optimization.
- **Validation and Benchmarking:** Validate the proposed framework using historical data from 2020 to 2024, focusing on quarterly earnings periods as benchmarks to evaluate robustness and scalability.

References

Ansari, Abdul Fatir, Lorenzo Stella, Caner Turkmen, Xiuyan Zhang, Pedro Mercado, Huibin Shen, Oleksandr Shchur, Syama Sundar Rangapuram, Sebastian Pineda Arango, Shubham Kapoor, Jasper Zscheigner, Danielle C. Maddix, Hao Wang, Michael W. Mahoney, Kai Torkkola, Andrew Gordon Wilson, Michael Bohlke-Schneider, and Yuyang Wang. 2024. "Chronos: Learning the Language of Time Series." *arXiv preprint arXiv:2403.07815*. [Link]

Ariyo, Adebiyi A., Adewumi O. Adewumi, and Charles K. Ayo. 2014. "Stock Price Prediction Using the ARIMA Model." In *2014 UKSim-AMSS 16th International Conference on Computer Modelling and Simulation*. [Link]

Bathla, Gourav. 2020. "Stock Price prediction using LSTM and SVR." In *2020 Sixth International Conference on Parallel, Distributed and Grid Computing (PDGC)*. [Link]

Björk, Tomas, Agatha Murgoci, and Xun Yu Zhou. 2014. "Mean–variance portfolio optimization with state-dependent risk aversion." *Mathematical Finance: An International Journal of Mathematics, Statistics and Financial Economics* 24 (1): 1–24

Ekambaram, Vijay, Arindam Jati, Pankaj Dayama, Sumanta Mukherjee, Nam H. Nguyen, Wesley M. Gifford, Chandra Reddy, and Jayant Kalagnanam. 2024. "Tiny Time Mixers (TTMs): Fast Pre-trained Models for Enhanced Zero/Few-Shot Forecasting of Multivariate Time Series." *arXiv preprint arXiv:2401.03955*. [Link]

Hagstrom, Robert G. 2024. *The Warren Buffett Way*. John Wiley & Sons

Istiake Sunny, Md. Arif, Mirza Mohd Shahriar Maswood, and Abdullah G. Alharbi. 2020. "Deep Learning-Based Stock Price Prediction Using LSTM and Bi-Directional LSTM Model." In *2020 2nd Novel Intelligent and Leading Emerging Sciences Conference (NILES)*. [Link]

Khan, Shakir, and Hela Alghulaiakh. 2020. "ARIMA model for accurate time series stocks forecasting." *International Journal of Advanced Computer Science and Applications* 11 (7)

Larcker, David F., and Anastasia A. Zakolyukina. 2012. "Detecting Deceptive Discussions in Conference Calls." *Rock Center for Corporate Governance*. [Link]

Mondal, Prapanna, Labani Shit, and Saptarsi Goswami. 2014. "Study of effectiveness of time series modeling (ARIMA) in forecasting stock prices." *International Journal of Computer Science, Engineering and Applications* 4 (2), p. 13

Petrică, Andreea-Cristina, Stelian Stancu, and Alexandru Tindeche. 2016. "Limitation of ARIMA models in financial and monetary economics.." *Theoretical & Applied Economics* 23 (4)

Selvin, Sreelekshmy, R Vinayakumar, EA Gopalakrishnan, Vijay Krishna Menon, and KP Soman. 2017. "Stock price prediction using LSTM, RNN and CNN-sliding window model." In *2017 international conference on advances in computing, communications and informatics (icacci)*. IEEE

Stevenson, Simon. 2007. "A comparison of the forecasting ability of ARIMA models." *Journal of Property Investment & Finance* 25 (3): 223–240

Appendices

A.1 Additional Tables A2

A.1 Additional Tables

Technical Indicators

Indicator/Concept	Description
Exponential Moving Average (EMA)	Emphasizes recent price data for responsiveness to changes. The smoothing factor assigns higher weights to recent data, making it effective for trend-following but more prone to false signals in volatile markets.
Simple Moving Average (SMA)	Averages prices over a period, providing stability and smoothing but lagging price movements. It is effective for overall trend analysis but less responsive to rapid changes.
Time-Series Moving Average	Adapts to the statistical properties of time-series data, offering smoother trend analysis and reducing sensitivity to sudden spikes.
Triangular Moving Average	Applies greater weight to data points at the center of the period, minimizing noise and reducing the influence of extreme highs or lows, especially in volatile markets.
Mass Index	Signals potential trend reversals by summing the ratios of the EMA of the price range (high - low). It identifies points where trends may reverse direction.
Relative Strength Index (RSI)	Measures price momentum on a scale of 0 to 100. Readings above 70 indicate overbought conditions, while below 30 indicates oversold conditions, signaling potential price reversals.
Bollinger Bands	Consists of an SMA with two standard deviation bands. Prices moving beyond the bands signal overbought or oversold conditions, helping identify high-volatility zones and potential reversals.
Momentum	Captures the speed of price changes by comparing the current price to a past price point. Rising momentum indicates trend strength, while declining momentum may signal trend reversals.
Moving Average Convergence Divergence (MACD)	Consists of two EMAs (e.g., 12-day and 26-day) and a signal line. Crossovers between the MACD line and signal line serve as entry/exit points, and divergence from price action indicates reversals.

Indicator/Concept	**Description**
On-Balance Volume (OBV)	Aggregates volume data to confirm price trends. Rising OBV with increasing prices signals buying pressure, while falling OBV with decreasing prices indicates selling pressure.
Parabolic SAR	Plots dots below or above price bars to indicate entry and exit points. A change in dot placement signals a trend reversal, guiding trend-following strategies and dynamic stop placement.
Typical Price	Calculated as the average of high, low, and close prices, it provides a smoothed value for overall trend analysis when combined with other indicators.
Directional Movement Index (DMI)	Consists of +DI, -DI, and the Average Directional Index (ADX). Crossovers between +DI and -DI indicate trend direction, while ADX confirms trend strength, valuable for trend-based strategies.

Fundamental Analysis Metrics

Metric/Concept	**Description**
Earnings Per Share (EPS)	Basic EPS is calculated by dividing net income by the weighted average number of shares. Diluted EPS considers convertible securities, generally yielding a lower value. EPS growth reflects profitability and growth potential, which attract growth-focused investors.
Price-Earnings (P/E) Ratio	Indicates growth expectations: High P/E implies high growth anticipation, while low P/E may suggest undervaluation. Market sentiment, industry trends, and economic cycles impact P/E variations.
PEG Ratio	The P/E ratio divided by EPS growth rate. A PEG ratio around 1 balances price and growth, helping to evaluate stock price justification across varying growth rates.
Dividend Yield	Calculated as annual dividends per share divided by stock price. High yields suggest strong cash flow but may indicate limited growth reinvestment or unsustainable payouts.
Price-to-Book (P/B) Ratio	Computed by dividing stock price by book value per share, indicating investor payments relative to company assets. A lower P/B may highlight undervaluation in asset-heavy industries.
Return on Equity (ROE)	Net income divided by shareholder equity, reflecting profitability relative to shareholder investments. High debt can artificially inflate ROE, so leverage should be considered.
Free Cash Flow (FCF)	Operating cash flow minus capital expenditures, indicating cash available for investments or shareholder returns. Sustained negative FCF could indicate inefficiencies or high growth spending.
Operating Margin	Operating income divided by revenue, measuring operational efficiency. It excludes factors like taxes and interest, focusing solely on operational profitability.
EBIT and EBITDA	EBIT represents earnings before interest and taxes; EBITDA adds back depreciation and amortization. EBITDA is useful for comparing companies with different capital structures.

Metric/Concept	Description
Capital Expenditure (CapEx)	Represents long-term investments essential for growth, though high CapEx may strain short-term cash flow. CapEx supports future revenue expansion.