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Master thesis

Large Language Models in Financial Decision-Making: Capabilities and Limitations

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Table of contents

List of abbreviations

AI	Artificial Intelligence
API	Application Programming Interface
CAPM	Capital Asset Pricing Model
CIK	Central Index Key
GICS	Global Industry Classification Standard
LLM	Large Language Model
LSEG	London Stock Exchange Group
LTM LLM	Long-term memory Large Language Model
ML	Machine Learning
S&P 1500	Standard and Poor's Composite 1500 Index
SHAP	Shapley Additive Explanations

List of Figures

List of Tables

1 Introduction

Historically, financial modeling and decision-making have relied heavily on well-structured numerical data for parametric estimation. This paradigm assumes that market variables follow specific probability distributions and maintain stable, largely linear relationships. The Capital Asset Pricing Model (CAPM), developed through the respective works of Sharpe (Sharpe 1964, p. 438), Lintner (Lintner 1965, p. 14), and Mossin (Mossin 1966, p. 778), demonstrates this tradition by formalizing the linear relationship between systematic risk and expected return of an asset. By utilizing historical data of asset returns, the risk-free rate, and market benchmarks, the model employs linear regression to derive the "Beta" coefficient. This coefficient serves as an estimator for predicting the expected return of an underlying security based on its sensitivity to systematic risk.

Similarly, the Black-Scholes Model, a widely used framework in derivatives pricing, requires precise inputs regarding the price of the underlying asset, the strike price, the time to expiration, the risk-free rate, and the volatility of the asset (Black et al. 1973, p. 644). By utilizing these variables within a partial differential equation framework, the model returns a theoretical estimate for the fair price of European-style options.

While these models provide the mathematical framework for modern finance, their applicability is inherently constrained by their parametric nature. They require extensive data preprocessing and assume that the complex, high-dimensional reality of financial markets can be captured through a constrained set of numerical inputs.

This reliance on structured inputs has long limited the process of automated financial analysis, as financial analysts were required to bridge the gap between raw financial statements and the structured variables required by such models. Literature suggests that this human intervention introduces significant cognitive biases, as analysts are often subject to over-optimism or suffer from a conflict of interest when interpreting corporate disclosures (Mokoteli et al. 2009, p. 385).

The emergence of Machine Learning (ML) began to challenge this hierarchy by introducing non-parametric approaches. Ensemble methods like Random Forests and Neural Networks significantly outperform traditional OLS-based strategies by capturing high-dimensional, non-linear interactions within tabular financial data (Gu et al. 2020, p. 2226). However, even these sophisticated architectures of ML models require a certain degree of so-called feature engineering, as they can not interpret raw information on their own. Consequently, the data still has to be preprocessed manually, as the models require a predefined set of input variables (features) to make their predictions.

The recent rise and advancement of Large Language Models (LLMs) marks a significant shift in how we can approach financial analysis. These models have evolved from simple sentiment analysis into systems that are capable of complex "Chain-of-Thought" reasoning. Unlike the fixed formulas of CAPM or Black-Scholes, LLMs can process raw, unformatted financial

data directly. They can interpret balance sheets and income statements without first requiring a human to calculate specific ratios. Nor do they require an analyst to first conduct feature engineering, as it was necessary in the aforementioned context of ML models. LLMs can extract relevant information from news headlines, ultimately being able to predict stock price movement even without explicitly being trained on this task (Lopez-Lira et al. 2025, p. 2).
However, a research gap remains regarding the ability of these models to perform ”zero-shot” analysis on raw financial data alone. By stripping away company names and dates, we can test if the model has internalized a deeper understanding of what actually constitutes a firm’s financial health and whether or not the underlying stock would be a good investment. Ultimately, this could position LLMs as fully autonomous financial advisors, without the need for human-mediated feature engineering or the constraints of traditional parametric models.
This thesis aims to investigate the capabilities and inherent limitations of LLMs in financial decision-making. Utilizing a dataset of 1500 companies from the S&P 1500 spanning 25 years, the study evaluates Gemini 2.5 Flash-lite’s ”zero-shot” reasoning in processing financial statements stripped of all identifiers. The model is prompted to generate specific trading recommendations based on these raw numbers, which are then used to construct investment portfolios. To address the ”black-box” nature of Artificial Intelligence (AI), Explainable AI techniques, specifically surrogate models and Shapley Additive ExPlanations (SHAP) are employed to gain insights into the model’s underlying reasoning. By testing these portfolios against portfolios derived from professional sell-side analysts’ recommendations, this work explores whether LLMs could reduce the reliance on traditional sell-side analysts, manual feature engineering, and rigid parametric models, ultimately allowing individual investors to conduct institutional-grade analysis on their own.
The study is organized into four sections: Section 2 details the data sources and preprocessing procedures, while Section 3 outlines the experimental design and methodology. Section 4 presents the empirical findings and evaluates the underlying logic of the resulting predictions. Finally, Section 5 provides concluding remarks, discusses the theoretical implications of the results, and suggests directions for future research.

2 Data

The dataset used for this thesis consists of all companies that were part of the S&P 1500 market index in July 2025. However, out of the original sample size of 1500, 17 companies had to be excluded due to data inconsistencies. Nonetheless, the remaining dataset is still sufficiently large and embodies a broad representation of the United States equity market across a diverse range of small-, mid-, and large-cap companies. The time span regarded in the analysis covers the 1st January of 2000 until the 1st January of 2025, wherein the underlying companies did not necessarily have to be part of the market index at all times.
Furthermore, since the dataset is a snapshot of the 2025 index composition, company presence

in the analysis varies historically depending on market entry dates and listing histories, resulting in an unbalanced panel across the 25-year span. Using 25 years of data ensures the analysis is not biased by short-term market anomalies and including data from the 2008 financial crisis as well as the 2020 pandemic, which both heavily affected the U.S. equity market, enables an evaluation of how both the LLM and analysts reason across different market phases. Ultimately, this approach makes the results of the analysis more robust and generalizable. A complete list of analyzed companies and their respective observation periods is provided in the Appendix.
Using the Python Application Programming Interface (API) for the London Stock Exchange Group (LSEG) workspace, all available balance sheets, cash flow as well as income statements were downloaded, resulting in quarterly intervals. Additionally, data on stock prices, economic sectors and consensus sell-side analyst ratings were also downloaded from LSEG. For every point in time, these ratings represent the consensus of professional financial analysts in the industry, ultimately serving as the primary human benchmark when evaluating the LLM's performance. In cases where a rating was unavailable for a specific date, the most recent previous rating was carried forward, as no conflicting recommendation had been issued.
To facilitate Capital Asset Pricing Model (CAPM) Regression, market-level data on Fama-French research factors was downloaded from the Kenneth R. French Data Library. The risk-free rate used in the regression analysis was again sourced from LSEG and is represented by the U.S. 3-Month Treasury Bill yield.
The process of generating and downloading the LLM-based investment ratings with Google's Gemini-2.5-flash-lite is detailed in the Methodology Section, as this represents part of the research rather than a raw data download.

3 Methodology

3.1 Generation of LLM Ratings

The LLM trading recommendations that serve as basis for the portfolio simulation were obtained using the API for Google's Gemini-2.5-Flash-Lite model. The choice for this model was primarily driven by the scale of the dataset encompassing almost 1500 companies over 25 years with quarterly financial reports resulting in tens of thousands of individual API requests. At this scale, the high API costs, restrictive rate limits and slower processing times of larger models become a hindrance. Gemini 2.5 Flash-lite is well suited for this task, offering the speed to process thousands of financial statements and the context window required for meaningful analysis. Unlike larger models, Flash-lite does not utilize an internal Chain of Thought mechanism, a process where the model generates intermediate logical steps before reaching a conclusion, but instead performs immediate, streamlined inference ideal for large volumes of data.
This process of obtaining answers from the model is called ”zero-shot prompting”, a process in which the model has not specifically been trained to perform the task at hand, but rather relies on its pre-trained general knowledge and reasoning capabilities to interpret the instructions and

provide a response. By using zero-shot prompting instead of a model that has been fine-tuned for this task, the study aims to evaluate the "out-of-the-box" financial intelligence of the LLM, ensuring that the results reflect the model's analytical power rather than specific patterns learned from a specialized training dataset.
To manage the scale of the dataset, a nested looping structure was implemented in Python to automate the generation of LLM ratings. The structure was designed to handle the scale of the data, ensure that financial statements were accurately matched to their respective reporting dates and remained strictly associated with the correct company throughout the process. The unique identifier distinguishing the companies is the Central Index Key (CIK).

- **Outer Loop:** Iterates over all unique CIKs. This ensures that the API calls are clearly separated between companies and no data spillovers occur that could influence the LLM's decision.

- **Inner Loop:** Iterates over all available reporting dates for a given CIK. Of all available financial reports, it gathers the unique reporting dates and sorts them in ascending order employing a 10-day window to account for submissions with the Securities and Exchange Commission that were filed slightly apart. If any report is missing, the date is skipped, therefore all recommendations are based on the same underlying information always consisting of Balance Sheet, Income Statement and Cash Flow Statement. For each reporting date, the financial metrics were flattened into anonymized string variables (bs_str, is_str, cf_str). Afterwards, it issues an individual API call for all present reporting dates.

To ensure reproducibility, the model's temperature was set to 0 to produce deterministic outputs. Higher temperature settings make the probability distribution for the predicted next token more uniform, causing unlikely tokens to be selected more frequently, introducing stochastic randomness into the responses (Holtzman et al. 2020, p. 6).
The system instructions used for all API calls are:

> *You are an experienced, data-driven financial analyst, that provides concise and accurate answers.*

The model was then provided with a standardized prompt to ensure consistency across all requests:

> *"Based on the following financial reports only, please provide an investment recommendation for the underlying company.*
> *Balance Sheet:*
> *{bs_str}*
> *Income Statement:*
> *{is_str}*
> *Cash Flow Statement:*

{*cf_str*}

Provide your answer using only one of the following signals: 'buy', 'hold', 'sell'."

By stripping away company identifiers and specific dates, this prompting style along with the system instructions forced the model to generate its response and trading recommendation based exclusively on the financial data at hand. A significant challenge in LLM-based research is look-ahead bias, or the "no-time-machine" requirement (Kaufman et al. 2012, p. 10). This occurs when a model uses information from a point in time after the prediction should have been made, data that would be unavailable in a real-world setting. For example, if a firm went bankrupt in 2015, the model might issue a *Sell* rating based on that stored knowledge, regardless of what the quarterly report actually shows. Similarly, the model's knowledge of exogenous shocks like the Covid-19 pandemic could lead to a generalized *Sell* recommendation for the majority of the portfolio leading up to or during that period. By removing company identifiers and specific dates, this prompting strategy, combined with the system instructions, compelled the model to generate recommendations based exclusively on the provided financial data. Variations of this prompt, as well as system instructions were tested, but this configuration yielded the most consistent results.

Ultimately, two variations of this approach were evaluated. In the first approach, each API call only contained the most recent filings for a given company. Consequently, one balance sheet, one income statement and one cash flow statement served as input for the LLM's decision. The second approach provided the model with a longitudinal view, incorporating data from the entire preceding year. This allows the model to potentially move beyond a static assessment and instead analyze financial trends and developments, possibly leading to a more refined investment recommendation. This configuration will be referred to as Long-term Memory LLM (LTM LLM), not to be confused with Long Short-Term Memory (LSTM), a specific recurrent neural network architecture.

To assess the presence of look-ahead bias, and ensure the LLMs' recommendations are actually based on fundamental financial analysis rather than stored knowledge, Gemini was explicitly prompted to infer the reporting year, economic sector, and company directly from the anonymized financial statements. Both LLM strategies achieved a sector prediction accuracy of approximately 45% and a reporting year accuracy of 8%, with a mean absolute difference of five years. Identifying the specific underlying company was almost entirely impossible. Consequently, these results confirm the efficacy of the data anonymization, validating the experimental design for the subsequent research.

The final sample consists of roughly 113,000 signals, representing the intersection of analyst and LLM recommendations for overlapping CIK-date combinations used in the main analysis. Due to the extensive length of the financial reports, an example of the API calls and prompt structures is provided in the Appendix.

3.2 Trading simulation framework

To evaluate the economic value of the LLM and analyst signals, a long-only portfolio simulation is implemented. By applying the signals to historical market data in chronological order and enforcing budget restraints, the simulation functions as a backtest and demonstrates how the respective trading strategy would have performed in a real-world scenario. The LLM was explicitly prompted to generate *Buy*, *Hold*, or *Sell* recommendations. To enhance comparability and streamline the portfolio simulation, analyst recommendations were standardized by mapping *Strong Buy* and *Strong Sell* signals to their respective base counterparts.

3.2.1 Portfolio Construction and Rebalancing

The portfolio is constructed using a discrete monthly rebalancing framework. The simulation logic is characterized by the following:

- **Rebalancing Frequency:** The portfolio is updated at discrete monthly intervals. This frequency ensures that trading actions align with the specific points in time when new financial data and trading signals are present in the dataset.

- **Portfolio Rebalancing:** At the start of each period, all existing holdings are liquidated at the current monthly closing price. This process converts the total portfolio value into cash, allowing for a complete reallocation based on the most recent recommendations. As discussed in Section 4.1.1, the distribution of trading signals is highly imbalanced and varies significantly between the LLM and analysts. By liquidating all positions at each interval, a fairer comparison is maintained. Otherwise, the high share of *Buy* signals from analysts would tie up the available capital immediately, preventing the simulation from responding to new signals.

- **Asset Allocation:** An equally weighted approach is used for capital distribution. After liquidation, the now available cash position is divided equally among all stocks that exhibit a *Buy* signal for the rebalancing month.

- **Execution Assumptions:** All transactions are assumed to be executed at the end-of-month closing price. Furthermore, the simulation allows for the purchase of partial units to ensure full capital utilization. This approach moves away from the budget constraints typically imposed by nominal share prices, as the entire cash balance is always fully invested regardless of the individual stock price. To isolate the impact of the signals, transaction costs and capital gains taxes are not considered in this simulation.

- **Signal Handling:** *Hold* signals are treated as neutral. Because the portfolio is fully liquidated at the start of each period, a *Hold* signal still results in the asset being sold and not included in the subsequent reallocation of capital.

3.2.2 Performance Attribution and Strategy Selection

To identify the superior LLM configuration, the simulation is first conducted over an initial five-year testing period. This phase contrasts signals generated using one year of historical data (LTM LLM) against those based only on the most recent financials. The superior approach is then applied to the subsequent validation period, the remainder of the available time, to be directly compared against the analysts' portfolio.
The primary performance metric is the Sharpe Ratio, a risk-adjusted measure that enables a standardized comparison between the LLM and sell-side analysts by calculating the excess return generated per unit of risk.
The ratio is derived by dividing the mean monthly excess return by the standard deviation of those returns, where the excess return is calculated as the portfolio return minus the risk-free rate. Afterwards, since it is common in financial modeling, the ratio is annualized as follows:

$$SR = \frac{\overline{R_p - R_f}}{\sigma(R_p - R_f)} \times \sqrt{12} \tag{1}$$

Where $\overline{R_p - R_f}$ denotes the average monthly excess return and $\sigma(R_p - R_f)$ represents the standard deviation of these returns.

3.2.3 Robustness Testing via Randomized Simulations

While the simulation design described in Section 3.2.1 utilizes all companies of the dataset, this section employs randomized simulations to ensure the results are not dependent on the specific composition or timing of the sample. This approach evaluates the consistency of the LLM's performance relative to analysts by testing their respective signals and resulting trading strategy across a wide array of randomly generated sub-portfolios and time windows.
To test the reliability of the findings, the simulation is repeated across 1,000 iterations for five distinct sample sizes ($N \in \{50, 100, 250, 500, 750\}$). For each iteration, the following parameters are randomized:

- **Temporal Variation:** A rolling time window of 10 years is randomly selected from the dataset. This ensures that the performance is not just the result of a specific market regime or a single favorable period.

- **Asset Sub-sampling:** Rather than utilizing the full universe, N stocks are randomly sampled from the dataset, given they possess both valid recommendation signals and corresponding stock price data throughout the selected period. This confirms whether the respective portfolio performances are a general trait across the investment universe, rather than being driven by a small number of high-performing stocks.

The simulation outcomes are aggregated using Kernel Density Estimation to visualize the distribution of performance metrics. Furthermore, hypothesis testing utilizing non-parametric bootstrap p-values is conducted. This approach is advantageous as it avoids the assumption of normally distributed returns. By resampling the paired differences in returns over 10,000 iterations, an empirical distribution is constructed. The p-value is then derived as the proportion of iterations where the LLM's mean return was less than or equal to the analysts' return. This metric approximates the probability that any observed difference in performance between the two groups could be attributed to random chance.

3.2.4 Sub-period Analysis: Bear Market Performance

To address the potential limitations of the LLM-based strategy, performance is evaluated during the 2008 Global Financial Crisis and the 2020 Covid-19 market crash. Although the randomized simulations in the previous section aimed to establish the overall robustness of the strategy, these targeted simulations demonstrate how it behaves during periods of extreme volatility and systemic decline. While the simulation uses the existing signals and portfolio logic, again including the entire dataset, these specific periods are isolated to evaluate the strategy's resilience. By examining whether the LLM signals adjusted to deteriorating market conditions or remained unresponsive to these shifts, specific constraints and risks are identified that may not be apparent during stable market regimes.

3.3 Analytical Framework

Since the trading signals are generated using an external API, direct access to the model's internal architecture and parameters is not possible. Consequently, the model is treated like a "black-box", meaning that the inputs and outputs are known, but the calculations included in obtaining the outputs are hidden.
In addition to simply querying the LLM to return a signal and list of reasons for its decision, two distinct methods are employed to bridge this gap between inputs and outputs.

3.3.1 Extended 3-Factor CAPM Regression

This analysis serves two purposes: Identifying factor loadings to reveal the strategy's sensitivity to market risk, firm size, and value factors, and isolating the portfolio alpha to allow for a performance comparison between the employed trading strategies. The model follows the formula below:

$$R_{p,t} - R_{f,t} = \alpha + \beta_1(R_{m,t} - R_{f,t}) + \beta_2(SMB_t) + \beta_3(HML_t) + \varepsilon_t \quad (2)$$

where $R_{p,t} - R_{f,t}$ is the portfolio excess return and α (*Jensen's Alpha*) represents the risk-adjusted abnormal return, serving as the primary measure of the LLM's and analysts' predictive value beyond market factors. The term $R_{m,t} - R_{f,t}$ denotes the market risk premium, while SMB_t (Small Minus Big) and HML_t (High Minus Low) capture return spreads of small-cap over large-cap stocks and undervalued (*value*) over expensive (*growth*) stocks, respectively.

Finally, ε_t denotes the residual error.

3.3.2 Surrogate Machine Learning Model

Two random forests are trained to gain further insights into the LLM's reasoning and contrast it to the analysts' reasoning. These serve as surrogate models that allow for the application of explainability methods to an otherwise hidden process. Since the raw financials fed into the LLM consist of hundreds of lines of data, this volume would obstruct any meaningful interpretability. Therefore, nine key financial metrics with proven significance in financial literature are computed for every company at every point in time. These metrics serve as the input features for the two Random Forests, while the existing LLM and analyst signals are used as the target variables for training. The following metrics were computed as inputs for the surrogate models:

- **Interest Coverage Ratio**: Defined as $\frac{EBIT}{\text{Interest Expense}}$, where EBIT stands for Earnings before Interest and Taxes, this ratio serves as a significant predictor for Earnings Per Share (EPS) and Return on Equity (ROE). While its predictive strength varies across performance levels, a higher ratio indicates a firm's improved capacity to cover debt obligations through its operating income (Naknok 2022, p. 13).

- **Return on Equity (ROE)**: Defined as $\frac{\text{Net Income}}{\text{Shareholder's Equity}}$, this metric measures how efficiently a firm generates profit from its equity base. It serves as a significant predictor for future stock returns, as the market is often slow to price in the persistence of high profitability, allowing the ratio to signal potential outperformance (Haugen et al. 1996, pp. 8, 10).

- **Working Capital to Total Assets**: Defined as $\frac{\text{Current Assets} - \text{Current Liabilities}}{\text{Total Assets}}$, this ratio measures a firm's net liquid assets relative to its total capitalization. Because firms approaching bankruptcy typically exhibit a shrinkage of this liquidity buffer, this metric serves as a primary indicator for identifying financial distress, indicating risky investments. (Altman 1968, p. 594).

- **Retained Earnings to Total Assets**: Defined as $\frac{\text{Retained Earnings}}{\text{Total Assets}}$, this ratio measures the cumulative profitability of a firm over time. This measure implicitly measures the age of a firm, as older companies have had more time to retain earnings. While this logic somewhat discriminates against younger firms, it is still a valid variable, because failure specifically occurs more often in a company's early years (Altman 1968, p. 595).

- **EBIT to Total Assets**: Defined as $\frac{\text{Earnings Before Interest and Taxes}}{\text{Total Assets}}$, this ratio measures the true productivity of a firm's assets independent of leverage or tax factors. Altman identifies this as the most significant contributor to his model's predictive power, as the long-term viability of a company is ultimately dependent on the earning power of its assets to prevent insolvency (Altman 1968, p. 595).

- **Sales to Total Assets**: Defined as $\frac{\text{Sales}}{\text{Total Assets}}$ and also called capital-turnover ratio, it measures the company's ability in generating sales from the firm's assets. Altman includes this variable, noting that while it has the least individual discriminating power, it is vital for the model's overall effectiveness as it interacts with other variables and ultimately captures the management's capability to handle competitive market conditions (Altman 1968, pp. 595, 596).

- **Operating Margin**: Defined as $\frac{\text{EBIT}}{\text{Total Revenue}}$, this ratio measures a firm's pricing power and market position. Novy-Marx utilizes a DuPont decomposition to show that margins represent a distinct measure of market power that helps predict the cross-section of expected returns (Novy-Marx 2013, p. 2).

- **Debt to Equity**: Defined as $\frac{\text{Total Debt}}{\text{Total Equity}}$, this ratio measures a firm's financial leverage and capital structure. Bhandari argues that the expected return on common stock is positively related to the Debt-to-Equity ratio, as it serves as a robust proxy for the risk of the firm's equity (Bhandari 1988, p. 18). This metric captures the financial risk inherent in the capital structure, serving as a valid indicator for equity risk premiums.

- **Debt to Assets**: Defined as $\frac{\text{Total Debt}}{\text{Total Assets}}$, this ratio measures the proportion of a firm's assets financed through debt. Campbell, Hilscher, and Szilagyi show that this ratio is a highly significant predictor for bankruptcy, as a higher value increases the predicted probability of failure or bankruptcy (Campbell et al. 2008, p. 2910). As the variable captures the total burden of obligations relative to the firm's resource base, it can act as an indicator for financial distress.

4 Results

This section presents the empirical findings of the comparative analysis between financial analysts and LLM-derived trading recommendations. The results are organized into the following parts: First, a descriptive overview of signal distributions, followed by an overall evaluation of portfolio performance derived from the respective recommendation sources. Next, a robustness check, aiming to test the strategies' stability across various market regimes and different company subsets, is performed. Afterwards, a closer examination of portfolio performance in bear market conditions is conducted. Finally, the section concludes with an exploration of the drivers behind the LLM's decision-making process.

4.1 Descriptive Analysis of Trading Signals

4.1.1 Overall Signal Distribution

Before evaluating portfolio performance, inspecting descriptive statistics of the three strategies already provides meaningful insights, as their recommendation distributions differ considerably. Figure 1 shows the overall distribution of *Buy*, *Hold* and *Sell* signals of all three signal sources. The signals labeled as LLM were obtained by querying Gemini with only the most recent finan-

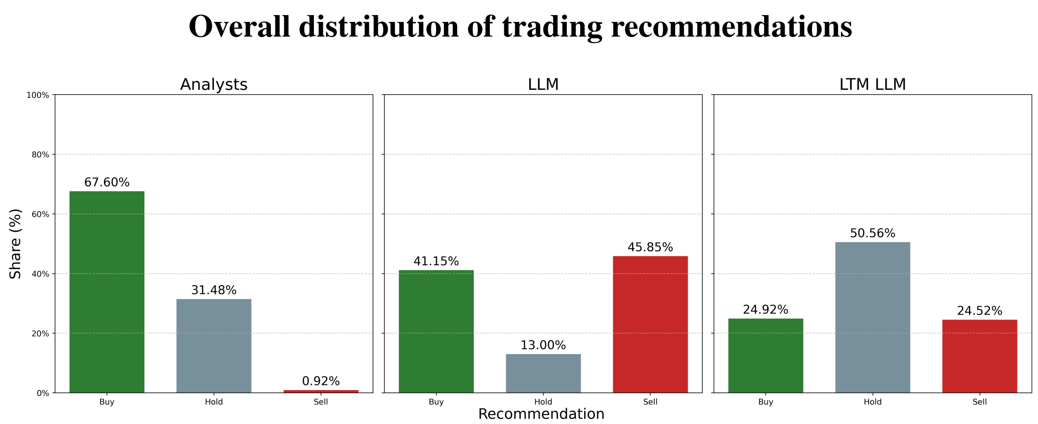


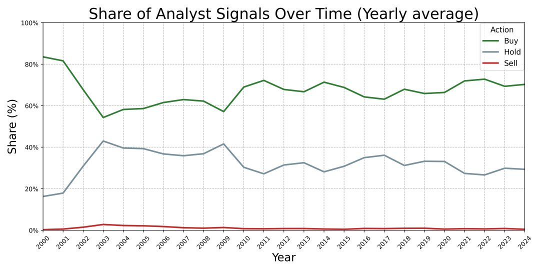
Figure 1: Overall signal shares across datasets. The graphic illustrates the contrast between a structural human *positivity bias*, the data-driven objectivity of the Base LLM and the centralized neutrality of the LTM LLM.

cial data available, while the signals labeled as LTM LLM were obtained by querying Gemini with additional financial data that covered the past year. Looking at Figure 1, we can observe a huge discrepancy in the share of *Sell* signals between analysts and LLM-derived signals. While they do not even make up 1% of all analyst signals, they constitute almost 46% of LLM-derived signals. This extreme share drops to roughly 25% when the model is given more context, though it remains far above the human level. The finding of extremely low *Sell* shares is consistent with previous literature, as Barber et al. report that *Sell* recommendations accounted for only 5.7%

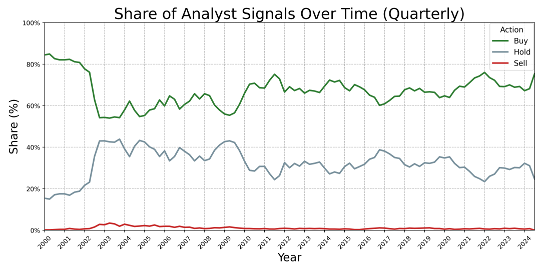
of their dataset (Barber et al. 2001, p. 538). This finding can be attributed to the high ”costs” of issuing *Sell* ratings for analysts (Womack 1996, p. 139) like jeopardizing the analysts’ relationship with the underlying firm or the reported self-selection-bias covered in (McNichols et al. 1997, p. 169). Generally, the LLM’s decision-making process seems to be more cautious and exhibits a rather bullish perspective. The significant jump in *Hold* signals for the LLM with more information hints to the phenomenon of *information dilution*. As Liu et al. demonstrate, additional context forces the model to process a larger set of potentially conflicting data, which can degrade its ability to reach a definitive conclusion (Liu et al. 2023, p. 158). Further, this increased uncertainty seems to trigger an *omission bias*, a documented tendency for LLMs to favor inaction over action when faced with complex scenarios (Cheung et al. 2025, p. 4), which a *Hold* signal is the embodiment of.

4.1.2 Longitudinal Analysis of Signal Trends

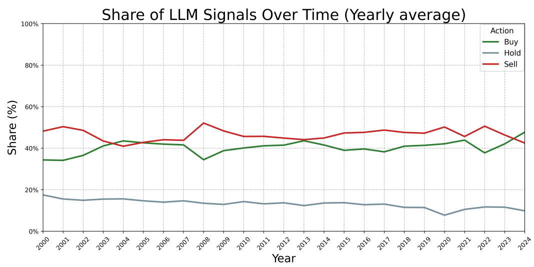
Comparison of trading signal distributions over time



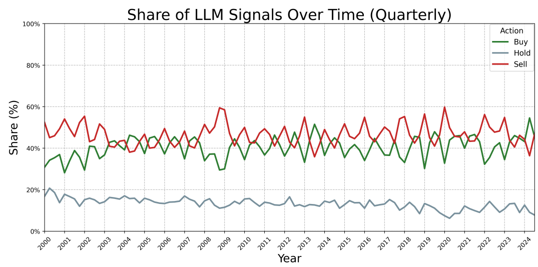
(a) Analyst Signals (Yearly Average)



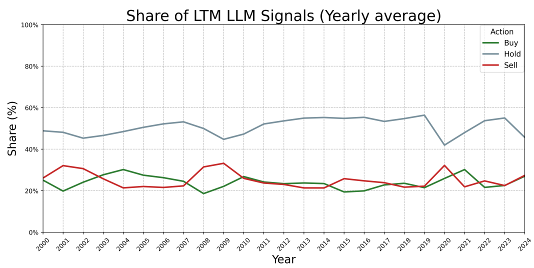
(b) Analyst Signals (Quarterly)



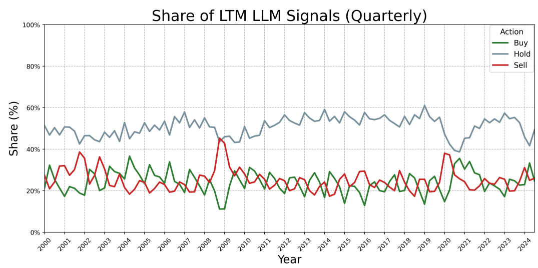
(c) LLM Signals (Yearly Average)



(d) LLM Signals (Quarterly)



(e) LTM LLM Signals (Yearly Average)



(f) LTM LLM Signals (Quarterly)

Figure 2: Longitudinal signal distributions across datasets. The plots contrast the structural optimism of sell-side analysts with the data-driven volatility of the Base LLM and the caution of the LTM LLM.

Figure 2 illustrates the temporal evolution of signal shares from 2000 to 2024, highlighting the contrast between the static distribution of human analyst recommendations and the more dynamic, reactive distributions produced by the base and LTM LLMs. Annual averages of signal shares are plotted on the left to show long-term trends, whereas the quarterly plots on the right offer a more detailed perspective on the distribution's volatility over time. The following observations can be made:

- **Human Analyst Bias:** The distribution of sell-side analyst recommendations is characterized by a persistent and structural *positivity bias*. Even during systemic shocks, such as the 2008 financial crisis or the 2020 pandemic, the share of *Sell* signals does not increase. At most, a *Hold* recommendation is issued to signal a less optimistic view, reflecting the tendency of analysts to leave recommendations unchanged for long periods of time, as noted by Jegadeesh et al. (2006, p. 17). This behavior is consistent with the mimicking of investment decisions and the mitigation of reputational risk described by Scharfstein et al. (1990, p. 465). By avoiding contrarian *Sell* ratings, analysts can effectively share the blame for poor forecasts within the consensus, further supporting the self-selection mechanism of McNichols et al. (1997, p. 169), where negative sentiment is expressed through neutral ratings or the discontinuation of coverage rather than explicit *Sell* recommendations.

- **Base LLM Objectivity:** The yearly average plot for the Base LLM (c) illustrates a balanced distribution, with *Buy* and *Sell* signal shares oscillating between 30% and 50%. This symmetrical profile reflects high sensitivity to macro-events, as the model reacted to the 2008 financial crisis with a sharp increase in *Sell* signals and a corresponding decrease in *Buy* signals. During the 2020 pandemic, it responded with a weaker spike in *Sell* recommendations and a reduction in *Hold* signals. On a quarterly basis, the distribution exhibits sharper fluctuations and signal reversals, as subplot (d) demonstrates. Because each recommendation is generated independently, these quarterly shifts demonstrate that the outputs are highly sensitive to the underlying data of the period rather than being influenced by previous decisions. Unlike the persistent trends seen in the analysts' data, the Base LLM distribution adapts to quarterly inputs without maintaining a long-term bias or path dependency.

- **LTM LLM Information Dilution:** The yearly average plot for the LTM LLM (e) exhibits a strong bias towards the *Hold* category, with values ranging between 40% to 60%. This rather neutral outlook consequently leads to lower shares of *Buy* and *Sell* ratings, but is still able to react to external shocks. This is displayed by the considerable drop in *Buy* as well as *Hold* ratings in the years 2008 and 2009 with a corresponding increase in the share of *Sell* ratings. During the 2020 pandemic, the LTM LLM was also able to react to the external shock as indicated by the drastic decline in the share of *Hold* ratings, reaching its lowest point, again with a corresponding increase in the share of *Sell* ratings. The distribution of quarterly rating shares, as displayed in subplot (f), again exhibits sharper fluctuations compared to the analysts' profile illustrated in subplot (b). This further highlights the input-sensitivity of the LLM and weaker presence of the aforementioned long-term biases. However, while the high share of *Hold* ratings does not mirror the human *positivity bias*, the inclusion of longitudinal data appears to result in *information dilution* and a more neutral prediction, as described by Cheung et al. (2025, p. 4) . Despite independent API calls, this heavy focus on neutral signals creates an effect similar to the tendency of sell-side analysts to leave recommendations unchanged for extended periods as described by Jegadeesh et al. (2006, p. 17).

Furthermore, of the 113,301 total signals, the analysts' ratings only differed from their previous recommendations 11,342 times, representing an average of 7.65 changes per CIK over the sample period. In contrast, the Base LLM and LTM LLM exhibited significantly higher turnover, with 51,958 and 46,603 switches (averaging 35.04 and 31.42 changes per CIK), respectively. This provides further evidence for the findings of Jegadeesh et al. (2006, p. 17) regarding the tendency of analysts to leave ratings unchanged for extended periods, and contrasts with the more dynamic and input-sensitive responses of the LLM-based strategies.

4.1.3 Cross-Sectional Analysis of Signal Distributions across GICS Sectors

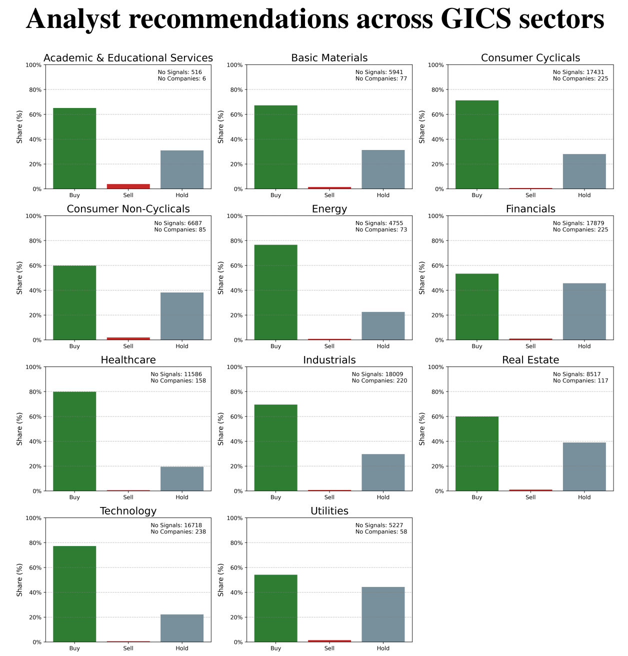
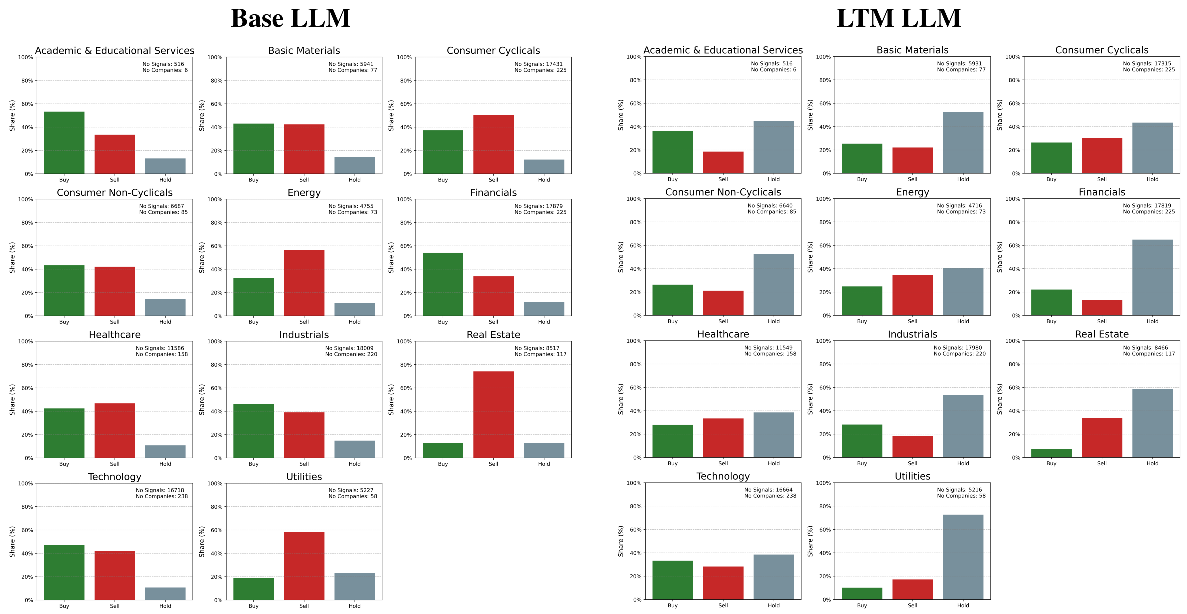


Figure 3: Distribution of analyst signals across economic sectors. The plot illustrates a strong *positivity bias* across all GICS industries, characterized by a dominance of *Buy* ratings and negligible share of *Sell* signals, regardless of specific sector risk profiles.

The cross-sectional analysis reveals how each recommendation source behaves across Global Industry Classification Standard (GICS) economic sectors. Figure 3 shows a high degree of homogeneity in recommendations issued by sell-side analysts. From stable sectors like Consumer Non-Cyclicals to those with significantly higher market risk, such as Information Technology, which exhibits high market betas and negative *HML* loadings as demonstrated by Fama et al. (1997, p. 157), analyst recommendations remain heavily skewed toward *Buy* ratings, with *Sell* signals being almost non-existent, regardless of the industry.



(a) Distribution of Base LLM recommendations across economic sectors. The plot reveals clear sectoral discrimination, with a higher concentration of *Sell* signals in capital-intensive industries such as Energy and Real Estate.

(b) Distribution of LTM LLM recommendations across economic sectors. While maintaining some sensitivity to sector-specific risks, the inclusion of longitudinal data results in a shift toward neutral *Hold* signals across most GICS industries.

Figure 4: Cross-sectional distribution of Base and LTM LLM recommendations across GICS sectors, highlighting the shift from structural sector discrimination in the baseline model to a broader consensus of neutral ratings when longitudinal data is integrated.

In contrast, the Base LLM in Figure 4a shows clear sectoral discrimination, as the share of *Sell* signals is highest in Energy, Real Estate, and Utilities. A possible reason for this bearishness could be the high capital intensity of these sectors, which are defined by their reliance on large-scale physical assets and high fixed costs (Hou et al. 2006, p. 1931). Unlike asset-light industries, these three sectors require significant, long-term investments in infrastructure, making them more vulnerable when economic conditions change. This is supported by Fama and French, who show that sectors like Utilities and Energy have distinct risk profiles due to this capital structure (Fama et al. 1997, p. 157).

Figure 4b illustrates, that even across sectors, the LTM LLM again exhibits a more centralized distribution, as the inclusion of longitudinal data appears to weaken its conviction compared to the Base LLM. While it appears to show some sensitivity to sector-specific risks, the additional context shifts its recommendations toward neutral signals, as the share of *Hold* signals is the highest across all sectors. Both the Base LLM and the LTM LLM diverge from the ubiquitous optimism of human analysts. While analysts are often good at assessing stocks within specific sectors of their expertise, they do not consistently identify industry-wide underperformance (Boni et al. 2006, p. 106). By differentiating across sectors, even with lower conviction, the LTM LLM avoids the homogeneity seen in analyst ratings and acknowledges the distinct risk-adjusted payoffs inherent in different industrial structures (Fama et al. 1997, p. 157).

4.2 Portfolio Performance Analysis

This section presents the results of the portfolio simulation described in Section 3.2.1, comparing the LLM-based strategies against human analyst benchmarks. To identify the optimal approach, the two LLM strategies are first compared over a test period. The performance of the superior approach is then verified during a validation period spanning the remainder of the time frame, with a portfolio following sell-side analyst recommendations serving as a baseline for comparison. The market portfolio, which serves as a further benchmark, is constructed by aggregating the prices of all stocks within the investment pool at each timestamp. These values are then normalized to the starting period to represent the cumulative development of an equally weighted index of the underlying investment pool.

4.2.1 Test Period Performance

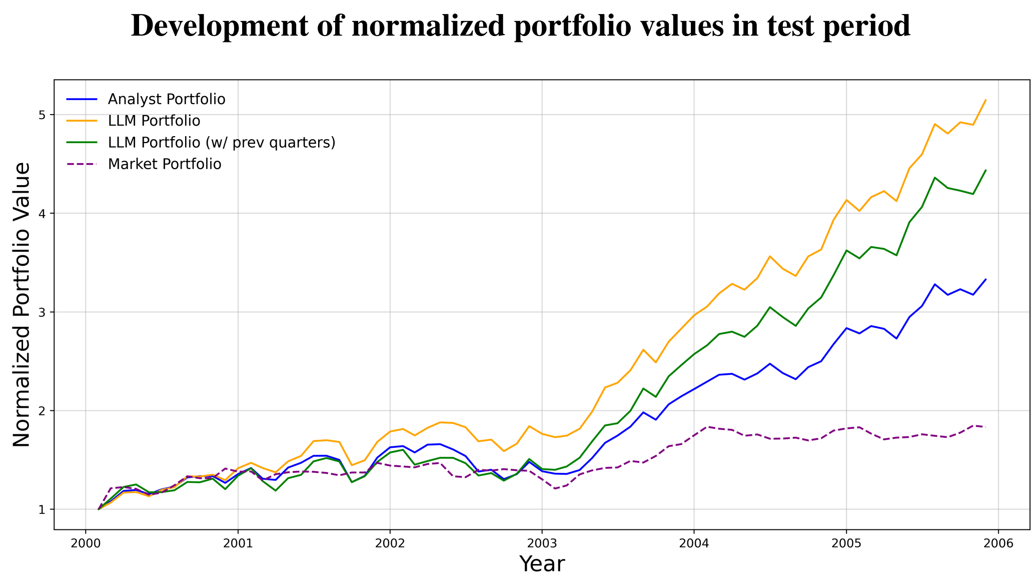


Figure 5: Comparison of normalized portfolio values for LLM and analyst-led strategies against an equally weighted market benchmark in test period 2000-2006. Both LLMs significantly outperform the analysts, with the Base LLM achieving the highest terminal value.

As Figure 5 illustrates, both portfolio strategies derived by following the LLM's recommendations are able to outperform the analysts' portfolio over the test period. However, the analysts' portfolio is able to considerably outperform the overall market through a strategic selection of stocks. Generally, all strategies appear to follow the underlying movement of the market index to some extent, essentially appearing as scaled versions of one another with similar degrees of sensitivity to the broader market trend.

Table 1 lists performance metrics about the underlying simulations alongside further statistics. Note that the number of executed transactions can exceed the number of total recommendations, because the entire portfolio is sold, once new recommendations become available to account for

Metric	Analyst	Base LLM	LTM LLM
Return Metrics			
Mean Monthly Return	1.88%	2.45%	2.27%
Annualized Mean Return	23.00%	31.66%	28.33%
Final Normalized Value	3.403	5.091	4.375
Risk Metrics			
Monthly Std. Deviation	5.27%	5.11%	5.91%
Annualized Std. Deviation	18.26%	17.69%	20.47%
Annualized Sharpe Ratio	1.086	1.507	1.199
Trading Activity			
Total Recommendations	21,705	21,705	21,705
Executed Transactions	27,744	16,183	10,996

Table 1: Portfolio simulation statistics in test period. LLM-based strategies consistently outperform the analyst benchmark.

the imbalance in overall signal distributions.
The numerical results confirm the visual evidence: The analysts' portfolio is inferior across nearly every metric. Although the LTM LLM exhibits higher volatility, its superior mean return yields a higher Sharpe Ratio than the analyst baseline, indicating better risk-adjusted performance. Overall, both LLM strategies outperform the human benchmark, with the Base LLM emerging as the superior model with a final normalized portfolio value of 5.091. Consequently, this strategy will be carried forward into the validation period. Notably, the LTM LLM requires the fewest executed transactions, while the analysts' strategy exhibits the highest count. However, this can be attributed to the simulation design clearing the entire portfolio once new signals become available. Nevertheless, The higher signal turnover documented in 4.1.2 would pose a clear disadvantage for both LLM-based strategies, as the inclusion of transaction costs would likely reduce the performance gap in favor of the analysts' strategy. As detailed by French (2008, p. 1554), such a high transaction frequency creates substantial costs that would reduce the realized returns, as the expenses of frequent trading can decrease the performance.

4.2.2 Validation Period Performance

Figure 6 compares the development of normalized portfolio values of the LLM-based strategy, only using the most recent financial data to obtain trading recommendations, against the analysts' portfolio, with the equally weighted market portfolio serving as a further benchmark again. The findings of the validation period confirm the results of the test period: Analysts outperform the overall market through selective stock picking, but the LLM portfolio significantly outperforms the analysts' portfolio with a final value that is 2.5 times higher. Both portfolios seem to be sensitive to the overall market to a similar extent, as shown by the dips in portfolio value that occurred during the Covid-19 pandemic, affecting the markets in 2020. The exact degree of market sensitivity of both portfolios will be discussed in Section 4.3.

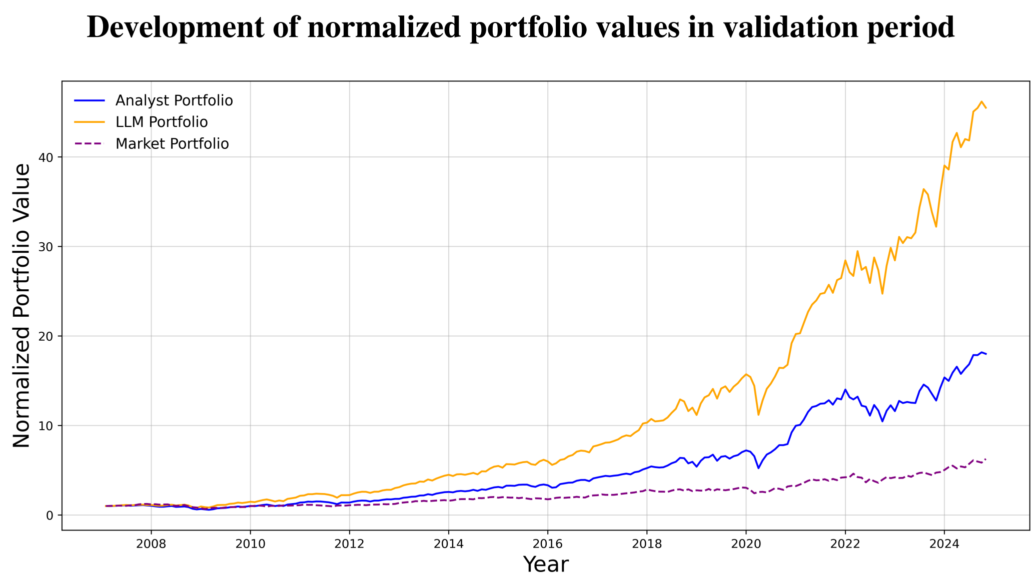


Figure 6: Comparison of normalized portfolio values for LLM and analyst-led strategies against an equally weighted market benchmark in validation period 2007-2025. The LLM significantly outperforms the analyst again, with similar sensitivity to macro economical shocks.

Consistent with the test period results discussed in Section 4.2.1, the analysts' portfolio remains inferior across every performance metric as shown in Table 2. The LLM-based strategy outperforms the analysts' portfolio, generating a higher mean return with smaller volatility. This combination again results in a superior Sharpe Ratio, confirming the model's ability to achieve better risk-adjusted returns. However, following Lo (2003, p. 37), it is important to treat these results as statistical estimates, as the true population parameters of the return distributions are unobservable and also just estimated from historical data. Nevertheless, the consistency of portfolio outperformance across both the test and validation periods suggests that the LLM strategy

Metric	**Analyst**	**Base LLM**
Return Metrics		
Mean Monthly Return	1.56%	1.99%
Annualized Mean Return	18.09%	24.35%
Final Normalized Value	19.400	48.744
Risk Metrics		
Monthly Std. Deviation	5.76%	5.68%
Annualized Std. Deviation	19.95%	19.67%
Annualized Sharpe Ratio	0.873	1.148
Trading Activity		
Total Recommendations	86,544	86,544
Executed Transactions	116,308	71,850

Table 2: Portfolio simulation statistics in validation period. The LLM-based strategy outperforms the analyst benchmark across simple return, as well as risk-adjusted metrics.

maintains an advantage over the human benchmark.

4.2.3 Predictive Accuracy and Classification Performance

Source	Category	Precision	Recall	F1-Score	Accuracy
LLM	Buy	0.4665	0.4418	0.4538	0.4709
	Hold	0.2868	0.1406	0.1886	
	Sell	0.3340	0.5131	0.4047	
Analyst	Buy	0.4431	0.6847	0.5380	0.4321
	Hold	0.2830	0.3355	0.3070	
	Sell	0.3074	0.0087	0.0170	

Table 3: Classification Performance of LLM vs. sell-side analysts. The LLM achieves higher overall accuracy by balancing signal types. While analysts exhibit a persistent *Buy* bias, yielding high *Buy* recall but near-zero *Sell* recall, the LLM provides greater utility through its superior ability to identify market declines.

Apart from overall portfolio performance, the technical quality of the generated signals can be evaluated by comparing the trading recommendations against realized market movements. Ground-truth labels for this classification analysis are defined as follows:

- **Actual Buy:** $P_{t+1} > P_t$
- **Actual Sell:** $P_{t+1} < P_t$
- **Actual Hold:** $\left|\frac{P_{t+1}-P_t}{P_t}\right| \leq 0.02$

Table 3 shows that while precision—the proportion of signals issued for a specific category that were correctly classified—is comparable between both sources, their overall predictive performance diverges significantly. The LLM drastically outperforms analysts in identifying market downturns, achieving a *Sell* recall—the model's ability to capture actual negative instances—of 0.5131 versus the analysts' 0.0087. This indicates that while analysts effectively avoid false alarms when issuing *Sell* ratings, they fail to identify over 99% of actual market declines. The *Sell* F1-score—representing the harmonic mean of precision and recall—confirms the LLM's superior balance, as it penalizes the near-zero recall of the analysts' strategy. Consequently, the analysts' high *Buy* recall likely is a result of the persistent *positivity bias*. While the analyst accuracy of 43.21%—the total share of correct predictions—is inflated by simply predicting the majority class in an overall growing market, the LLM's higher accuracy of 47.09% is of greater utility as it stems from a balanced ability to identify both market growth and declines.

4.2.4 Statistical Significance

While Sections 4.2.1 and 4.2.2 showed a clear advantage of the LLM-based portfolio strategies, over the human benchmark, it remains unclear, whether this outperformance was merely a result of favorable market conditions or the lucky selection of a few outperforming stocks. Therefore, this section presents the results of the robustness testing detailed in Section 3.2.3.

Distributional robustness and statistical significance of performance metrics

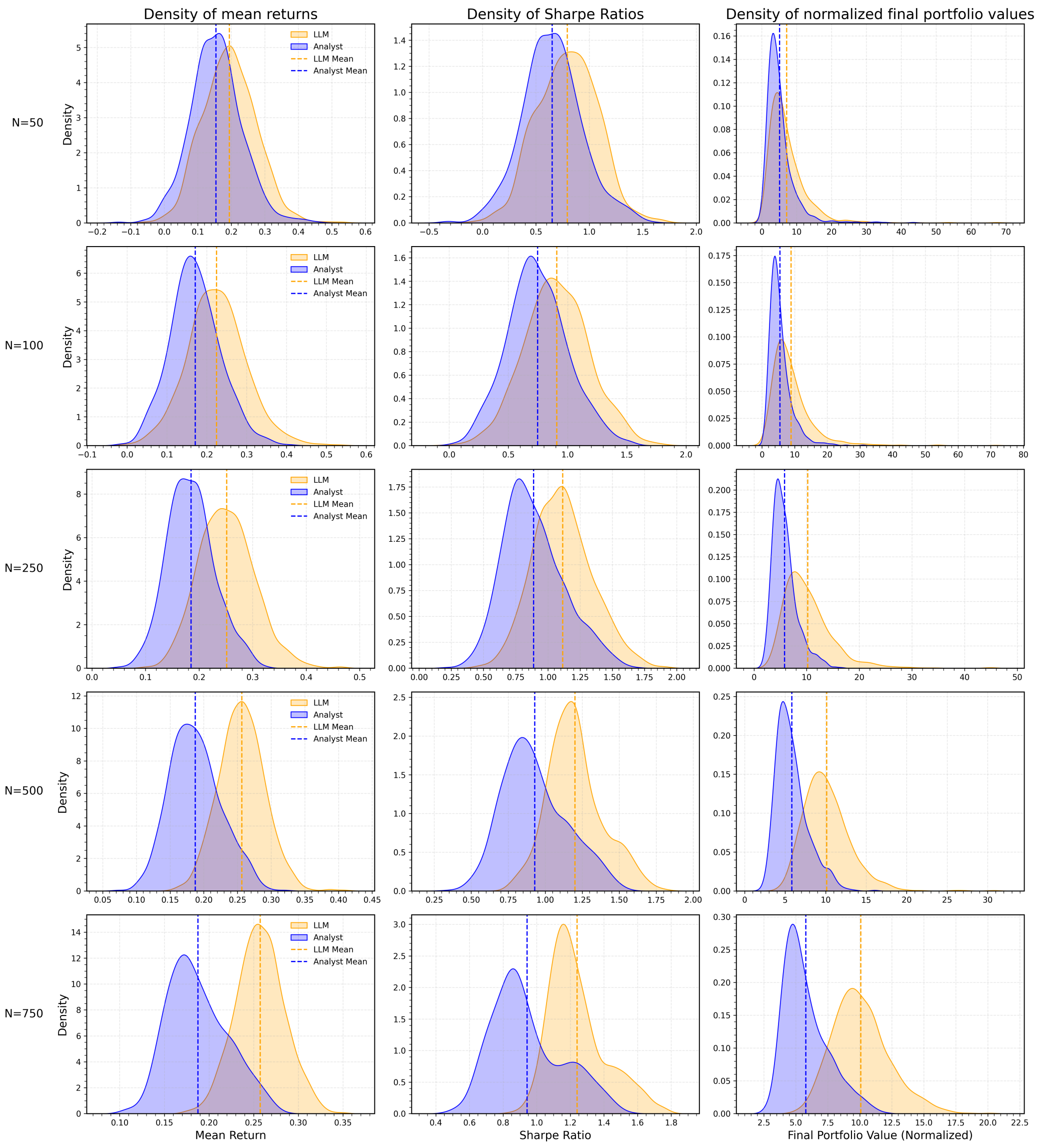


Figure 7: Kernel density estimates for mean returns (left), Sharpe Ratios (center), and final normalized portfolio values (right) for $N \in \{50, 100, 250, 500, 750\}$. The blue and orange dashed lines represent the LLM and analyst means, respectively, showing increased disparity and robustness as N grows.

Figure 7 includes the densities of realized normalized final portfolio values, as well as densities of mean returns, to provide a more complete assessment of performance. Following Kipp and Koziol (Kipp et al. 2020, p. 357), the arithmetic mean is the correct measure to estimate expected wealth increase and serves as the unbiased estimator for significance testing. However, it does not account for the volatility drag, the reduction in compound growth caused by periodic variance, which distinguishes the actually realized path from the arithmetic expectation. Therefore, final portfolio values are included to illustrate the realized wealth accumulation, the primary objective for investors aiming to maximize terminal wealth in a multi-period framework (Estrada 2009, p. 5).

As N increases from 50 to 750, the visual evidence confirms the overall robustness and superiority of the LLM-based strategy. For mean returns, the distributions exhibit a clear tightening as density plots become narrower and more peaked. This reflects a reduction in the variance of results as the sample mean converges toward its expected value according to the *Law of Large Numbers*, a statistical property that allows observed average returns to serve as proxies for expected-return conditions (Fama et al. 1973, p. 611). In contrast, the densities for final portfolio values become broader as N increases, as the compounding of returns over longer horizons increases the dispersion of terminal wealth. Despite this, the overlap between the distributions across all performance metrics decreases as the LLM-based strategy outperforms the analyst-based portfolio more clearly as the sample size increases.
The hypothesis testing results, as presented in Table 4, further substantiate these findings. The statistical analysis follows the hypothesis below:

> $H_{0,r}$: *The returns generated by following the LLM portfolio strategy are smaller or equal to the returns generated by the Analysts' strategy:* $r_{LLM} \leq r_{Analyst}$.

To account for investment risk, the same testing procedure is applied to risk-adjusted returns. The analysis follows the hypothesis below:

> $H_{0,SR}$: *The Sharpe Ratio generated by following the LLM portfolio strategy is smaller or equal to the Sharpe Ratio generated by the Analysts' strategy:* $SR_{LLM} \leq SR_{Analyst}$.

The computation of p-values follows the percentile bootstrap procedure described by (Efron 1979, pp. 3–5). In this approach, the p-value is the proportion of bootstrap mean differences falling below the null threshold of zero. This non-parametric method avoids assuming a specific distribution, relying on the empirical distribution of the data instead.

Sample Size	**Mean Return (μ)**		**Sharpe Ratio (SR)**	
N	**LLM**	**Analyst**	**LLM**	**Analyst**
50	0.1941***	0.1543	0.7930***	0.6525
100	0.2246***	0.1709	0.9087***	0.7460
250	0.2515***	0.1849	1.1148***	0.8887
500	0.2564***	0.1874	1.2016***	0.9287
750	0.2573***	0.1876	1.2397***	0.9421

Note: *** denotes $p < 0.001$ based on 10,000 bootstrap resamples.

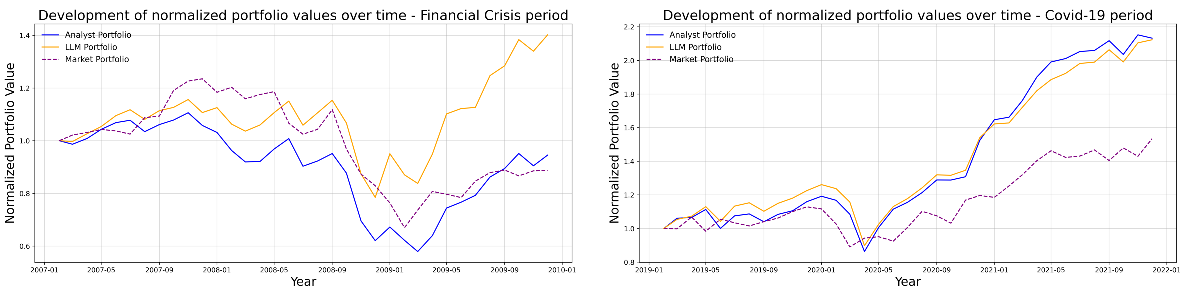
Table 4: Statistical significance of performance metrics across sample sizes. Bootstrapped results confirm that the LLM consistently generates higher mean returns and Sharpe Ratios compared to analysts.

The results in Table 4 show that the LLM-based strategy's outperformance is already statistically significant in the smallest sample size. Even at N=50, the null hypotheses $H_{0,r}$ and $H_{0,SR}$ are rejected on every conventional significance level. As N increases, the mean returns for both portfolios mostly stabilize after N=250, with the LLM strategy maintaining a consistent lead. Interestingly, while the raw returns plateau, the Sharpe Ratios continue to improve beyond this point. This improvement in Sharpe Ratios, even after mean returns have stabilized, is likely driven by risk diversification that occurs as the sample size increases, which reduces the portfolio's volatility. Since the portfolio simulations abstract from transaction costs, taxes, and management fees, the resulting Sharpe Ratios are not benchmarked against historical fund performances but instead are only compared within the framework of this study.

4.2.5 Bear Market Performance

Sections 4.2.2 and 4.2.4 established the overall outperformance and respective significance of the LLM-based strategy over the analysts' trading strategy. However, possible limitations of this seemingly superior strategy might become apparent in especially stressful and uncertain market conditions. This section presents the results of a sub-period analysis covering two distinct market events: The 2008 financial crisis and the Covid-19 pandemic. To allow for a more robust assessment of strategy resilience, a portfolio simulation covering 1 year preceding and following the respective events is conducted for both investment strategies.

Strategic resilience: Sub-period performance analysis



(a) **Great Financial Crisis (2007–09):** LLM mitigates structural decline, maintaining higher value and recovering faster than analysts.

(b) **Covid-19 Era (2019–21):** LLM fails to mitigate the exogenous shock; defensive strategy results in a slower recovery than analysts.

Figure 8: Comparison of normalized portfolio values across distinct stress regimes. The plots highlight the divergence in performance between structural and exogenous shocks.

As Figure 8a illustrates, the LLM-based strategy was able to mitigate the impact of the global financial crisis better than the analysts' strategy. While both portfolios followed the overall market movement and suffered considerable losses, the LLM portfolio dropped to a normalized value of 0.8 at its lowest point, while the analyst portfolio dropped to 0.6, even performing worse than the overall market. Furthermore, the LLM portfolio was able to recover from this systemic crisis faster than the analyst portfolio. These findings are supported by the statistics covered in Table 5, as the LLM strategy exhibits a considerably higher annualized mean return of 14.36% versus only 0.45%. While its standard deviation of returns is slightly higher, the considerable difference in mean returns ultimately yields a higher Sharpe Ratio for the LLM

Metric	Financial Crisis (2007–09) Analyst	Financial Crisis (2007–09) LLM	Covid-19 Era (2019–21) Analyst	Covid-19 Era (2019–21) LLM
Return Metrics				
Mean Monthly Return	0.29%	1.39%	2.66%	2.60%
Annualized Mean Return	0.45%	14.36%	33.34%	32.68%
Final Normalized Value	1.013	1.479	2.315	2.281
Risk Metrics				
Monthly Std. Deviation	7.10%	7.48%	6.82%	6.46%
Annualized Std. Deviation	24.58%	25.90%	23.62%	22.39%
Annualized Sharpe Ratio	0.067	0.574	1.316	1.357
Signal Analysis				
Buy signals	7,198 (62%)	4,612 (40%)	10,655 (68%)	6,788 (43%)
Sell signals	127 (1%)	5,545 (47%)	121 (1%)	7,353 (47%)
Hold signals	4,374 (37%)	1,542 (13%)	4,919 (31%)	1,554 (10%)

Table 5: Portfolio metrics and signal shares across stress regimes. The LLM outperforms analysts during the financial crisis, where a 47% *Sell* signal share mitigated the structural decline. During Covid-19, the strategy is on par at best. The model's defensive strategy fails to benefit from the rapid recovery, which the high share of *Buy* signals, issued by analysts, did.

portfolio of 0.574 versus 0.067. This is likely caused by the continuing *positivity bias* inherent in the sell-side recommendations, as the share of *Sell* signals issued by human analysts during this major economic crisis is still only at 1%, therefore suffering the full impact of this event.

Figure 8b presents a different performance profile. While the 2008 global financial crisis was a systemic, endogenous event resulting from a predictable buildup of financial instability (Crotty 2009, p. 564), the Covid-19 pandemic is regarded as a black swan event, an exogenous and largely unpredictable shock to the global economy (Ahmad et al. 2021, p. 556). As the graphic shows, the LLM-based strategy suffers an almost identical drawdown to the analyst baseline. Furthermore, in the subsequent months, the LLM portfolio recovers slightly slower, likely due to its more defensive strategy reflected in the signal shares. Table 5 shows that despite lower mean returns during this period, the LLM's reduced volatility still yields a higher Sharpe Ratio. However, the narrowed performance gap suggests that the impact of black swan events uncovers a limitation in the LLM-based portfolio strategy: Its reliance on the quarterly financial inputs that might not reflect an imminent threat in time. In contrast, sell-side analysts have access to a broader information set, possibly allowing for more rapid adjustments. A sustained low *Sell* share of 1% during this crash could therefore either reflect their overall tendency to leave ratings unchanged over time, or a conviction that the crisis would be short-lived.

4.3 CAPM Results: Risk-Adjusted Returns and Factor Loadings

This section presents the results of the CAPM regression following Equation 2 discussed in Section 3.3.1. The Three-Factor model is employed to maintain model parsimony and avoid the potential redundancy of additional components, as Fama et al. (2015, p. 2) observe that additional variables of the Fama-French Five-Factor model can render traditional ones redundant. Furthermore, the existing high R^2 values suggest that the current specification captures the systematic risk profile sufficiently well.

Variable	**LLM**	**Analysts**
Constant (α)	0.0086***	0.0035***
Market (β)	0.9649***	1.0228***
Size (SMB)	-0.0571	-0.0772*
Value (HML)	-0.1370***	-0.1832***
R-squared	0.882	0.944
Observations	226	226

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Fama-French Three-Factor Regression: LLM vs. Analyst Performance. The LLM strategy produces a significantly larger alpha, indicating superior risk-adjusted returns after controlling for market, size, and value factors.

As Table 6 shows, the LLM-based strategy produces a significantly higher *Jensen's Alpha* than the analyst baseline, demonstrating its superior ability to generate risk-adjusted returns after controlling for systematic factors. Both regressions exhibit high R^2 values of 88.2% and 94.4%, respectively. This strong linear relationship is expected, given that the benchmark is an equally weighted market portfolio of the investment pool. Furthermore, the analysts' tendency to issue *Buy* ratings, reaching a share of 80% at times, naturally results in a return profile that tracks the underlying market closely. Additionally, the LLM portfolio exhibits a smaller market beta that is statistically significant on any conventional level, indicating higher resilience to market volatility. Regarding factor loadings, the SMB coefficient is statistically insignificant for the LLM portfolio and negligible for the analysts, suggesting neither strategy is driven by a size premium. However, the HML coefficients reveal that both strategies maintain a significant exposure to growth stocks, favoring companies with lower book-to-market ratios. Notably, the LLM achieves a superior alpha despite lower growth exposure than the analysts, suggesting that its outperformance is driven by idiosyncratic security selection rather than a mere systematic preference for growth stocks.

4.4 Drivers of LLM Decision-Making

Section 4 has established a clear performance advantage for the LLM-based strategy. While the signal distributions themselves and CAPM regressions offer initial insights into how and why these strategies differ, this section presents the results of a more granular investigation into the underlying logic of that outperformance. The objective is to determine what can potentially be learned from the LLM to improve future investment decisions. First, the direct qualitative reasoning provided by the LLM is examined, followed by a quantitative analysis using surrogate machine learning models to isolate the fundamental drivers of both the LLM and analyst ratings.

4.4.1 Direct LLM Reasoning Analysis

Rating	Rank	Top N-Grams	Frequency
Buy	1	Free cash flow	2,512
	2	Short-term investments	2,217
	3	Cash flow generation	2,189
Sell	1	Free cash flow (Negative)	2,963
	2	Negative free cash	2,664
	3	High debt levels	1,321
Hold	1	Operating cash flow	1,046
	2	Positive net income	794
	3	Net income EPS	685

Table 7: Frequency analysis of top 3-grams from direct LLM decision rationales. The results highlight a primary focus on liquidity metrics, specifically free cash flow and short-term solvency, as the dominant drivers for rating assignments.

Table 7 presents the most frequent 3-grams extracted from the qualitative justifications provided by querying the LLM directly. The results reveal a consistent internal logic, highlighting a clear preference for specific financial metrics. Free cash flow and liquidity dominate across all categories, suggesting that the LLM's outperformance likely stems from a preference for solvency measures over accrual-based earnings. This focus reflects the empirical finding that earnings performance attributable to the accrual component is less persistent than the cash flow component (Sloan 1996, p. 291). By anchoring its signals in cash-based metrics, the LLM effectively avoids valuation distortions and potential management manipulation.

4.4.2 Surrogate Machine Learning Model Evaluation

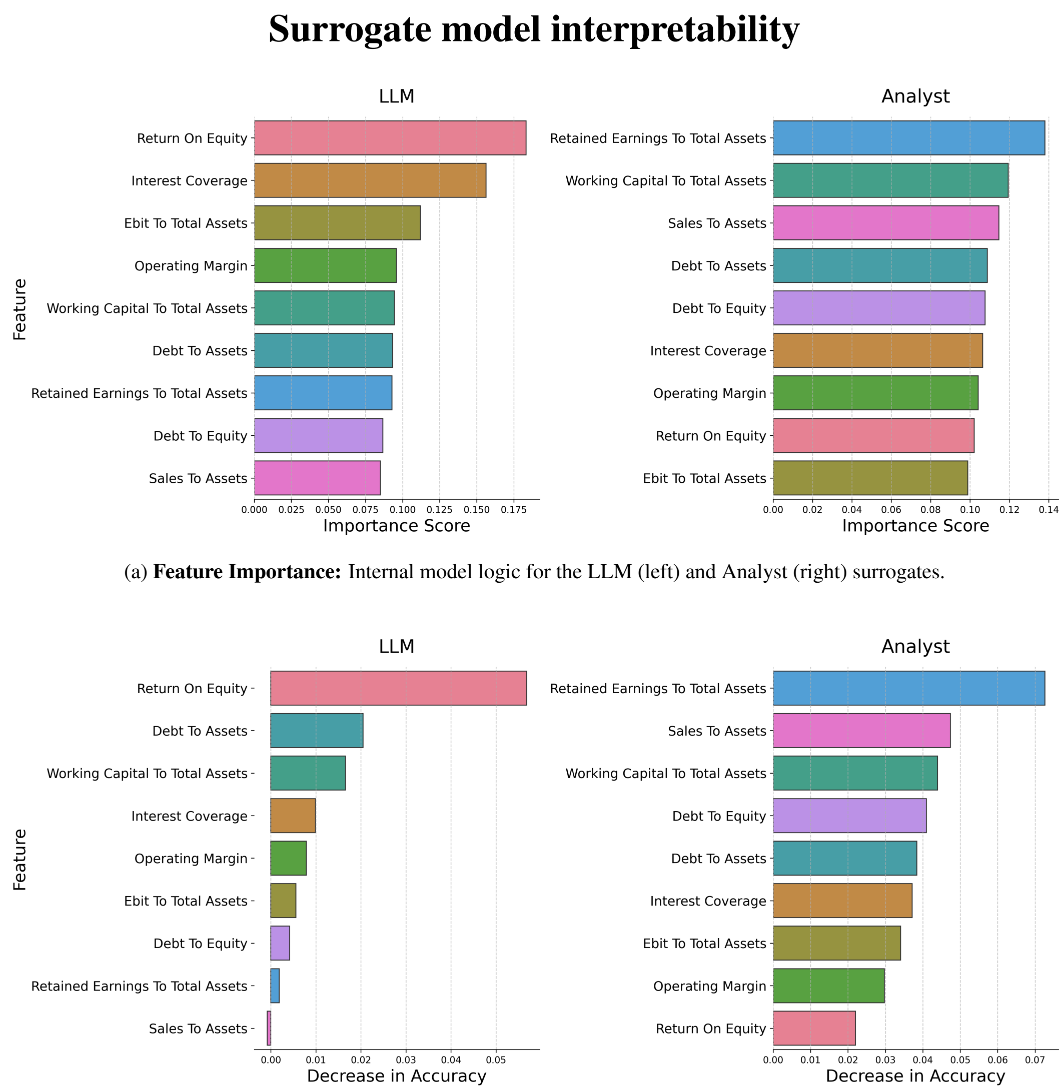
Before analyzing the drivers of the model's performance, the fidelity of the surrogate Random Forests is evaluated. This ensures the surrogate model accurately replicates the agents' decision-making logic, validating the subsequent use of feature importance, SHAP values, and permutation importance for interpretability.

	LLM Surrogate			**Analyst Surrogate**		
Class	Precision	Recall	F1	Precision	Recall	F1
Buy	0.62	0.76	0.68	0.77	0.95	0.85
Hold	0.33	0.06	0.09	0.74	0.38	0.50
Sell	0.73	0.77	0.75	0.76	0.11	0.19
Accuracy		0.67			0.77	
Macro Avg F1		0.51			0.51	

Table 8: Surrogate Random Forest performance. Both achieve a 0.51 macro F1-score, validating their use for SHAP analysis. Class imbalance inflates analyst accuracy, while the LLM struggles with *Hold* predictions.

The performance of the surrogate models is summarized in Table 8. Both models achieve a macro-averaged F1-score of 0.51, indicating that both Random Forest surrogates capture the underlying decision logic of their agent similarly well. The high *Buy* recall and overall higher accuracy of the analysts' surrogate model are likely caused by the highly imbalanced dataset towards *Buy* ratings again. In contrast, the LLM surrogate performs poorly regarding the *Hold* signal class. Nevertheless, these fidelity levels confirm that the surrogates are a reliable proxy for the agents, justifying the use of feature importance and SHAP values to interpret their decision drivers.

4.4.3 Feature Importance and Permutation Feature Importance



(a) **Feature Importance:** Internal model logic for the LLM (left) and Analyst (right) surrogates.

(b) **Permutation Feature Importance:** Generalizable predictive power evaluated on unseen data.

Figure 9: Comparison of Gini-based and permutation feature importance. Both metrics show the LLM prioritizes operational efficiency and solvency (*Return on Equity*, *Debt to Assets*), whereas human analysts anchor on historical accumulation (*Retained Earnings to Total Assets*).

Figure 9 illustrates the primary decision drivers of the surrogate models, utilizing the computed financial metrics discussed in Section 4.4.2 rather than the extensive raw inputs used to generate the original trading signals. Gini-based feature importance is derived from the internal splitting logic of the trained model itself (Strobl et al. 2007, p. 3), while permutation importance measures the drop in prediction accuracy when a feature is randomly shuffled in a holdout dataset (Fisher et al. 2019, pp. 9, 40). Utilizing both metrics ensures generalizability, confirming that the identified drivers capture robust underlying patterns rather than noise.

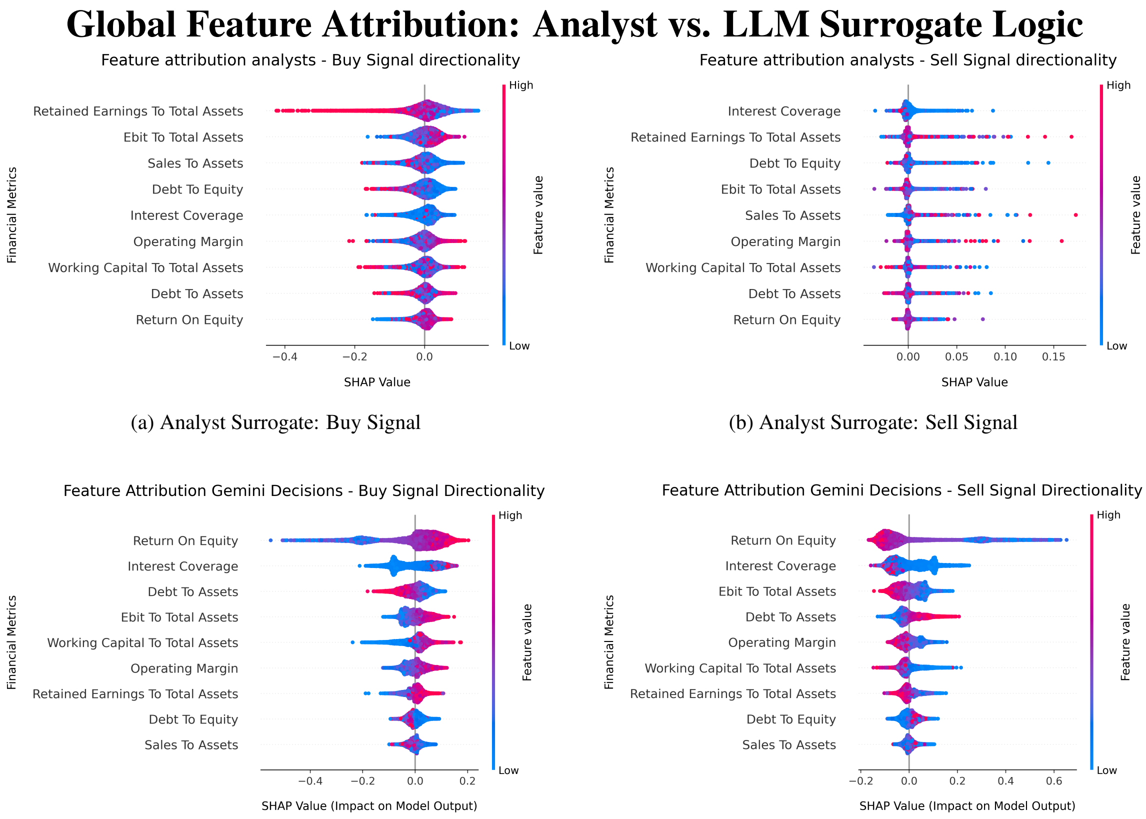
The feature importance profiles reveal that the LLM and the human analysts rely on fundamentally different drivers to base their recommendations on. For the LLM, *Return on Equity* emerges as the primary driver across both metrics. While *Debt to Assets* ranks only sixth in the internal splitting logic, it emerges as the second most important feature for out-of-sample prediction. This indicates that the LLM's generalizable predictions ultimately depend heavily on current profitability and structural solvency, rather than just the metrics used most frequently during training.

In contrast, the analyst surrogate relies mostly on historical accumulation and revenue generation, anchoring on *Retained Earnings to Total Assets* and *Sales to Assets* consistently. This could potentially be caused by human analysts systematically overweighting metrics that are susceptible to accounting accruals and multi-period accumulation. The LLM appears to filter out these distortions, prioritizing operational efficiency and leverage instead. This considerable difference in feature prioritization likely explains the performance deviations between the two portfolios during the historical simulations.

4.4.4 SHAP Values

To move beyond purely magnitude-based feature importance, this section employs SHAP values to analyze the features' directional impact in the surrogate models' decision logic. Introduced by Lundberg and Lee (Lundberg et al. 2017, p. 2), SHAP values are grounded in cooperative game theory and calculate the marginal contribution of each feature to a prediction. While the previously discussed feature importances isolate how much a feature matters for overall predictive performance, global SHAP beehive plots reveal how high and low values of a feature push predictions toward or away from specific recommendation classes. Figure 10 presents the SHAP beehive distributions for the *Buy* and *Sell* classifications across both surrogate models. Here, the vertical axis at zero represents the mean baseline prediction for the respective class. Each point represents a single firm-month observation, its horizontal placement quantifies the feature's marginal impact on the prediction, and its color indicates the underlying feature magnitude. The *Hold* class is excluded, as it generally reflects a lack of conviction and yields less informative feature attributions. Within each subplot, features are sorted by their mean absolute SHAP value representing the global importance for the respective class.

The LLM surrogate demonstrates high structural symmetry, where *Buy* and *Sell* signals appear as logical inverses. High *Return on Equity* and low *Debt to Assets* drive positive attributions



(a) Analyst Surrogate: Buy Signal

(b) Analyst Surrogate: Sell Signal

(c) LLM Surrogate: Buy Signal

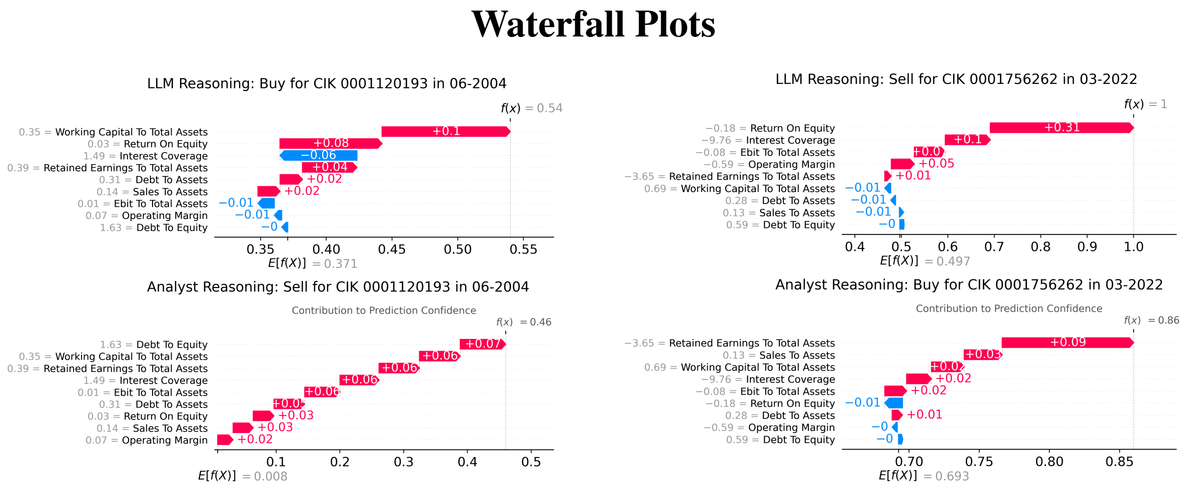
(d) LLM Surrogate: Sell Signal

Figure 10: Comparative SHAP beehive distributions illustrating feature importance and directional impact. The plots contrast the symmetric decision logic of the LLM against the asymmetric, accrual-sensitive heuristics of human analysts.

for the *Buy* class, while their inversions serve as major drivers for *Sell* recommendations. This consistency confirms that the LLM views current operational health and structural solvency as critical. By anchoring on these persistent metrics, the model exhibits a stable valuation framework that holds true regardless of the specific trading signal.

The analyst surrogate exhibits a more asymmetric relationship regarding its primary drivers. While *Retained Earnings to Total Assets* is the top-ranked feature by magnitude, SHAP directionality reveals that analysts actually penalize high values of this metric. This clarifies that the previously noted susceptibility to accruals is not a preference for historical accumulation, but a tendency to issue *Buy* signals even when high accruals are pushing the prediction in the opposite direction. In the *Buy* class, this negative signal is often overridden by the positive momentum of growth indicators like *Sales to Assets*. It is only visible in the *Sell* class, that once these indicators are absent, the burden of accruals actually determines the recommendation. This indicates that analysts require an accumulation of risk factors, where stagnant growth must coincide with poor structural metrics before they are willing to abandon a bullish position.

To examine these global patterns in a more practical context, Figure 11 illustrates SHAP waterfall plots for specific contradictory observations. The baseline $\mathbb{E}[f(x)]$ represents the average



(a) LLM Buy signal versus Analyst Sell signal

(b) LLM Sell signal versus Analyst Buy signal

Figure 11: Comparative SHAP waterfall plots for contradictory recommendations. The plots contrast the LLM's concentrated reliance on operational metrics against the analyst's dependence on multiple fundamental factors.

prediction probability for the respective class across the dataset. Notably, the analyst surrogate exhibits a substantially higher expected value for *Buy* classifications than the LLM, capturing the bullish bias of human analysts. From this baseline, each feature's marginal contribution is added to compute the final model output with colors again indicating the feature's magnitude.

The observation for CIK 0001756262 in March 2022 exemplifies the models' divergent priorities. The LLM surrogate issues a confident *Sell* signal, primarily driven by a negative *Return on Equity* contributing heavily to the classification. This reinforces the LLM's strict focus on current operational profitability. In contrast, the analyst surrogate issues a *Buy* recommendation for the same firm, already anchored on a high base probability for this class itself. Furthermore, as the global beehive plots indicate that analysts view high accruals negatively, this specific bullish prediction is bolstered by a low *Retained Earnings to Total Assets* ratio. This demonstrates that the analyst model uses low historical accruals to justify bullish positions, effectively allowing this single metric to override severe underlying operational weaknesses.

The observation for CIK 0001120193 in June 2004 demonstrates how the analyst model aggregates multiple weak fundamentals to reach a *Sell* decision. The LLM surrogate issues a *Buy* recommendation, primarily driven by healthy liquidity (*Working Capital to Total Assets*) and profitability (*Return on Equity*). This confirms the LLM's consistent reliance on persistent operational anchors. In contrast, the analyst surrogate issues a *Sell* decision for the same firm, which is anchored on a near-zero base probability for this class. Furthermore, instead of reacting to a single structural flaw, this negative prediction is driven by multiple influencing factors like elevated leverage (*Debt to Equity*) and high accruals (*Retained Earnings to Total Assets*). This demonstrates that the analyst surrogate requires broad fundamental weakness to exit a position, directly contrasting with the LLM's more targeted decision-making.

5 Conclusion

This thesis aimed to investigate the capabilities and inherent limitations of LLMs in financial decision-making. To overcome the constraints of traditional parametric frameworks and the documented cognitive biases of sell-side analysts in finance, the study researched whether LLMs could perform zero-shot analysis on unformatted raw financial data. To achieve this, a long-only portfolio simulation was conducted utilizing 1500 companies over a 25-year period. Google's Gemini 2.5 Flash-lite model was tasked with generating the underlying investment recommendations from anonymized financial statements, which were then tested against portfolios derived from professional sell-side analyst consensus.

The empirical results demonstrate a clear outperformance of the LLM-based strategy over the human benchmark. The LLM achieved significantly higher risk-adjusted returns, generating a superior Sharpe Ratio and a larger *Jensen's Alpha* after controlling for systematic market factors. Moreover, the LLM exhibited a capability to identify market downturns and adjust its trading recommendations accordingly, whereas human analysts displayed a persistent *positivity bias* across all market regimes and economic sectors. Explainable AI techniques further revealed that this outperformance is based on the model's focus on free cash flow and short-term liquidity over accrual-based earnings, ultimately relying on structural solvency.

Despite these promising results, this study has notable drawbacks as it makes certain assumptions and relies on simplifications. The simulation framework did not account for transaction costs, capital gains taxes, or management fees. Given the significantly higher signal turnover exhibited by the LLM compared to the sticky ratings of human analysts, including these costs would likely reduce the realized outperformance of the model. Furthermore, the study restricted the LLM's context exclusively to financial statements released quarterly. While this isolated its fundamental reasoning, it made the model vulnerable to exogenous black swan events, like the Covid-19 pandemic, as it could not react in time. Additionally, attempts to provide the model with longitudinal data via the LTM LLM approach resulted in *information dilution*, causing the model to default to neutral *Hold* signals, thus highlighting a limitation in processing extensive context windows.

These limitations suggest several promising areas for future research. Studies could create more realistic trading frameworks by integrating trading frictions, allowing short-selling, or taking *Strong Buy* and *Strong Sell* signals into account. Furthermore, research could move beyond raw financial statement analysis by providing models with unstructured, real-time data such as macroeconomic indicators, corporate earnings call transcripts, daily news sentiment or Twitter feeds to better manage exogenous shocks. Ultimately, while these findings suggest that generalized LLMs can successfully bypass traditional modeling constraints to replace sell-side analysts for individual investors, future research into fine-tuned, domain-specific models could unlock even greater predictive capabilities for both private and institutional applications.

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Appendix A: Company overview

Overview of companies per time in the dataset

Table 9: Company overview

CIK	Start	End	CIK	Start	End	CIK	Start	End	CIK	Start	End	CIK	Start	End
0000009092	1999-03	2023-12	0001023128	1999-12	2023-12	0000277135	2000-03	2023-12	0000817720	2002-03	2024-06	0001561894	2013-06	2023-12
0001808834	1999-03	2023-12	0001054905	1999-12	2023-12	0000749251	2000-03	2023-12	0001174922	2002-12	2023-12	0001547903	2013-12	2023-12
0001466593	1999-03	2023-12	0001053507	1999-12	2023-12	0000746515	2000-03	2023-12	0001120193	2002-12	2023-12	0001448893	2013-12	2023-12
0001047335	1999-03	2023-12	0001051470	1999-12	2023-12	0000732717	2000-03	2023-12	0001115055	2002-12	2023-12	0001438133	2013-12	2023-12
0001046025	1999-03	2023-12	0001050797	1999-12	2023-12	0000732712	2000-03	2023-12	0001069183	2002-12	2023-12	0001433270	2013-12	2023-12
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0000899629	1999-03	2023-12	0001048477	1999-12	2023-12	0000723612	2000-03	2023-12	0001089063	2002-11	2024-02	0001326732	2013-12	2023-12
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0000715072	1999-03	2023-12	0001042893	1999-12	2023-12	0000354190	2000-03	2023-12	0001065280	2002-06	2023-12	0001562401	2013-09	2023-12
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0000719220	1999-03	2023-12	0001043219	1999-12	2023-12	0000355811	2000-03	2023-12	0001144980	2002-06	2023-12	0001567683	2013-09	2023-12
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0001022408	1999-06	2024-03	0001095073	1999-12	2023-12	0000799233	2000-03	2023-12	0001179929	2003-09	2023-12	0001584509	2014-03	2024-09
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0000728535	1999-12	2023-12	0000898293	2000-02	2024-08	0001744489	2000-03	2024-09	0001091667	2010-06	2023-12	0000275880	2019-09	2023-12
0000729986	1999-12	2023-12	0000923120	2000-02	2024-08	0000796343	2000-03	2024-11	0001092699	2010-06	2023-12	0001767258	2019-09	2023-12
0000731012	1999-12	2023-12	0001003078	2000-02	2024-08	0000002488	2000-04	2023-12	0001288469	2010-06	2023-12	0001771515	2019-09	2023-12
0000216228	1999-12	2023-12	0000916789	2000-02	2024-02	0000010795	2000-03	2024-09	0001395942	2009-12	2023-12	0001727263	2018-12	2023-12
0000107263	1999-12	2023-12	0000764478	2000-02	2024-02	0000002969	2000-03	2024-09	0001341766	2009-12	2023-12	0001682745	2018-12	2023-12
0000105770	1999-12	2023-12	0000016918	2000-02	2024-02	0000723125	2000-03	2024-08	0001262039	2009-12	2023-12	0001670592	2018-12	2023-12
0000104894	1999-12	2023-12	0000895421	2000-02	2023-12	0001078271	2000-03	2024-06	0001730168	2009-11	2024-11	0001314727	2018-09	2024-09
0000060519	1999-12	2023-12	0000048465	2000-01	2024-10	0000927653	2000-03	2024-03	0001157408	2008-03	2024-06	0001083446	2018-06	2023-12
0000064996	1999-12	2023-12	0000072331	2000-01	2024-10	0001688568	2000-03	2024-03	0001403161	2008-03	2024-09	0001333986	2018-06	2023-12
0000065984	1999-12	2023-12	0000315189	2000-01	2024-10	0000008670	2000-03	2024-06	0001423221	2008-04	2024-10	0001609550	2018-06	2023-12
0000067716	1999-12	2023-12	0000711404	2000-01	2024-10	0000017843	2000-03	2024-06	0001410636	2008-06	2023-12	0001689796	2018-06	2023-12
0000072741	1999-12	2023-12	0000737758	2000-01	2024-10	0000021076	2000-03	2024-06	0001418135	2008-06	2023-12	0001720635	2018-06	2023-12
0000073124	1999-12	2023-12	0000771497	2000-01	2024-10	0000080424	2000-03	2024-06	0001420800	2008-06	2023-12	0001722684	2018-06	2023-12
0000073309	1999-12	2023-12	0000794170	2000-01	2024-10	0000106040	2000-03	2024-06	0001417398	2008-06	2024-09	0001723089	2018-06	2023-12
0000074208	1999-12	2023-12	0000810136	2000-01	2024-10	0000109563	2000-03	2024-06	0000700923	2008-09	2023-12	0001724521	2018-06	2023-12
0000742278	1999-12	2023-12	0000909832	2000-02	2024-09	0000040533	2000-04	2023-12	0001400810	2010-06	2023-12	0000827876	2019-09	2024-09
0000074260	1999-12	2023-12	0000883241	2000-01	2024-10	0000319201	2000-03	2024-06	0000755001	2008-12	2023-12	0001725057	2018-06	2023-12
0000078890	1999-12	2023-12	0000006281	2000-01	2024-11	0000721371	2000-03	2024-06	0001434588	2008-12	2023-12	0001261333	2018-07	2024-01
0000091142	1999-12	2023-12	0000936395	2000-01	2024-11	0000730464	2000-03	2024-06	0000913760	2009-06	2024-09	0001531152	2018-08	2024-02
0000091576	1999-12	2023-12	0000063754	2000-02	2023-11	0000789019	2000-03	2024-06	0001104485	2009-09	2023-12	0000933136	2018-09	2023-12
0000091767	1999-12	2023-12	0000795266	2000-02	2023-11	0000880117	2000-03	2024-06	0001320414	2009-09	2023-12	0001628369	2018-09	2023-12
0000093751	1999-12	2023-12	0000876167	2000-02	2023-11	0000896156	2000-03	2024-06	0001464423	2009-09	2023-12	0001698990	2018-09	2023-12
0000097216	1999-12	2023-12	0000039368	2000-02	2023-12	0000912093	2000-03	2024-06	0001465128	2009-09	2023-12	0001724965	2018-09	2023-12
0000099780	1999-12	2023-12	0000070318	2000-02	2023-12	0000943819	2000-03	2024-06	0000046250	2009-09	2024-03	0001728951	2018-09	2023-12
0000103145	1999-12	2023-12	0000886982	2000-02	2023-12	0001049521	2000-03	2024-06	0000080172	2009-10	2023-12	0001736946	2018-09	2023-12
0000078814	1999-12	2023-12	0001090872	2000-01	2024-10	0000707549	2000-03	2024-06	0001433660	2008-12	2023-12	0001726978	2018-06	2023-12
0001020569	1999-12	2023-12	0000106640	2000-03	2023-12	0001109354	2002-03	2023-12	0001517302	2013-06	2023-12	0001968487	2024-02	2024-05

Appendix B: Example API Call

Example API Call: Apple Inc. (CIK: 0000320193), March 2010

Based on the following financial reports only, please provide an investment recommendation for the underlying company.

Balance Sheet:
Cash and Short-Term Investments: 23155000000.0
Cash and Cash Equivalents: 10018000000.0
Short-Term Investments, Total: 13137000000.0
Derivative Financial Instruments, Hedging, Short-Term: 77000000.0
Loans and Receivables, Net, Short-Term: 4629000000.0
Trade Accounts and Trade Notes Receivable, Net: 2886000000.0
Trade Accounts and Trade Notes Receivable, Gross: 2943000000.0
Provision for Trade Accounts and Trade Notes Receivable: 57000000.0
Receivables, Other, Total: 1743000000.0
Inventory, Total: 638000000.0
Prepaid Expenses, Short-Term: 190000000.0
Other Current Assets, Total: 3647000000.0
Deferred Tax Asset, Short-Term: 1142000000.0
Other Current Assets: 2505000000.0
Total Current Assets: 32336000000.0
Investments, Long-Term: 18549000000.0
Investments, Available-for-Sale, Held-to-Maturity, Long-Term: 18549000000.0
Marketable Securities, Long-Term: 18549000000.0
Property, Plant, and Equipment, Net, Total: 3504000000.0
Property, Plant, and Equipment, Excluding Assets Leased Out, Net, Total: 3504000000.0
Property, Plant, and Equipment, Gross, Total: 5555000000.0
Property, Plant, and Equipment, Excluding Assets Leased Out, Gross: 5555000000.0
Land and Buildings, Gross: 2968000000.0
Leasehold Improvements, Gross: 1798000000.0
Plant, Machinery, and Equipment, Gross: 2587000000.0
Property, Plant, and Equipment, Accumulated Depreciation, Total: 2051000000.0
Property, Plant, and Equipment, Excluding Assets Leased Out, Accumulated Depreciation, Total: 2051000000.0
Other Non-Current Assets, Total: 1845000000.0
Deferred Tax Asset, Long-Term: 129000000.0
Other Non-Current Assets: 1716000000.0
Intangible Assets, Total, Net: 823000000.0
Goodwill, Cost in Excess of Assets Purchased, Net: 480000000.0
Intangible Assets, Excluding Goodwill, Net, Total: 343000000.0
Intangible Assets, Other, Net: 343000000.0
Total Non-Current Assets: 24721000000.0
Total Assets: 57057000000.0
Trade Accounts Payable and Accruals, Short-Term: 6897000000.0
Trade Accounts and Trade Notes Payable, Short-Term: 5666000000.0
Accrued Expenses, Short-Term: 1231000000.0
Income Tax Payable, Short-Term: 255000000.0
Other Current Liabilities, Total: 5077000000.0
Deferred Income, Short-Term: 2885000000.0
Other Current Liabilities: 2192000000.0
Total Current Liabilities: 12229000000.0
Deferred Tax, Investment Tax Credits, Long-Term: 3241000000.0
Deferred Tax Liability, Long-Term: 3241000000.0
Other Non-Current Liabilities, Total: 2239000000.0
Deferred Revenue, Long-Term: 941000000.0
Other Non-Current Liabilities: 1298000000.0
Total Non-Current Liabilities: 5480000000.0
Total Liabilities: 17709000000.0
Shareholders' Equity, Parent Shareholders, Total: 39348000000.0
Common Equity, Parent Shareholders: 39348000000.0
Common Equity, Contributed: 9553000000.0
Common Share Capital, Including Share Premium, Total: 9553000000.0
Equity, Non-Contributed Reserves and Retained Earnings: 29795000000.0
Retained Earnings, Total: 29670000000.0
Comprehensive Income, Accumulated, Total: 125000000.0
Investments, Unrealized Gains/Losses: 125000000.0
Common Equity, Total: 39348000000.0
Total Shareholders' Equity: 39348000000.0
Total Liabilities and Equity: 57057000000.0
Common Shares Issued, Total: 25469293322.1336
Common Shares Outstanding, Total: 25469293322.1336
Common Shares, Treasury, Total: 0.0
Common Shares, Issued, Issue: 25469293322.1336
Common Shares, Outstanding, Issue: 25469293322.1336
Common Shares, Treasury, Issue: 0.0
Asset Allocation Factor, Issue: 1.0
Derivative Financial Instruments, Hedging, Total: 77000000.0
Investments, Total: 31686000000.0
Loans and Receivables, Total: 4629000000.0
Accounts and Notes Receivable, Trade, Gross, Total: 2943000000.0
Other Assets, Total: 5492000000.0
Income Tax Payable, Long-Term and Short-Term: 255000000.0
Payable and Accrued Expenses: 6897000000.0
Trade Accounts Payable, Total: 5666000000.0
Accrued Expenses: 1231000000.0
Net Debt: -23155000000.0
Accruals, Short-Term: 10089000000.0
Asset Accruals: 46559000000.0
Cash and Cash Equivalents, Total: 10018000000.0
Cash and Short-Term Investments, Total: 23155000000.0
Investments, Permanent: 18549000000.0
Net Book Capital: 16193000000.0
Net Operating Assets: 16193000000.0
Provisions, Total: 3241000000.0
Shareholders' Equity, Common: 39348000000.0
Cash and Short-Term Investments, Net of Debt: 23155000000.0
Tangible Total Equity: 38525000000.0
Tangible Book Value: 38525000000.0
Total Book Capital: 39348000000.0
Total Capital: 39348000000.0
Total Long-Term Capital: 44828000000.0
Total Fixed Assets, Net: 24241000000.0

Unearned Revenue, Total: 3826000000.0
Working Capital: 20107000000.0
Working Capital, Non-Cash: -3048000000.0
Working Capital, Excluding Other Current Assets and Liabilities: 21537000000.0
Book Value, Excluding Other Equity: 39348000000.0
Net Debt, Including Preferred Equity and Minority Interest: -23155000000.0
Other Short-Term and Long-Term Assets, Total: 5492000000.0
Other Short-Term and Long-Term Liabilities, Total: 6375000000.0
Total Current Assets, Excluding Total Inventory: 31698000000.0
Tangible Book Value, Excluding Other Equity: 38525000000.0
Trade Accounts and Trade Notes Receivable, Net, Total: 2886000000.0
Provision for Doubtful Accounts and Notes Receivable, Total: 57000000.0
Current Assets, Excluding Cash and Short-Term Investments, Total: 9181000000.0
Cash, Short-Term Investments, and Accounts Receivable, Total: 26041000000.0
Cash In Hand and With Banks, Total: 1773000000.0

Income Statement:
Revenue from Goods and Services: 13499000000.0
Sales of Goods and Services, Net, Unclassified: 13499000000.0
Total Revenue: 13499000000.0
Cost of Operating Revenue: 7874000000.0
Cost of Goods Sold, Total: 7874000000.0
Gross Profit, Industrial Property, Total: 5625000000.0
Selling, General and Administrative Expenses, Total: 1646000000.0
Selling, General and Administrative Expenses, Unclassified: 1112000000.0
Labor Related Expenses, Including Stock-Based Compensation in SGA: 108000000.0
Research and Development Expenses: 426000000.0
Operating Expenses, Total: 9520000000.0
Operating Profit Before Non-Recurring Income and Expenses: 3979000000.0
Other Non-Operating Income and Expenses, Total: 50000000.0
Provision for Income Tax, Unclassified: 955000000.0
Normalized Pretax Profit: 4029000000.0
Income Before Tax: 4029000000.0
Income Tax Expense: 955000000.0
Net Income After Tax: 3074000000.0
Income Before Discontinued Operations and Extraordinary Items: 3074000000.0
Net Income Before Minority Interest: 3074000000.0
Net Income After Minority Interest: 3074000000.0
Income Available to Common Shareholders: 3074000000.0
Net Income, Basic, Including Extraordinary Items, Common, Total: 3074000000.0
Income Available to Common Shareholders, Excluding Extraordinary Items: 3074000000.0
Shares Used to Calculate Basic EPS, Total: 25411344000.0
EPS, Basic, Including Extraordinary Items, Common, Total: 0.12097
EPS, Basic, Excluding Extraordinary Items, Common, Total: 0.12097
EPS, Basic, Excluding Extraordinary Items, Normalized, Total: 0.12097
EPS, Basic, Including Extraordinary Items, Common Issue: 0.12097
EPS, Basic, Excluding Extraordinary Items, Common Issue: 0.12097
EPS, Basic, Excluding Extraordinary Items, Normalized Issue: 0.12097
EPS, Basic, Discontinued Operations and Extraordinary Items: 0.0
Net Income, Diluted, Including Extraordinary Items, Common, Total: 3074000000.0
Diluted Income Available to Common Shareholders, Excluding Extraordinary Items: 3074000000.0
Shares Used to Calculate Diluted EPS, Total: 25840584000.0
EPS, Diluted, Including Extraordinary Items, Common, Total: 0.11896
EPS, Diluted, Excluding Extraordinary Items, Common, Total: 0.11896
EPS, Diluted, Excluding Extraordinary Items, Normalized, Total: 0.11896
EPS, Diluted, Including Extraordinary Items, Common Issue: 0.11896
EPS, Diluted, Excluding Extraordinary Items, Common Issue: 0.11896
EPS, Diluted, Excluding Extraordinary Items, Normalized Issue: 0.11896
EPS, Diluted, Discontinued Operations and Extraordinary Items: 0.0
Dividends Per Share, Common, Gross, Issue: 0.0
Dividends Per Share, Common, Net, Issue: 0.0
Earnings Before Interest and Taxes: 3979000000.0
Earnings Before Interest, Taxes, Depreciation, and Amortization: 4195000000.0
Depreciation and Amortization, Supplemental: 216000000.0
Depreciation Expense, Total, Supplemental: 216000000.0
Depreciation, Depletion, and Amortization, Total: 216000000.0
Depreciation, Total: 216000000.0
Research and Development Expense, Capitalized, Total, Supplemental: 426000000.0
Research and Development, Supplemental: 426000000.0
Stock-Based Compensation Expense, Net of Tax, Supplemental: 138600000.0
Stock-Based Compensation Expense, Pretax, Supplemental: 231000000.0
Stock-Based Compensation Tax Benefit, Supplemental: 92400000.0
Normalized After-Tax Profit: 3074000000.0
Normalized Net Income from Continuing Operations: 3074000000.0
Normalized Net Income, Bottom Line: 3074000000.0
EBIT, Normalized: 4029000000.0
EBITDA, Normalized: 4245000000.0
Income Before Tax and Provision for Loan Losses: 4029000000.0
Cost of Goods Sold, Including Operating, Maintenance, and Utilities, Total: 7874000000.0
Cost of Goods Sold, Excluding Depreciation: 7874000000.0
Operating Expenses: 9520000000.0
Selling, General and Administrative Expenses, Excluding Research and Development: 1220000000.0
Dividends Per Share, Common, Gross, Issue, By Ex-Date: 0.0
Dividends Per Share, Common, Gross, Issue, By Payable Date: 0.0
Dividends Per Share, Common, Gross, Issue, By Period End Date: 0.0
Tax Adjusted Operating Income: 3074000000.0
Operating Expenses, Excluding Non-Cash Charges, Total: 9304000000.0
Income Available to Common Shareholders Before Depreciation and

Amortization: 3290000000.0
Estimated Tax Rate: 0.4

Cash Flow Statement
Profit/Loss Starting Line (Cash Flow): 3074000000.0
Non-Cash Items Reconciliation Adjustments (Cash Flow): 918000000.0
Depreciation, Depletion, Amortization, Including Impairment (Cash Flow): 216000000.0
Depreciation, Depletion of Property, Plant, and Equipment (Cash Flow): 216000000.0
Deferred Income Tax and Income Tax Credits (Cash Flow): 468000000.0
Assets Sale Gain/Loss (Cash Flow): 3000000.0
Share-Based Payment (Cash Flow): 231000000.0
Cash Flow from Operations Before Changes in Working Capital: 3992000000.0
Working Capital (Cash Flow): -1662000000.0
Accounts Receivable (Cash Flow): 211000000.0
Inventory (Cash Flow): -62000000.0
Other Assets (Cash Flow): -205000000.0
Accounts Payable (Cash Flow): -974000000.0
Other Liabilities, Total (Cash Flow): -632000000.0
Net Cash Flow from Operations: 2330000000.0
Capital Expenditures, Net (Cash Flow): 301000000.0
Property, Plant, and Equipment, Net (Cash Flow): 274000000.0
Property, Plant, and Equipment Purchases (Cash Flow): 274000000.0
Intangible Assets, Net, Total (Cash Flow): 27000000.0
Intangible Assets Purchased/Acquired (Cash Flow): 27000000.0
Capital Expenditures, Total: 301000000.0
Acquisition/Disposal of Business and Assets Sold/Acquired, Net (Cash Flow): -325000000.0
Acquisition of Business (Cash Flow): 325000000.0
Investments Excluding Loans (Cash Flow): 460000000.0
Investment Securities Sold/Purchased, Net, Total (Cash Flow): 460000000.0
Investment Securities Sold/Matured (Cash Flow): 12602000000.0
Investment Securities Purchased (Cash Flow): 12142000000.0
Other Investing Cash Flow: 83000000.0
Net Cash Flow from Investing Activities: -83000000.0
Stock, Total, Issuance/Retirement, Net (Cash Flow): 160000000.0
Stock Issuance/Retirement, Net, Excluding Options and Warrants (Cash Flow): 160000000.0
Common Stock, Net (Cash Flow): 160000000.0
Common Stock Issued/Sold (Cash Flow): 160000000.0
Debt, Long-Term and Short-Term, Issuance/Retirement, Total (Cash Flow): 161000000.0
Debt Issued/Reduced, Short-Term, Total (Cash Flow): 161000000.0
Debt Issued, Short-Term (Cash Flow): 161000000.0
Other Financing Cash Flow: -159000000.0
Net Cash Flow from Financing Activities: 162000000.0
Net Change in Cash, Total: 2409000000.0
Net Cash from Continuing Operations: 2409000000.0
Net Cash, Beginning Balance: 7609000000.0
Net Cash, Ending Balance: 10018000000.0
Income Tax Paid/Reimbursed (Cash Flow Supplement): 1164000000.0
Cash Flow from Operations Before Changes in Working Capital and Interest: 3992000000.0
Common Stock Buyback, Net: -160000000.0
Depreciation, Depletion, Amortization (Cash Flow): 216000000.0
Free Cash Flow to Equity: 2190000000.0
Free Operating Cash Flow: 2029000000.0
Levered Free Operating Cash Flow: 2029000000.0

Provide your answer using only one of the following signals: 'buy', 'hold' or 'sell'.

Eidesstattliche Erklärung

Ich versichere an Eides Statt, dass ich die Arbeit selbstständig verfasst, keine anderen als die angegebenen Hilfsmittel und Quellen benutzt habe, alle wörtlich oder sinngemäß aus anderen Werken übernommenen Aussagen als solche gekennzeichnet habe und dass die Arbeit weder vollständig noch in wesentlichen Teilen Gegenstand eines anderen Prüfungsverfahrens gewesen ist und dass ich die Arbeit weder vollständig noch in wesentlichen Teilen bereits veröffentlicht habe sowie dass das in Dateiform eingereichte Exemplar mit den eingereichten gebundenen Exemplaren übereinstimmt.

Ort, Datum Unterschrift