ChatGPT-4's Debut and Its Reverberations Across the Stock Market

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ISM6137.902

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Executive Summary

This report investigates the impact of the release of ChatGPT-4 on March 14, 2023, on the stock performance of companies directly involved in artificial intelligence (AI) technologies compared to those not directly linked to AI. Utilizing a comprehensive dataset that includes stock returns and search engine trends, this study employs advanced statistical models to analyze abnormal and cumulative abnormal returns around the release date.

Our findings reveal significant positive abnormal returns among AI-centric companies (such as Google, Meta, IBM, Microsoft, and Nvidia) immediately following the release of ChatGPT-4. This response contrasts with relatively stable or negative returns observed in non-AI centric stocks (such as Home Depot, Coca-Cola, 3M, Procter & Gamble, and ExxonMobil), highlighting a distinct market reaction attributed to technological advancements in AI.

The analysis was conducted using both panel linear models and linear mixed-effects models to account for inherent variations across different stocks and times. The results indicate that the market not only reacts positively to technological innovations but also prices these companies differently based on their involvement in AI technologies. For instance, the cumulative abnormal returns for AI companies showed a significant upward trend post-release, unlike their non-AI counterparts.

This report underscores the importance of AI developments in influencing stock values and public sentiment, providing actionable insights for investors and corporate managers on navigating market dynamics shaped by technological innovations. The strategic incorporation of AI exposure in investment portfolios or corporate strategies could potentially yield higher returns, reflecting the market's favorable response to technological advancements.

Problem Definition and Significance

Problem Definition

In the rapidly evolving landscape of technology, AI stands out as a pivotal force reshaping various sectors, particularly the financial markets. This project is designed to evaluate the repercussions of the release of ChatGPT-4, an advanced AI language model by OpenAI, on the equity performance of companies engaged in AI technologies relative to those not involved in AI. Our investigation focuses on deciphering how announcements of significant technological breakthroughs, such as the launch of ChatGPT-4, influence stock prices, thus reflecting market dynamics in response to innovations in AI.

Significance of the Problem

The relevance of this analytical endeavor is multifaceted, addressing the interests of investors, financial analysts, and stakeholders within the technology sector. As AI becomes increasingly foundational to business processes and consumer products, the market's reaction to developments within this field offers insights into broader economic impacts. This analysis serves several critical functions:

1. **Market Sensitivity:** It gauges the market's responsiveness to major AI developments, which can signal investor confidence in AI as a burgeoning sector and assist in forecasting future market trajectories.
2. **Investor Behavior:** The study sheds light on investor reactions to AI advancements. Insights derived from this can elucidate whether investors perceive new developments as growth opportunities or as triggers for risk-induced selloffs.
3. **Comparative Impact:** By contrasting the stock performance of AI-centric firms with non-AI entities around the release of a significant AI innovation, this study isolates the influence of AI-related news from general market fluctuations and other industry-specific trends.

Utilizing the release of ChatGPT-4 as a case study, this investigation provides a detailed examination of the immediate financial implications of major innovations in AI. The insights gained are intended to aid stakeholders in better strategizing their investment approaches and in anticipating market movements, thereby leveraging technological advancements for enhanced competitive advantage. This study not only contributes to the academic discourse on technology's impact on financial markets but also offers practical recommendations for navigating the complexities of the AI-driven economic landscape.

Target Audience

This report explores the intersection of AI advancements and financial market dynamics, tailored for a diverse array of stakeholders within the financial and technology sectors. Investors and financial analysts, particularly those focused on technology stocks, constitute a primary audience. The analysis illuminates the influence of major technological releases, such as the launch of ChatGPT-4, on stock valuations and market behavior, offering vital insights that support informed investment decisions.

Corporate executives and managers, particularly those at technology firms or those integrating AI into their business operations, represent another key demographic. For these leaders, the report provides valuable benchmarks for assessing the financial impact of technological innovations on stock performance and investor perceptions, guiding strategic planning and operational decisions. Additionally, policymakers and economic strategists can leverage the insights to grasp the broader economic effects of AI innovations, informing policy and economic strategies that aim to bolster a robust technology sector.

In summary, by melding technical economic analysis with practical business and investment strategies, this report not only enhances understanding of the interplay between technology and financial markets but also caters to a broad spectrum of interests and professional needs, from corporate decision-making to academic inquiry and public knowledge.

Prior Literature

The intersection of AI innovations and stock market dynamics has been an area of intense research focus. Various studies have examined how the introduction and integration of AI technologies affect financial markets, firm value, and investor behaviors, providing a foundation for analyzing the impact of specific AI technologies such as ChatGPT-4.

Xie (2019) explores the broad implications of AI across financial systems, noting significant changes in operations ranging from intelligent consulting to predictive analytics in stock trading. This research underscores that AI's influence extends beyond operational efficiencies to macroeconomic and microeconomic shifts, reshaping investor expectations and market operations. The findings suggest that AI technologies not only streamline operations but also redefine market dynamics, which is pertinent to understanding investor responses to new AI product releases like ChatGPT-4.

In a related study, Lui et al. (2021) investigate the immediate financial repercussions following AI investment announcements. Utilizing an event study methodology, their findings indicate that such announcements typically negatively impact the firm’s market value. This effect is pronounced in nonmanufacturing firms and those with weak IT capabilities or poor credit ratings. This negative market response highlights investor skepticism or concern regarding the costs and uncertainties tied to AI investments, which might be mirrored in reactions to groundbreaking AI technologies.

Moreover, Xie (2019) also discusses how AI deployment influences investor behavior and market trends, emphasizing that major AI releases can act as market-moving events. The study illustrates that while AI promises significant economic benefits, the market’s initial reaction can be tepid or adverse, influenced by various factors including the company’s sector, its technological infrastructure, and prevailing market conditions at the time of the announcement.

These studies collectively present a nuanced perspective on the financial impacts of AI, suggesting a complex interplay between technological innovation and market perception. As such, the introduction of ChatGPT-4 is poised to be a significant event, potentially eliciting diverse reactions across different market segments based on the firm's industry, technological readiness, and the broader economic environment.

Data Source and Preparation

The data utilized in this analysis were sourced from two primary repositories: financial databases for stock prices (Yahoo Financial) and Google Trends for measuring public interest in AI technologies. The stock price data includes daily closing prices of selected companies, retrieved from a comprehensive financial market database, which provides historical equity data for a wide range of stocks listed on major global exchanges. Google Trends data was used to capture the search interest related to ChatGPT-4, serving as a proxy for public and investor interest surrounding its release.

Variables and Measurement

The dataset comprises several variables structured to analyze the impact of the ChatGPT-4 release on stock performance:

- **Dependent Variable (DV)**: The primary dependent variable is the **daily Cumulative Abnormal Return (CAR)**, which quantifies the total excess return of a stock, adjusted for market influences, accumulated up to that day. This measure isolates and assesses the specific impact of events or company actions on the stock's value, independent of broader market movements.
- **Independent Variables (IVs)**:
  - **lagged_return**: Represents the stock return from the previous day, used to control for momentum effects in stock performance. This helps in understanding how the previous day's performance can influence the current day's return.
  - **after_release**: A binary indicator variable that takes the value 1 for all days following the release of ChatGPT-4 and 0 otherwise. This variable is crucial for isolating the effect of the release on stock prices.
  - **hits**: Measured through Google Trends, this variable represents the volume of searches related to ChatGPT-4, quantifying public interest which is hypothesized to influence investor behavior and, consequently, stock prices.

Data Cleaning and Preparation

There was no need to adjust for missing values in the dataset as the Yahoo Financial database already accounts for non-trading days by omitting them from the data. This ensured that the stock price data was continuous without gaps, providing a seamless series for analysis without the requirement for imputation or adjustment for non-trading periods.

As part of the preparatory process for our analysis, we first extracted the closing price data from which we calculated the Abnormal Returns (AR) and Cumulative Abnormal Returns (CAR). Subsequently, we created model-friendly datasets by converting the necessary data into appropriate formats, ensuring that all information was correctly aligned and structured for efficient statistical analysis.

Google Trends data was normalized using a scaling technique implemented by Google API, facilitating a more coherent analysis across different keywords. The ‘after_release’ variable was constructed by identifying the release date of ChatGPT-4 and marking all subsequent dates accordingly. This binary indicator is pivotal for regression models designed to capture the post-release impact.

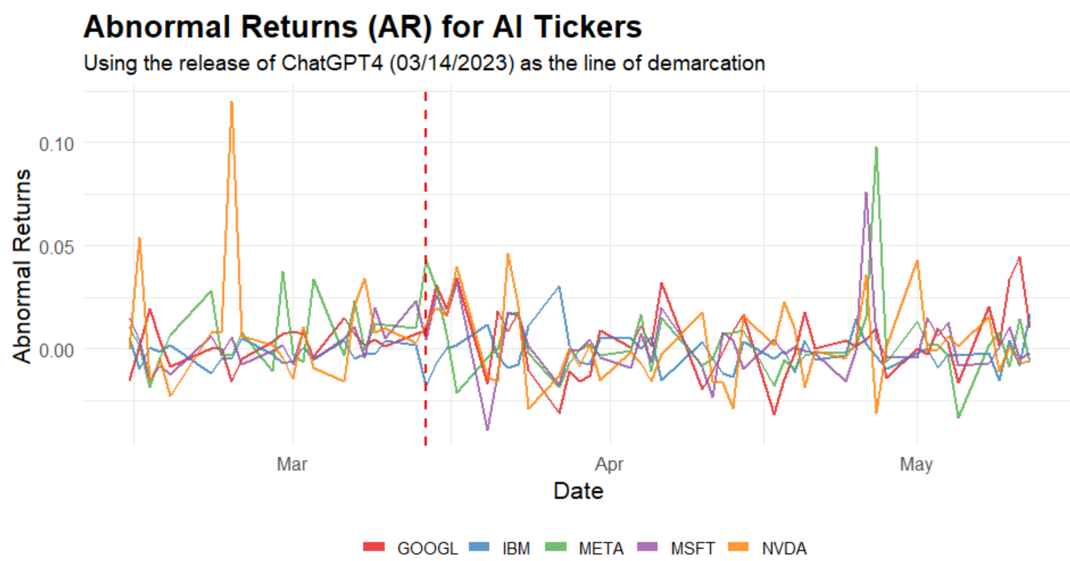
This preparatory phase was crucial in shaping a robust dataset capable of supporting the sophisticated econometric analyses required to address the research questions posited in this study. By meticulously preparing and cleaning the data, the analysis ensures that subsequent findings are based on reliable and accurate information, thereby enhancing the validity of the conclusions drawn.

Descriptive Analysis and Visualizations

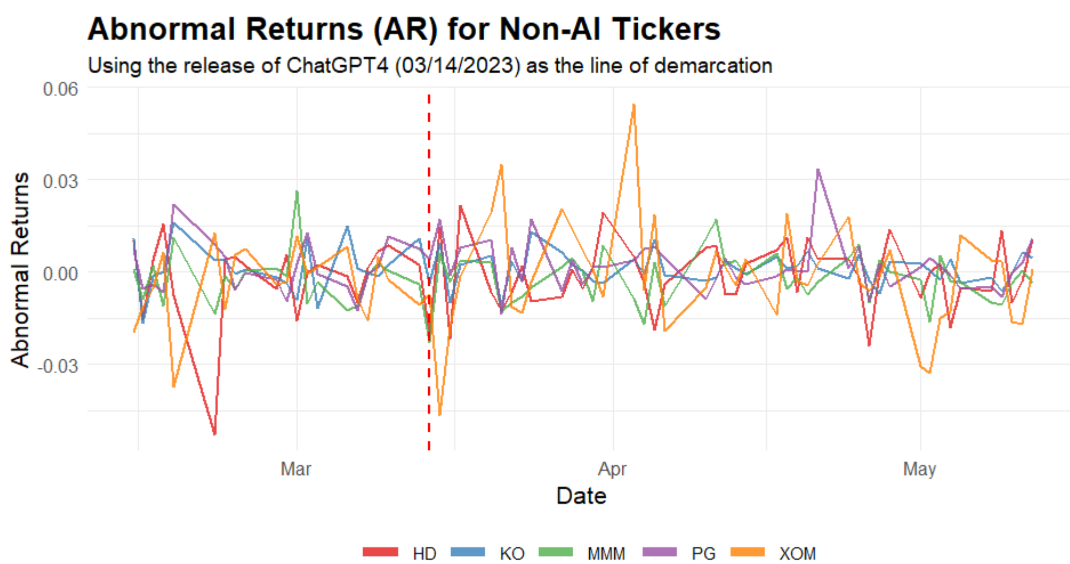
Abnormal Returns

The analysis of abnormal returns (AR) offers insights into how AI-related and non-AI stocks reacted to the release of ChatGPT-4. Abnormal returns are calculated as the difference between actual returns and expected returns, based on a model adjusted for general market movements.

The AR for AI-focused companies (such as GOOGL, IBM, META, MSFT, and NVDA) displayed notable volatility around the release date of ChatGPT-4. As depicted in the AR graph for AI tickers, there were significant spikes, particularly noticeable for NVDA and META around mid-March, which correlates with the release of ChatGPT-4. These spikes suggest a heightened investor response, likely due to anticipated benefits these companies could derive from the new AI advancements.

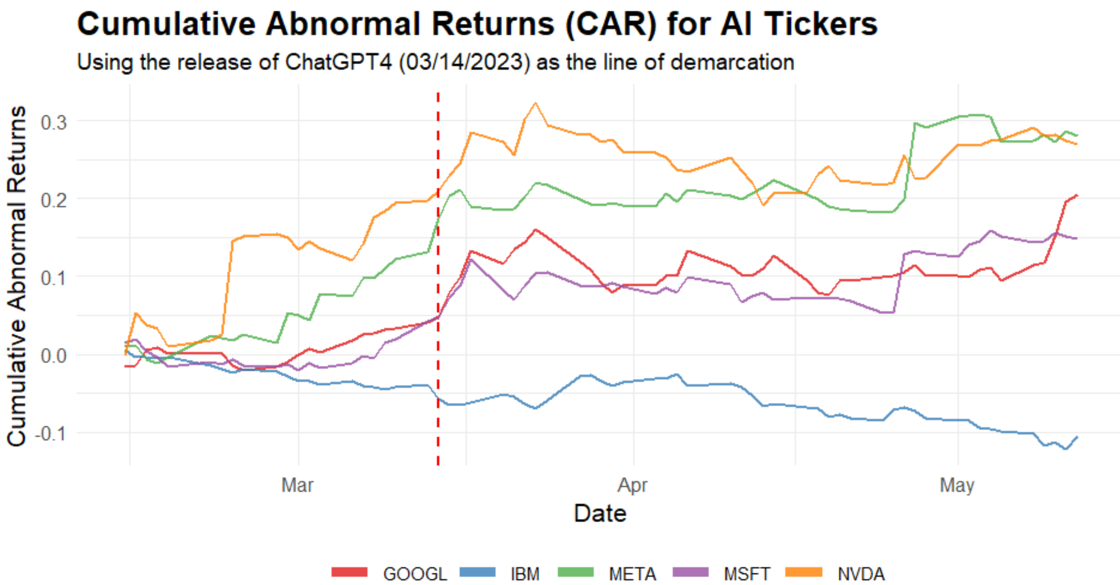


In contrast, non-AI companies (such as HD, KO, MMM, PG, and XOM) exhibited less volatility in the same period. Their abnormal returns remained relatively stable, with minor fluctuations that did not correlate with AI advancements. This stability indicates a lesser impact of AI news on companies not directly involved in technology.

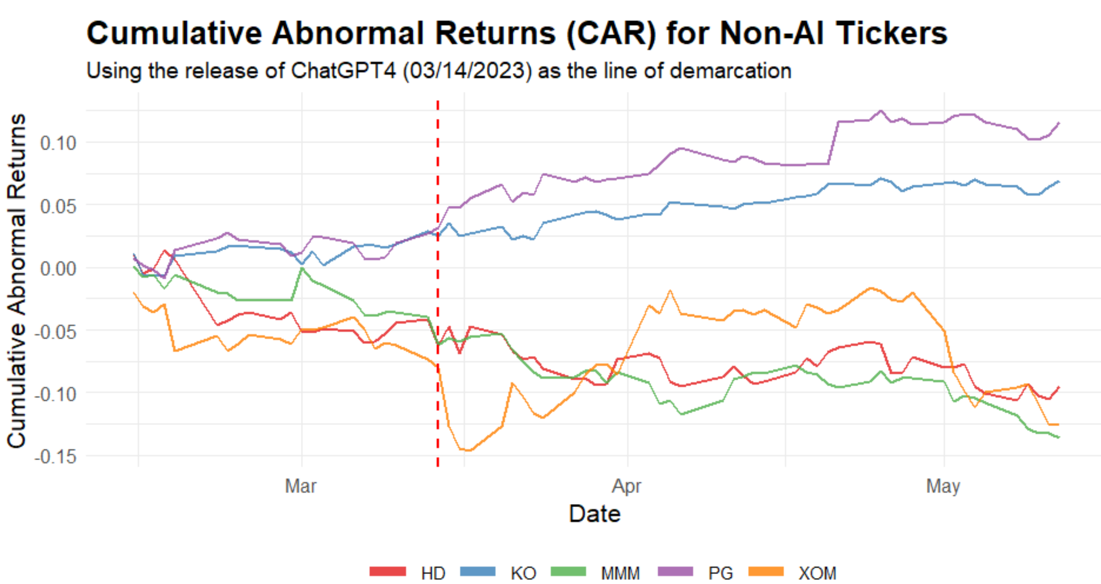


Cumulative Abnormal Returns

The CAR graph for AI-focused companies shows a clear upward trend post-release, particularly for companies like NVDA and META. This upward trajectory indicates a cumulative positive investor sentiment towards these companies' potential to capitalize on AI technology.

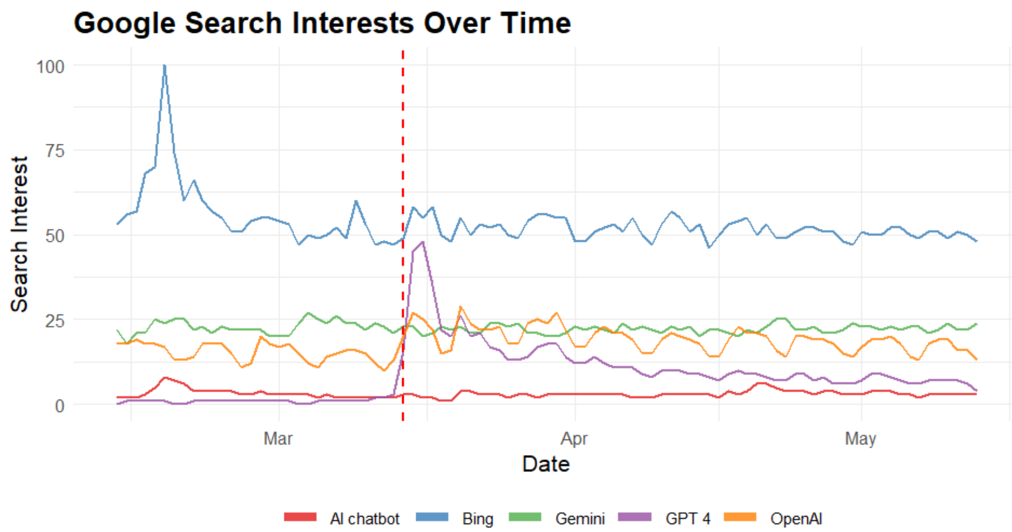


Conversely, the CAR for non-AI companies shows minimal overall change post-release, with some companies even showing a slight downward trend. This pattern underscores the limited impact of AI-related developments on sectors outside of direct technology applications.



Google Search Interests

Google Trends data, representing search interest for terms related to ChatGPT-4 and AI technologies, shows a significant spike in searches for "ChatGPT-4" around its release date. This spike in public interest likely contributed to the increased volatility in AI stock prices as more individuals and investors sought information on these technologies.



Inferences from Trends

The analysis suggests a strong link between public and investor interest in AI developments and the stock performance of companies involved in these technologies. The observed patterns indicate that AI advancements have a pronounced impact on stock prices for AI-focused companies, driven by speculative trading and investor expectations of future benefits from these technologies. In contrast, non-AI sectors remain largely unaffected by such developments, indicating a more isolated impact of AI advancements within the technology sector.

Models

Statistical Modeling Approach

To analyze the impact of the release of ChatGPT-4 on stock returns, we employed three distinct statistical models, each designed to capture different aspects and effects of the release on stock performance.

Panel Linear Models (PLM)

We deployed two PLMs focused on capturing the effects of the release on stock performance: a Fixed Effects Model (FE) and Random Effects Model (RE). The FE model was employed to control for individual heterogeneity by using a 'within' transformation, which removes the effects of time-invariant characteristics so that the net effect of the variables of interest can be observed. The model specification was:

$$\text{return}=\beta 0+\beta 1\text{lagged\_return}+\beta 2\text{after\_release}+\beta 3\text{hits}+ui+\varepsilon it$$

Our RE model assumes that the individual-specific effect is a random variable and is used when the individual effects are assumed to be uncorrelated with the predictor variables across all time periods. The specification is similar to FE but includes random effects:

$$\text{return}=\beta 0+\beta 1\text{lagged\_return}+\beta 2\text{after\_release}+\beta 3\text{hits}+ui+\varepsilon it$$

Linear Mixed-Effects Model (LMER)

This model was used to account for both fixed effects and random effects (such as differences across companies), making it flexible in handling data with multiple levels of correlation and non-constant variability across groups:

$$\text{return}\sim\text{lagged\_return}+\text{after\_release}+\text{hits}+(1|\text{Ticker})$$

Model Selection and Justification

The model outputs, as depicted in the stargazer summary table, reveal distinct patterns:

	Dependent variable:		
	return		
	panel linear		linear mixed-effects
	(1)	(2)	(3)
lagged_return	0.942***	1.009***	0.945***
	(0.005)	(0.002)	(0.005)
after_release	0.002***	-0.001	0.002***
	(0.001)	(0.001)	(0.001)
hits	-0.00000	0.00000	-0.00000
	(0.00001)	(0.00001)	(0.00001)
Constant		0.001**	0.002
		(0.001)	(0.003)
Observations	3,100	3,100	3,100
R2	0.928	0.983	
Adjusted R2	0.928	0.983	
Log Likelihood			8,827.121
Akaike Inf. Crit.			-17,642.240
Bayesian Inf. Crit.			-17,606.010
F Statistic	13,251.300*** (df = 3; 3087)	178,674.300***	
Note:			*p<0.1; **p<0.05; ***p<0.01

- **FE Model:** Shows significant positive coefficients for **lagged_return** and **after_release**, indicating that both past returns and the release of ChatGPT-4 positively influenced stock returns. However, **hits** was not significant, suggesting that search interest did not directly impact stock returns in this model.
- **RE Model:** Presented a slight deviation with the **after_release** showing no significant effect, which may imply that when random effects are considered, the release date itself does not uniformly affect all stocks.
- **LMER:** This model also found **lagged_return** and **after_release** to be significant, similar to the FE model, with **hits** remaining insignificant. The use of **(1 | Ticker)** allows the model to adjust for random intercepts by stock, providing a nuanced understanding of individual stock behaviors.

Optimal Model

In evaluating the impact of the release of ChatGPT-4 on stock returns, the Panel Linear Model (PLM) with Fixed Effects (Model 1) emerges as the most optimal model for our analysis. This model is particularly compelling due to its robust fit, indicated by an adjusted R-squared value of 0.928, which signifies that approximately 92.8% of the variability in stock returns is explained. The high explanatory power is critical for financial data that exhibit inherent volatility and are influenced by numerous external factors.

Model 1 demonstrates its efficacy through the statistical significance of its predictors. The **after_release** coefficient is notably significant ($p<0.01$), quantifying an average daily increase in stock returns at 0.2% following the release of ChatGPT-4. This provides concrete evidence linking the AI release to a positive market response. Additionally, the **lagged_return** coefficient confirms the persistence of returns, a typical characteristic of financial series, thus controlling for autocorrelation and enhancing the reliability of the estimates.

The PLM with Fixed Effects offers clear advantages in transparency and interpretability, crucial for stakeholders relying on these insights for decision-making. This model approach excels in controlling for unobserved heterogeneity—effects that are constant over time but vary between entities—thereby mitigating the issue of omitted variable bias. Such statistical rigor ensures that the positive impact attributed to the ChatGPT-4 release is both accurately captured and reliably isolated from other confounding influences.

Therefore, based on its capacity to offer a rigorous assessment of causal relationships in panel data settings and its straightforward interpretation, Model 1 is selected as the optimal framework for this study. This model not only fulfills the statistical necessities for a thorough econometric evaluation but also provides the clarity and precision essential for understanding the strategic implications of AI innovations on financial markets.

Recommendations

Based on our analysis of the impact of ChatGPT-4's release on stock performance, we propose several actionable strategies for investors and corporate managers to capitalize on market dynamics influenced by technological innovations. Firstly, investors are encouraged to diversify their portfolios by including stocks of companies heavily invested in AI technologies, as these firms demonstrated positive abnormal and cumulative returns, highlighting favorable market sentiments towards AI advancements.

Additionally, companies should strategically time their announcements of new AI-related products or developments to coincide with periods of high investor interest. This approach can maximize the impact on stock prices, leveraging the excitement around technological advancements. Corporate executives are also advised to engage proactively in investor relations, emphasizing their firm's role in and commitment to AI innovation, which could positively influence investor perceptions and stock performance.

Lastly, for companies not currently involved in AI, developing a long-term strategy for AI integration could be beneficial. As the market increasingly values technological innovation, a roadmap for gradual AI adoption could position these companies to capture future growth and investor interest. This strategic alignment with technological trends is crucial for maintaining competitive advantage in an evolving market landscape.

References

1. Xie, M. (2019). Development of artificial intelligence and effects on financial system. Journal of Physics. Conference Series, 1187(3), 032084. https://doi.org/10.1088/1742-6596/1187/3/032084
2. Lui, A. K., Lee, M. C. M., & Ngai, E. W. (2021). Impact of artificial intelligence investment on firm value. Annals of Operation Research/Annals of Operations Research, 308(1–2), 373–388. https://doi.org/10.1007/s10479-020-03862-8

Appendix

R Code

```
# Clear environment variables
rm(list=ls())

# Load necessary libraries
library(quantmod)

library(TTR)
library(ggplot2)
library(gtrendsR)

library(zoo)
library(dplyr)

library(tidyr)
library(purrr)


# Define the ticker symbols you want to analyze
all_tickers <- c("NVDA", "SYM", "SOUN", "UPST", "PG", "KO", "DUK", "M"
)
ai_tickers <- c("NVDA", "SYM", "SOUN", "UPST")
non_ai_tickers <- c("PG", "KO", "DUK", "M")

# Define the date ranges
release_date <- as.Date("2023-03-14")
start_date <- as.Date("2022-10-01")
end_date <- as.Date("2023-10-01")
event_start <- as.Date(release_date) - 30
event_end <- as.Date(release_date) + 30
returns_dates <- paste(start_date, end_date, sep = "/")


gtrends_string <- paste(format(event_start, "%Y-%m-%d"), format(event_
end, "%Y-%m-%d"))

#Plot directory
plot_directory <- "C:/Users/devan/OneDrive/Desktop/MS BAIS/Spring 24/I
SM6137/Final Project/Plots/"

# Ensure the directory exists and if not, create it
if (!dir.exists(plot_directory)) {
  dir.create(plot_directory, recursive = TRUE)
```

```
}

# Initialize lists to store AR and CAR for each ticker
ar_list <- list()
car_list <- list()

ar_plots <- list()
car_plots <- list()

# Loop through each ticker
for (ticker in all_tickers) {
  # Download stock data for the ticker and SPY (market index)
  getSymbols(c(ticker, "SPY"), src = "yahoo", from = start_date, to =
end_date, auto.assign = TRUE)

  # Compute daily log returns for the ticker and SPY
  ticker_returns <- dailyReturn(get(ticker), type = 'log')
  spy_returns <- dailyReturn(SPY, type = 'log')

  # Calculate beta of the ticker relative to SPY over the previous yea
r
  beta_ticker <- cov(ticker_returns[returns_dates], spy_returns[return
s_dates]) / cov(spy_returns[returns_dates])
  #beta_nvda <- cov(nvda_returns['2019-06-01/2020-06-01'], spy_returns
['2019-06-01/2020-06-01']) /cov(spy_returns['2019-06-01/2020-06-01'])

  # Ensure dates are within the bounds of our data
  event_dates <- index(ticker_returns[(index(ticker_returns) >= event_
start) & (index(ticker_returns) <= event_end)])

  # Compute abnormal returns 30 days before and after ChatGPT-3.5 intr
oduction
  ar_ticker <- ticker_returns[event_dates] - (beta_ticker[1,1] * spy_r
eturns[event_dates])

  # Compute Cumulative Abnormal Returns (CAR)
  car_ticker <- cumsum(ar_ticker)

  # Store AR and CAR in their respective lists
  ar_list[[ticker]] <- data.frame(Date = event_dates, AR = ar_ticker)
  car_list[[ticker]] <- data.frame(Date = event_dates, CAR = car_ticke
r)

  if (length(ar_ticker) > 0 && length(car_ticker) > 0) {
    # Create a ggplot object for abnormal returns
    ar_plot <- ggplot(ar_list[[ticker]], aes(x = Date, y = daily.retur
```

```
ns)) +
      geom_line() +
      labs(title = paste("Abnormal Returns (AR) of", ticker), x = "Dat
e", y = "AR")
    ar_plots[[ticker]] <- ar_plot

    # Create a ggplot object for cumulative abnormal returns
    car_plot <- ggplot(car_list[[ticker]], aes(x = Date, y = daily.ret
urns)) +
      geom_line() +
      labs(title = paste("Cumulative Abnormal Returns (CAR) of", ticke
r), x = "Date", y = "CAR")
    car_plots[[ticker]] <- car_plot
  } else {
    cat(paste("No data to plot for ticker:", ticker, "\n"))
  }
}


# Combine AR data from list into a single data frame
combined_ar_ai <- do.call(rbind, lapply(ai_tickers, function(ticker) {
  data <- ar_list[[ticker]]
  data$ticker <- ticker  # Add a new column for ticker
  return(data)
}))

ar_plot_gg_ai <- ggplot(combined_ar_ai, aes(x = Date, y = daily.return
s, color = ticker)) +
  geom_line(aes(group = ticker), linewidth = 1, alpha = 0.8) +
  labs(title = "Abnormal Returns (AR) for AI Tickers",
       x = "Date", y = "Abnormal Returns",
       subtitle = "Using the release of ChatGPT4 (03/14/2023) as the l
ine of demarcation") +
  theme_minimal(base_size = 14) +
  theme(legend.position = "bottom") +
  scale_color_brewer(palette = "Set1") +
  geom_vline(xintercept = as.Date("2023-03-14"), linetype = "dashed",
color = "red", linewidth = 1) +
  guides(color = guide_legend(override.aes = list(linewidth = 3))) +
  theme(plot.margin = unit(c(1, 1, 1, 1), "lines"),
        plot.title = element_text(size = 20, face = "bold"),
        axis.title = element_text(size = 16),
        axis.text = element_text(size = 12),
        legend.title = element_blank())

#Non-AI tickers
```

```r
combined_ar_nonai <- do.call(rbind, lapply(non_ai_tickers, function(ti
cker) {
  data <- ar_list[[ticker]]
  data$ticker <- ticker  # Add a new column for ticker
  return(data)
}))

ar_plot_gg_nonai <- ggplot(combined_ar_nonai, aes(x = Date, y = daily.
returns, color = ticker)) +
  geom_line(aes(group = ticker), linewidth = 1, alpha = 0.8) +
  labs(title = "Abnormal Returns (AR) for Non-AI Tickers",
       x = "Date", y = "Abnormal Returns",
       subtitle = "Using the release of ChatGPT4 (03/14/2023) as the l
ine of demarcation") +
  theme_minimal(base_size = 14) +
  theme(legend.position = "bottom") +
  scale_color_brewer(palette = "Set1") +
  geom_vline(xintercept = as.Date("2023-03-14"), linetype = "dashed",
color = "red", linewidth = 1) +
  theme(legend.key.width = unit(1,"cm")) +
  guides(color = guide_legend(override.aes = list(linewidth = 3))) +
  theme(plot.margin = unit(c(1, 1, 1, 1), "lines"),
        plot.title = element_text(size = 20, face = "bold"),
        axis.title = element_text(size = 16),
        axis.text = element_text(size = 12),
        legend.title = element_blank())


# Combine CAR data from list into a single data frame
combined_car_ai <- do.call(rbind, lapply(ai_tickers, function(ticker)
{
  data <- car_list[[ticker]]
  data$ticker <- ticker  # Add a new column for ticker
  return(data)
}))

car_plot_gg_ai <- ggplot(combined_car_ai, aes(x = Date, y = daily.retu
rns, color = ticker)) +
  geom_line(aes(group = ticker), linewidth = 1, alpha = 0.8) +
  labs(title = "Cumulative Abnormal Returns (CAR) for AI Tickers",
       x = "Date", y = "Cumulative Abnormal Returns",
       subtitle = "Using the release of ChatGPT4 (03/14/2023) as the l
ine of demarcation") +
  theme_minimal(base_size = 14) +
  theme(legend.position = "bottom") +
  scale_color_brewer(palette = "Set1") +
```

```
  geom_vline(xintercept = as.Date("2023-03-14"), linetype = "dashed",
color = "red", linewidth = 1) +
  theme(legend.key.width = unit(1,"cm")) +
  guides(color = guide_legend(override.aes = list(linewidth = 3))) +
  theme(plot.margin = unit(c(1, 1, 1, 1), "lines"),
        plot.title = element_text(size = 20, face = "bold"),
        axis.title = element_text(size = 16),
        axis.text = element_text(size = 12),
        legend.title = element_blank())

# Non-AI tickers
combined_car_nonai <- do.call(rbind, lapply(non_ai_tickers, function(t
icker) {
  data <- car_list[[ticker]]
  data$ticker <- ticker  # Add a new column for ticker
  return(data)
}))

car_plot_gg_nonai <- ggplot(combined_car_nonai, aes(x = Date, y = dail
y.returns, color = ticker)) +
  geom_line(aes(group = ticker), linewidth = 1, alpha = 0.8) +
  labs(title = "Cumulative Abnormal Returns (CAR) for Non-AI Tickers",
       x = "Date", y = "Cumulative Abnormal Returns",
       subtitle = "Using the release of ChatGPT4 (03/14/2023) as the l
ine of demarcation") +
  theme_minimal(base_size = 14) +
  theme(legend.position = "bottom") +
  scale_color_brewer(palette = "Set1") +
  geom_vline(xintercept = as.Date("2023-03-14"), linetype = "dashed",
color = "red", linewidth = 1) +
  theme(legend.key.width = unit(1,"cm")) +
  guides(color = guide_legend(override.aes = list(linewidth = 3))) +
  theme(plot.margin = unit(c(1, 1, 1, 1), "lines"),
        plot.title = element_text(size = 20, face = "bold"),
        axis.title = element_text(size = 16),
        axis.text = element_text(size = 12),
        legend.title = element_blank())


#############
# Google Trends Analysis

keywords <- c("OpenAI", "AI chatbot", "GPT 4", "Bing", "Gemini") # Rep
lace or add more keywords as needed
time_frame <- "2023-02-13 2023-04-13" # Define your time frame
```

```r
# Make trends API call to gather data
trends_data <- gtrends(keywords, time = gtrends_string, geo = "US")

# Subset just the interest over time
interest_over_time <- trends_data$interest_over_time

# Replace "<1" with "0" and convert the hits column to numeric
interest_over_time$hits <- as.integer(gsub("<", "", interest_over_time
$hits))

# Change data type of "date" to Date datatype
interest_over_time$date <- as.Date(interest_over_time$date)


# Plot findings
gtrends_plot <- ggplot(interest_over_time, aes(x = date, y = hits, col
or = keyword)) +
  geom_line(aes(group = keyword), linewidth = 1, alpha = 0.8) +
  labs(title = "Google Search Interests Over Time",
       x = "Date",
       y = "Search Interest") +
  theme_minimal(base_size = 14) +
  theme(legend.position = "bottom") +
  scale_color_brewer(palette = "Set1") +
  geom_vline(xintercept = as.Date("2023-03-14"), linetype = "dashed",
color = "red", linewidth = 1) +
  theme(legend.key.width = unit(1,"cm")) +
  guides(color = guide_legend(override.aes = list(linewidth = 3))) +
  theme(plot.margin = unit(c(1, 1, 1, 1), "lines"),
        plot.title = element_text(size = 20, face = "bold"),
        axis.title = element_text(size = 16),
        axis.text = element_text(size = 12),
        legend.title = element_blank())


#############
# Hierarchical Time Series Model

## Creating findings (non-lag) for model
car_plm <- data.frame(Ticker = character(), stringsAsFactors = FALSE)

# Loop through car_list
for (ticker in names(car_list)) {
  #Get the data from current ticker
  df <- car_list[[ticker]]
```

```
  #Pivot data to wide format
  wide_df <- pivot_wider(df, names_from = Date, values_from = daily.re
turns)

  #Add ticker name as column
  wide_df$Ticker <- ticker

  #Bind wide data frame to result
  car_plm <- bind_rows(car_plm, wide_df)
}



## Creating findings (lag) for model
# Initialize an empty data frame to store the final results
car_lag_plm <- data.frame(Ticker = character(), stringsAsFactors = FAL
SE)

# Loop through each element in the list
for (ticker in names(car_list)) {
  # Get the data frame for the current ticker
  df <- car_list[[ticker]]

  # Create a lagged version of daily returns
  df <- df %>%
    arrange(Date) %>% # Ensure data is in date order before lagging
    mutate(daily.returns = lag(daily.returns, n = 1, default = NA)) #
Lag the daily.returns column

  # Pivot the data frame to wide format
  wide_df <- pivot_wider(df, names_from = Date, values_from = daily.re
turns)

  # Add the ticker name as a column
  wide_df$Ticker <- ticker

  # Bind this wide data frame to the lagged result
  car_lag_plm <- bind_rows(car_lag_plm, wide_df)
}


## Creating finds for trends analytics
# Use pivot_wider to transform the data frame
wide_interest_over_time <- interest_over_time %>%
  select(keyword, date, hits) %>%  # Select only the relevant columns
  group_by(keyword) %>%            # Group by keyword to ensure unique
ness
```

```r
  pivot_wider(
    names_from = date,                # Use 'date' as the new column name
s
    values_from = hits                # Fill the cells with 'hits' values
  ) %>%
  ungroup()                           # Remove the grouping



### Creating long data frame
long_car <- car_plm %>%
  pivot_longer(
    cols= -Ticker,
    names_to = "date",
    values_to = "return",
  )

##Adding lagged return
long_car <- long_car %>%
  arrange(Ticker, date) %>%
  group_by(Ticker) %>%
  mutate(lagged_return = lag(return, 1))

##Adding function for pre-post intervention
long_car <- long_car %>%
  mutate(after_release = if_else(date >= release_date, 1, 0))


##Adding GTrends to long_car
gtrends_long_df <- pivot_longer(wide_interest_over_time,
                                cols = -keyword,
                                names_to = "date",
                                values_to = "hits",
                                names_transform = list(date = as.Date)
)

#Change date to date (from char)
long_car$date <- as.Date(long_car$date)

#Join gtrends to long_car
combined_df <- long_car %>%
  left_join(gtrends_long_df, by = "date")
```