Predicting Short-term Stock Returns with Options Indicators: Comparative Analysis of Magnificent 7, SPY, and S&P 500 Index

Abstract

We investigate the predictive power of non-price indicators for short-term stock returns for the Magnificent 7 stocks and SPY, leveraging weekly options data. By analyzing open interest and volume distributions, we forecast weekly and monthly-aggregated returns around option expirations. We show that these options trading dynamics are crucial predictors of stock returns, even amid market turbulence. Notably, the lagged open interest call and put, as well as call and put volume retain statistical significance in predicting returns with proper controls. Both in-sample (2013-2022) and out-of-sample (2023) tests confirm the predictors' robustness, consistently outperforming the S&P 500 and NASDAQ 100 indexes, as well as the aggregated Magnificent 7 active trading strategies. Integrating traditional variables from Fama and French (2012, 2015) and Amihud and Mendelson (1980) further enhances our models' predictive efficacy. Additionally, we explore return volatility forecasting using our predictors through GARCH modeling, further highlighting their strategic importance in investment performance.

Keywords: information content, open interest, option volume, weekly option maturity.

JEL Classification: G13, G14

1. Introduction

The predictability of stock returns has been a focal point of empirical financial research for decades. Financial economists and practitioners have challenged the "random walk" hypothesis, uncovering evidence that stock returns may not be entirely unpredictable. This shift in understanding, described by Cochrane (1999) as a "new fact in finance," has spurred numerous empirical studies demonstrating varying degrees of return predictability, primarily over long-term horizons. However, recent studies, such as those by Kostakis et al. (2023) and Demetrescu et al. (2023), have questioned the validity of these conclusions, and critcized the statistical methodologies and highlighting potential spurious inferences from persistent predictive regressions.

While long-term stock return predictability has been extensively studied, short-term predictability remains relatively underexplored. Kostakis et al. (2023) provide evidence of short-term (monthly) predictability using correctly sized and justified test statistics, uncovering significant predictors such as the price-to-earnings ratio and book-to-market value ratio. They demonstrate that return predictability diminishes over longer periods, offering explanations for why some evidence supporting long-term predictability disappears under persistence-controlled instrumental variable estimation.

This study aims to explore weekly return predictability of stocks by utilizing weekly options data to capture immediate market trends, especially for major market players. Specifically, we investigate the predictive potential of non-price indicators—open interest and trading volume—derived from weekly maturing options on underlying assets. Our focus is on the largest U.S. companies, collectively known as the "Magnificent 7" (APPLE, MICROSOFT, AMAZON, GOOGLE, META, TESLA, and NVIDIA), and the SPDR S&P 500 ETF (SPY). These companies are selected for their significant representation of various growing sectors and technological advancements, making them popular among investors. SPY is included to represent broader market activities. We generate weekly returns for the SPY and Magnificent 7 stocks using our predictors and construct portfolios based on these predicted returns.[1] Our strategy consistently outperforms the S&P 500 Index active trading (AT) strategy, which involves reacting to previous period returns with long or short positions—a dynamic trading approach distinct from traditional buy-and-hold. For the S&P 500 active trading (AT) strategy, we utilize the S&P 500 Index (Ticker: INX) actual returns, referring to it as "S&P 500." By thoroughly analyzing open interest and volume data from weekly call and put options of these stocks and the ETF from 2013 to 2022, we aim to forecast short-term stock returns based on each option's maturity.

In our out-of-sample analysis using options data from January to August 2023, we add the NASDAQ 100 Index (Ticker symbol: NDX) and the NASDAQ-based Invesco QQQ Trust ETF (Ticker symbol: QQQ) and forecast weekly returns for the Magnificent 7 stocks, SPY, and QQQ. We compare these forecasts with the active trading strategies of the two indexes and the aggregated Magnificent 7 stocks, demonstrating that our predictors deliver superior performance.

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[1] When referring to the predicted weekly/monthly aggregated returns for the SPDR S&P 500 ETF using our indicators and its portfolios, we will denote this as "SPY".

A plethora of literature has emerged focusing on various predictive factors, encompassing fundamental variables such as those explored by Shiller (1981), LeRoy and Porter (1981), Campbell and Shiller (1988), Fama and French (1988, 2012, 2015), Cochrane (2008), Chen (2009), Binsbergen and Koijen (2010), Golez and Koudijs (2018) and Kostakis et al. (2023). Additionally, technical variables, as investigated by Charles et al. (2017), Neely et al. (2014), and economic variables, as studied by Wohar et al. (2005) and Jordan et al. (2014), have been scrutinized for their predictive power. Furthermore, researchers have explored the role of information demand, as highlighted in studies by Cronopoulos et al. (2018), among others. Corporate events and news surrounding stocks have also been investigated as potential predictors, as evidenced by research conducted by Jin et al. (2012), Hayunga and Lung (2014), Lin and Lu (2015), Chan et al. (2015), and Ge et al. (2016).

The options market presents a unique arena for investors seeking diverse avenues of profit with higher leverage. Within this context, factors such as volume (Roll et al., 2010; Johnson & So, 2012), the put-call ratio (Pan & Poteshman, 2006; Cremers & Weinbaum, 2010), implied volatility spread and skew (Cremers & Weinbaum, 2010; Xing et al., 2010; Muravyev & Ni, 2020), and the dynamics of open interest and options volume distribution (Bhuyan & Yan, 2001; Bhuyan & Chaudhury, 2005; Bhuyan et al., 2010) have been identified as significant predictors.

Chakravarty et al. (2004) observed that informed traders in the options market could lead to new information about stock prices manifesting in option prices before affecting the stock itself. Bergsma et al. (2020) used trading activity via moneyness levels of options as a measure of informed trading and for predicting future stock prices. They proposed a volume-weighted average moneyness measure to capture option trading activity at different moneyness levels and showed that stock returns increased with this measure. Using machine learning techniques, Goyenko and Zhang (2022) found that option characteristics were dominant predictors of stock returns, identifying option illiquidity as the most important predictor of both stock and option returns. These observations serve as the foundational premise for our empirical study on the information content of options' open interest and volume. By incorporating dynamic predictors and control variables with robustness checks, our study advances beyond static analysis frameworks, offering a nuanced view of the evolving relationship between predictors and stock returns.

Our findings reveal that return predictors based on open interest call (OIC), open interest put (OIP), volume of call (VC), and volume of put (VP) exhibit commendable accuracy. This accuracy is not confined to specific option weeks or trade initiation days alone. Our study aligns with Bhuyan and Yan (2001), demonstrating the significant explanatory and predictive power of various price predictors derived from open interests and volumes.

Our study suggests that activity within the equity options market contains valuable insights into future short-term stock returns, offering opportunities for profitable trading strategies. This information is particularly relevant when understanding the true distribution of the underlying asset is crucial (Copeland & Galai, 1983; Easley et al., 1998; Pan & Poteshman, 2006; Goyal & Saretto, 2009; Bali & Hovakimian, 2009; Xing et al., 2010; Cremers & Weinbaum, 2010; An et al., 2014).

Despite incorporating established variables from prior literature as controls, our predictors retain substantial predictive capability, highlighting their distinctiveness in forecasting short-run stock returns. This significant finding suggests that these predictors should be considered alongside established market variables in future research. Additionally, contrary to the findings of Fodor et al. (2010), our primary predictors' lagged versions, OIC and OIP, exhibit significance in short-run return prediction when specific controls are applied. This resilience underscores the robustness and efficacy of our methodology in capturing market dynamics. We also demonstrate that the predictive power of non-price indicators remains robust even during unprecedented market conditions.

1.1 Rationale Behind Sample Selection:

In this study, we deliberately focus on a select group of highly influential stocks and ETFs to address specific research objectives and methodological considerations:

a) *High Impact and Influence:* The "Magnificent 7" and SPY are major assets with significant market impact and high trading volumes, making them ideal for studying market dynamics. Our analysis of these influential entities, alongside comparisons with the S&P 500 and Magnificent 7 active trading strategies, aims to reveal insights into the relationship between options market indicators and short-term stock returns that may be missed in broader studies.

b) *Specific Research Objectives:* We focus on understanding the predictive power of non-price indicators within this high-impact market segment, enabling a detailed examination of options market activity and stock performance particularly relevant to these major market players.

c) *Methodological Considerations:* Selecting this specific set of stocks and ETFs allows for a controlled, rigorous analysis of our hypotheses. While acknowledging the limitations of not using a full sample, our focused approach provides targeted insights into key market players and their interactions with options indicators.

d) *Validation and Robustness:* Our extensive in-sample (2013-2022) and out-of-sample (January-August of 2023) tests, including additional benchmarks like the NASDAQ 100 index and Invesco QQQ Trust ETF, confirm the robustness of our findings. Incorporating traditional variables from established literature further strengthens the reliability of our predictions, highlighting the value of our focused approach.

The upcoming sections are structured as follows: Section 2 reviews relevant literature. Section 3 details the data and methodology. Section 4 presents the model for stock return prediction. Section 5 explores trading strategies and compares returns with the S&P 500 active trading strategy. Section 6 discusses out-of-sample analysis and performance comparison. Lastly, Section 7 summarizes the findings and conclusions.

2. Literature Review

The intricate interlinkages between the options market and the stock market have been extensively explored in the literature. However, scant attention has been given to comprehensively evaluating the joint impact of both open interest and volume on return predictability.

Easley et al. (1998) challenge the prevalent notion that option market prices are exclusively derived from underlying stock prices. They propose that stock prices lead the option volume, and option volume, in turn, leads the stock price changes. In contrast, Bhuyan and Chaudhury (2005) and Bhuyan and Yan (2001) argue that the combined net open interest of call and put options provides a more insightful indication of future stock price movements than total volume alone. Our study builds on this premise, exploring the informational dynamics of the stock options market using open interest and volume, specifically in the context of trading the Magnificent 7 stocks and SPY. We find that both open interest and volume powerfully predict stock returns.

Multiple studies delve into the predictability surrounding corporate events. Ge et al. (2016) examine stock return predictability around corporate news days utilizing option volume. Augustin et al. (2019) find evidence of informed options trading activity preceding M&A announcements, as well as informed options trading by advisor banks ahead of client firm mergers.

Yoon (2017) highlights the liquidity dynamics of options, emphasizing that options with shorter maturities tend to be more liquid, making them apt for estimating short-term variations in risk aversion. Yoon's work further contends that time-varying risk aversion holds predictive power for future excess returns, especially for horizons longer than one week, and maintains significance even in the presence of other forecasting variables.

Klemkosky (1978) investigates option expiration effects based on weekly return data, revealing negative returns on underlying stocks in the expiration week and positive returns in the subsequent week. Officer and Trennepohl (1981) scrutinize the price behavior of equities near option expiration dates, suggesting that optionable stocks may experience downward pressure two days before expiration.

Harris and Shafer (2022) find that open interest provides informative signals and increases with the magnitude of stock return momentum, especially for short-sale-constrained equities with negative return momentum. Chan et al. (2002) discover that stock net trade volume holds robust predictive ability for stock and option quote revisions, whereas option net trade volume lacks incremental predictive ability. Conrad et al. (1994) and Gervais et al. (2001) establish that the predictive power of extreme equity trading volume on subsequent returns is most pronounced when contemporaneous returns are non-extreme.

Rapach et al. (2010) advocate for forecast combination using multiple predictors, asserting its superiority over the historical average. Hwang and Sohn (2010) find that the real options model exhibits superior return predictability, particularly in firms with a high probability of exercising liquidation options. An et al. (2014) reveal that stocks with significant increases in call option implied volatilities over the previous month tend to yield high future returns, while those with large increases in put option implied volatilities exhibit lower future returns. Chronopoulos et al. (2018) identify predictability in the sign of asset returns, and their findings persist across various utility functions, estimates of transaction costs, and levels of risk aversion. Cremers and Weinbaum (2010) establish that both changes and levels in volatility spreads have significance for future stock returns. Johnson and So (2012) discovered that the ratio of options trading volume to stock trading volume (O/S) predicts the returns of the options' underlying stocks over a one-week horizon, with high O/S indicating negative returns. Sasaki (2016) uncovers the predictive power of the skewness risk premium and variance risk premium for future aggregate stock market index returns.

Ge et al. (2016) assert that purchases of calls opening new positions serve as the most potent predictor of returns, followed by call sales closing out existing purchased call positions. Lakonishok et al. (2007) use a unique dataset to describe the distribution of option open interest among investors, revealing that non-market-maker investors have four times as much purchased call open interest as purchased put open interest. Schachter (1988) explores the potential insights provided by option open interest on equity returns, discovering a significant drop in abnormal option open interest before earnings announcements.

While existing studies have made notable contributions to understanding various aspects of options trading, such as expiration effects, trading volume dynamics, and the role of informed traders, there remains a notable gap concerning the joint impact of open interest and volume on return predictability. This research seeks to address this gap by employing a novel approach that integrates both open interest and volume to enhance our understanding of stock return dynamics.

3. Data and Methodology

The daily closing data for call and put options utilized in this study is sourced from the Option Metrics daily database, accessed through WRDS. Our in-sample analysis spans three consecutive option weeks from each option initiation day, commencing from 02 January 2013, and extending to 31 December 2022. Our primary attention is directed towards the Magnificent 7 stocks, namely, Amazon Inc. (AMZN), NVIDIA (NVDA), Tesla (TSLA), Meta Platforms (META), Apple Inc. (AAPL), Microsoft Inc. (MSFT), Alphabet (GOOG), and the SPDR S&P 500 ETF Trust[2]. These weekly options, featuring one-week expiration dates, are typically listed on Thursday and expire on Friday of the subsequent week. This compressed timeframe, both in terms of listing and expiration, is a deliberate design to catalyze trading activity, particularly among retail options traders. The shortened expiration period, enhancing sensitivity to underlying price changes, renders these short-term options particularly appealing to investors and speculators. In our out-of-sample analysis, we expand the dataset to incorporate new options data from January to August 2023, including the NASDAQ 100 Index (ticker symbol: NDX) and the NASDAQ-based Invesco QQQ Trust ETF. By

[2] The designation "Magnificent 7" was bestowed upon this group of seven stocks in 2023, acknowledging their robust performance and remarkable capability to drive indexes upward, seemingly independent of assistance from smaller stocks.

including these NASDAQ-focused benchmarks, we evaluate the model's robustness and efficacy across various market scenarios.

For each stock and the ETF, with a set of call and put options maturing at T (current time T_0), let S_t represent the stock price and R_t represent the stock return at time t. Define $\{X_i$, i=1, 2, ..., m$\}$ as the set of strike (or exercise) prices for call options and $\{Y_j$, j=1, 2, ..., n$\}$ as the set of strike prices for put options. The payoff at maturity for the buyer of a call option with a strike price X_i is given by P_{ic}= Max $[0, S_T - X_i]$. Similarly, for a strike price Y_j, the put option buyer's payoff at maturity is P_{jp}= Max $[0, Y_j - S_T]$. For any t in the interval $[T_0, T]$, $Price_c$ is the call option price calculated as the average of the bid and ask price for call options, $Price_p$ is the put option price calculated as the average of the bid and ask price for put options, OC represents open interest for the call option, OIC and DC represent the net open interest and volume, respectively, of call options with the strike price X_i, OP represents open interest for put option, OIP and DP represent the net open interest and volume respectively of put options with strike price Y_j. The option moneyness metric for call options is defined as S/K, and for put options, it is defined as K/S, where S represents the current spot price and K is the exercise price. It is an important measure of trading activity, especially by informed investors for the out-of-the-money options (e.g., see Bergsma et al. 2020, and the references there). However, options contracts with moneyness metric values below 0.88 or above 1.12 are excluded from our analysis due to their poor liquidity. We calculate OIC_t, our first indicator, as:

$$OIC_t = \frac{\sum_{i=1}^{m} X_i \times OC_{it} \times Price_{cit}}{\sum_{i=1}^{m} OC_{it} \times Price_{cit}} \tag{1}$$

Similarly, we calculate OIP_t as:

$$OIP_t = \frac{\sum_{j=1}^{n} Y_j \times OP_{jt} \times Price_{pjt}}{\sum_{j=1}^{n} OP_{jt} \times Price_{pjt}} \tag{2}$$

The return predictors OIC and OIP can be conceptualized as expected terminal stock prices. This expectation is based on the discrete distribution of open interests for all call and put options on the stock maturing at time T.

We also calculate the volume of call and put options as two other return predictors as follows:

$$VC_t = \frac{\sum_{i=1}^{m} X_i \times DC_{it}}{\sum_{i=1}^{m} DC_{it}} \tag{3}$$

and,

$$VP_t = \frac{\sum_{j=1}^{n} Y_j \times DP_{jt}}{\sum_{j=1}^{L} DP_{jt}} \tag{4}$$

We chose short holding periods (weekly maturity) due to the rapid dissemination of financial information in today's digital age and the short time horizon of active traders. After predicting returns using specified predictors and controls, we evaluate if the predicted returns generate a profitable portfolio. We develop an open interest-based risk-active strategy using stocks and options. The weekly portfolio return for each stock is compared with the weekly S&P 500 active trading (AT) strategy return. Various performance metrics, including cumulative returns, coefficient of variation, and Sharpe ratios, are calculated for each stock, SPY, and the S&P 500 Index to analyze the performance of the trading strategy.

We construct an open interest measure as a weighted average, giving more weight to options with higher strike prices. This measure is based on the idea that positive private information held by informed investors leads to a more favorable stock price and return distribution at time T, resulting in an expected equilibrium stock price and return higher than the current price (S_t) and return (R_t). Informed investors, based on their optimistic outlook, may engage in speculative strategies by buying out-of-the-money call options or selling in-the-money put options (Bergsma et al., 2020). Consequently, this shifts the distribution of their positions towards higher strike prices, increasing the weight of higher strike call options and higher strike put options. This reflects their optimism and translates into a higher return predictor.

Open interest measures the number of outstanding contracts, involving both buyers and sellers, and cannot exclusively reflect buyer or seller sentiment. However, increased activity at higher strikes, through buying calls or selling puts, can indicate optimistic investor sentiment. This assumption is based on the idea that informed investors' actions, driven by private information, impact open interest distribution. Additionally, optimistic investors may hedge against adverse movements by purchasing out-of-the-money put options with lower strikes. This hedging strategy, influenced by the risk of information reversals, may emphasize lower strike put options and moderate the return predictor's impact, reflecting a strategic response to manage potential losses while considering evolving information dynamics.

By analyzing shifts in open interest distribution, we aim to capture the sentiment and strategies of informed investors, despite open interest data limitations. Optimistic investors tend to avoid in-the-money call options, resulting in a positive bias in the price predictor due to the emphasis on higher strikes. This reflects their confidence in the stock's upward potential. Conversely, pessimistic investors are likely to buy out-of-the-money put options or sell in-the-money call options, leading to a negative influence on the return predictor. These strategies align with their negative outlook and result in a higher weight on lower strike put options or call options sold, reflecting the negative information they hold.

Beyond informed investors, liquidity traders and uninformed participants introduce forecast errors to the return predictor through their stochastic actions in the options market. Sequential information-arrival suggests open interests may reflect positions taken by less sophisticated traders. These traders must interpret conflicting signals from both optimistic and pessimistic informed traders, adding noise to market activity and influencing the return predictor.

4. Empirical Findings

Table 1 summarizes the key predictors—open interest (OIC, OIP) and volume (VC, VP)—for the Magnificent 7 stocks, SPY, and the S&P 500 using weekly option data from 2013 to 2022. It includes the number of observations (N), minimum, maximum, mean, and standard deviation for each metric, highlighting the variability and central tendencies. For example, AAPL and MSFT show stable figures, while AMZN and TSLA exhibit significant variation, indicating differing levels of market activity and investor interest. Our dataset, spanning a decade of weekly data, includes 110,410 observations. Given the volume, we provide a monthly summarization in tables and a visual weekly summary. Notably, the minimum average implied volatilities for the Magnificent 7 stocks and SPY are almost zero, underscoring their high liquidity levels.

[Table 1 here]

To assess multicollinearity, we examine the Pearson correlation coefficients between the predictor variables and the stock return. Table 2 presents the correlation results, indicating the absence of multicollinearity within the model.

[Table 2 here]

Figure 1 shows histograms of the empirical distributions of the normalized predictors and stock returns on each trade initiation day. These histograms illustrate the shape, central tendency, and spread of each variable's distribution. Notably, all four predictors and the return distribution exhibit a roughly bell-curve pattern, supporting our dynamic panel regression model's assumption of normality. This enhances the reliability of our results, reduces potential biases, and ensures accurate hypothesis tests.

[Figure 1 here]

4.1 Empirical Model

We forecast returns for each Magnificent 7 stock and SPY on each option initiation date using OIC, OIP, VC, and VP, along with some control variables (thus, the findings apply to the Magnificent

7 stocks and SPY). These indicators are normalized by subtracting the stock's closing price from each indicator and dividing by the closing price. We use a merged CRSP and Compustat database for firm-level data, incorporating firm-level and time-fixed effects to account for unobserved heterogeneity and broader temporal influences. This approach helps mitigate omitted variable bias and address endogeneity concerns. A dynamic panel regression model is employed to handle reverse causality issues. Our regression model for predicting returns is as follows:

$$return_{it} = \alpha_0 + b_1 return_{it-1} + b_2 OIC_{it} + b_3 VC_{it} + b_4 OIP_{it} + b_5 VP_{it} + b_6 OIC_{it-1} + b_7 OIP_{it-1} + b_8 VC_{it-1} + b_9 VP_{it-1} + b_{10} VIX_{it} + b_{11} momentum_{it} + b_{12} Amihud's\_illiquidity_{it} + \lambda + \zeta + \varepsilon_{it} \tag{5}$$

In Equation 5, the control variable "momentum" measures the speed of stock price changes, sourced from the WRDS Fama-French portfolio dataset. Momentum provides insights into price velocity, rather than just absolute levels. Additionally, "Amihud's_illiquidity" is used to gauge price impact and is computed as follows:

$$Amihud's\_illiquidity_{it} = \frac{|Daily\ stock\ return_{it}|}{Closing\ price_{it} \times Daily\ trading\ volume_{it}} \tag{6}$$

The control variable "VIX" reflects market expectations for near-term changes in the S&P 500 Index[3]. Lagged terms of the main indicators are also included in the model. Firm-fixed effects (λ) account for firm-specific characteristics that remain constant over time, while time-fixed effects (ζ) capture time-related factors affecting all firms, such as market-wide events. These controls enhance the robustness of our analysis, allowing us to assess the impact of options market activity on stock returns. Regression results are shown in Table 3[4]. The regression analysis shows a significant negative relationship between OIC and OIP and stock returns across all columns. A one-unit increase in call

[3] The daily VIX index can be found on the St. Louis FRED website at https://fred.stlouisfed.org/series/VIXCLS/

[4] The choice of regression specification is grounded in data engineering principles to address the persistence and heterogeneity in stock returns. The results provide convincing evidence through statistically significant coefficients and robust model specifications, enhancing the credibility of our findings. The findings are applicable to the Magnificent 7 stocks and SPY.

option open interest correlates with a decrease in stock returns by about 0.0071 to 0.0077 units (Columns 1 and 4). Similarly, a one-unit increase in put option open interest correlates with a decrease in stock returns by approximately 0.0124 and 0.0061 units (Columns 3 and 4). Increased open interest in call options signal bearish sentiment, increased selling pressure or market caution, as investors could be hedging or uncertain about future stock price increases. Conversely, higher open interest in put options might reflect hedging or speculative bets on a market decline. The negative impact on stock returns suggests that increased interest in both types of options is associated with cautious or pessimistic market sentiment.

Elevated open interest in call (OIC) and put options (OIP) suggests increased trading activity and market sentiment, which may reflect hedging or speculative behavior. High OIC and OIP could signal market caution or uncertainty, impacting liquidity and reducing returns. Increased trading activity often leads to higher transaction costs and short-term price volatility. A lower OIP relative to stock prices, with many puts being out-of-the-money (OTM), may signal reduced downside risk and market optimism. Conversely, a higher OIC relative to stock prices, with many calls being OTM, may indicate bullish sentiment or speculative bets on price increases. This study supports the idea of informed trading as discussed by Chakravarty et al. (2004), demonstrating its impact on stock returns.

Options markets provide insights into future stock movements. Changes in options volume reflect information arrival and liquidity [Pan and Poteshman, 2006; Goyenko and Zhang, 2022]. Our analysis shows a significant positive relationship between options volume (VC, VP) and stock returns. This positive coefficient implies that, while holding other variables constant, a one-unit increase in VC corresponds to a 0.0056, 0.0044, 0.0064, and 0.0048 unit increase in return (Columns 1, 2, 3, and 4 respectively). Similarly, a one-unit increase in VP is associated with 0.0104, 0.0082, and 0.0113 units increase (Columns 1, 2, and 3), and a 0.0038 increase in return (Column 4). This suggests that higher trading volumes in call and put options are associated with higher stock returns, indicating greater investor activity and interest. Our findings align with Chan et al.'s (2002) research on stock net trade volume.

Our study explores how open interest and volume together impact stock and option quote revisions, advancing the discussion on volume and return predictability. High option volumes often signal anticipated price movements, with traders using options for various strategic purposes. This empirical evidence highlights the interplay between option volumes, stock returns, and investor behavior, reinforcing the value of options markets for market participants, related to influential entities. Our findings align with Harris and Shafer (2022) on open interest providing signals for stock return momentum, and support Bhuyan and Yan (2001) on the effectiveness of price predictors derived from open interest and trading volume in forecasting stock prices. So, non-price indicators like current open interest and trading volumes (both call and put) are significant predictors of short-term stock returns. This suggests that market participants' current activity in options markets can provide valuable insights into future price movements.

[Table 3 here]

Control variables such as momentum, VIX, and Amihud's illiquidity are crucial in influencing stock returns. A negative relationship between momentum and returns suggests that stocks with high recent performance tend to revert to the mean, reflecting possible mean reversion dynamics. Investors might adjust their expectations, anticipating a slowdown in the stock's outperformance. This is supported by literature combining short-term momentum with medium-term mean reversion (e.g., Giner and Zakamulin, 2023). Additionally, VIX, which measures market volatility, shows a significant negative relationship with returns. High volatility implies increased uncertainty, leading investors to seek safer assets and resulting in lower returns for riskier stocks.

Although the relationship between Amihud's illiquidity and stock returns is insignificant, it suggests that illiquid stocks might face larger price impacts during increased trading, potentially leading to lower returns due to investors demanding a risk premium. Illiquidity can also complicate trading, affecting order execution. Our study aligns with Rapach et al. (2010) on the benefits of combining multiple predictors for more accurate forecasts. By integrating open interest and volume with other controls, our research supports using diverse information sources for better return predictions. Despite including established variables like momentum, profitability, investment (Fama & French, 2012, 2015), and illiquidity (Amihud & Mendelson, 1980), our predictors still demonstrate strong forecasting power. Additionally, lagged versions of OIC and OIP show significant predictive relationships with returns, highlighting their relevance in forecasting future stock performance. But their influence is weaker compared to current values. This underscores the importance of recent market activity in forecasting short-term returns.

4.2 Robustness check for the empirical model

To test the robustness of our model in Equation 1, we introduce a new set of controls: the 10-day moving average return, the book-to-market ratio, and returns lagged by 2 and 3 option initiation dates. The updated regression model for evaluating the robustness of the previous return predictions is as follows:

$$return_{it} = \alpha_0 + b_1\ return_{it-1} + b_2\, OIC_{it} + b_3\, VC_{it} + b_4\, OIP_{it} + b_5\, VP_{it} + b_6\, OIC_{it-1} + b_7\, OIP_{it-1} + b_8\, VC_{it-1} + b_9\, VP_{it-1} + b_{10}\, MA10_{it} + b_{11}\, BM\_ratio_{it} + b_{12}\, return_{it-2} + b_{13}\, return_{it-3} + \lambda + \zeta + \varepsilon_{it} \tag{7}$$

In Equation 7, $MA10$ is the moving average for a 10-day rolling period, BM_ratio is the book-to-market ratio, $return_{it-2}$ and $return_{it-3}$ are the lagged return variables. The regression results in Table 4 confirm the findings from Table 3. Open interest in call (OIC) and put (OIP) options remains significantly negatively related to stock returns, indicating that higher open interest is associated with lower returns. Specifically, a one-unit increase in call open interest decreases stock returns by 0.0067 and 0.0058 units, while a one-unit increase in put open interest results in a 0.0105- and 0.0142-unit decrease. In contrast, both call and put volumes (VC and VP) show a significant positive relationship with returns. A one-unit increase in call volume leads to a 0.0039 and 0.0045 unit rise in stock returns, and a one-unit increase in put volume results in a 0.0091- and 0.0141-unit increase. Additionally, the significant negative coefficient for the book-to-market ratio in Column 1 suggests that lower book-to-market ratios (growth stocks) tend to have higher returns. High market values relative to book values may reflect investor optimism about future gains, with growth stocks potentially accepting lower current returns in anticipation of future growth.

[Table 4 here]

The regression results also show that lagged returns (Columns 1 and 2) have statistically significant negative coefficients, indicating that recent high returns are linked to lower future returns, supporting the mean reversion hypothesis. This suggests that stocks with recent strong performance may experience a correction, with returns moving back toward the average. Additionally, the negative coefficient for the 10-day moving average return suggests that stocks with recent short-term underperformance tend to have lower future returns. This implies that high short-term returns might signal overvaluation, leading to a potential correction and lower returns in the following period.

Our findings align with Goyenko & Zhang (2022), confirming that option characteristics like volume, a proxy for illiquidity, significantly predict stock returns. Additionally, our results support Fodor et al. (2010), who found that changes in options' open-interest levels predict future equity returns. We observe that increases in call open interest (OIC) are positively related to future equity returns, while increases in put open interest (OIP) are negatively related. However, unlike Fodor et al. (2010), we find that this relationship becomes more pronounced when accounting for certain controls.

4.3 Predictive Power of Non-Price Indicators in Unprecedented Market Conditions

The pandemic caused significant market volatility and altered trading behaviors due to economic uncertainty and extensive fiscal and monetary interventions, leading to increased trading volume and costs (Piccotti & Saba, 2024). We use a comparative analysis to assess how COVID-19 impacted the predictive power of non-price indicators. Defining the "Pre-pandemic period" as 2013-

2019 and focusing on 2020-2021, we analyze how these indicators performed during the pandemic. By comparing data from 2020 and 2021 with the pre-pandemic period, we evaluate whether non-price indicators exhibited unique predictive power during the crisis and how their effectiveness differs from normal market conditions. This approach aims to reveal the impact of COVID-19 on forecasting stock returns and identify any changes in predictive accuracy during the crisis. We use Equation 5 to conduct the analysis for both timeframes. The results are reported in Table 5.

[Table 5 here]

The results for both the pre-pandemic period (Columns 1, 2, and 3) and the pandemic period (Columns 4, 5, and 6) illustrate that lagged returns and non-price indicators exert a significant influence on short-term stock returns. Across both periods, OIC and OIP consistently demonstrate robust predictive power for stock returns, evidenced by their significant negative impact. Similarly, VC and VP exhibit a significant positive impact on returns in both periods. The lagged versions of all non-price predictors also show significant predictive power for stock returns for both periods. For both current open interest and volume distributions, the marginal effects are significantly more pronounced during the pandemic. The larger coefficients during the pandemic indicate an intensified market sensitivity to options trading activity. The persistent significance of these variables during the COVID-19 pandemic suggests that the extraordinary market conditions amplified the predictive power of non-price indicators. The differential coefficients between periods underscore how the predictive power of these indicators is accentuated during market stress compared to the more stable pre-pandemic era. The positive and significant momentum coefficient during the pandemic reflects the robust performance of technology stocks, which saw substantial gains during this period. This trend underscores heightened investor confidence and increased trading activity in the technology sector during market turbulence.

4.4 Return Volatility Forecasting

Volatility, which measures return dispersion, is a key metric in financial analysis. Accurate forecasting of volatility is essential for assessing the risk of holding stocks or portfolios and for crafting effective risk management strategies, particularly with options and derivatives. Precise volatility predictions are crucial for options traders, as they significantly impact option values and inform trading strategies that exploit volatility shifts. Ho et al. (2012) highlight the value of using information and sentiment from the options market to forecast stock market volatility.

In our study, which employs quantitative models to analyze stock returns using options open interest and volume, forecasting volatility is crucial. Our models are calibrated based on these volatility forecasts. To predict volatility for each stock on every option initiation day, we use predictors like OIC, OIP, VC, and VP, along with specific control variables. The regression equation for our volatility forecasting is as follows:

$$volatility_{it+1} = \alpha_0 + b_1\, volatility_{it} + b_2\, S\&P500\_volatility_{it} + b_3\, OIC_{it} + b_4\, VC_{it} + b_5\, OIP_{it} + b_6\, VP_{it} + b_7\, VIX_{it} + b_8\, MA10_{it} + b_9\, gpm_{it} + b_{10}\, Amihud's\_illiquidity_{it} + b_{11}\, MA20_{it} + b_{12}\, momentum_{it} + \lambda + \zeta + \varepsilon_{it+1} \quad (8)$$

In Equation 8, $volatility_{it+1}$ is the volatility forecast for the time $t+1$. The term $volatility_{it}$ serves a dual purpose, addressing endogeneity issues in the dynamic panel regression and encapsulating the persistence of stock volatility over time. The term $S\&P500\_volatility_{it}$ accounts for historical movements in market volatility. Additionally, the inclusion of VIX_{it}, commonly known as the “fear index”, provides a measure of market expectations regarding volatility over the next 30 days based on option prices. And gpm_{it} is the gross profit margin on each option initiation day for each stock. The regression results are presented in Table 6.

[Table 6 here]

In Table 6, the predictors—OIC, OIP, VC, and VP—show significant relationships with forecasted volatility. Increased OIC is associated with lower volatility on the subsequent option initiation day, decreasing by 0.326% without fixed effects and 0.63% and 0.52% with fixed effects, with significance at the 1% level. This indicates that higher call open interest, signaling bullish sentiment, is linked to reduced forecasted volatility. Conversely, a rise in OIP correlates with increased volatility, with increases of 0.122% without fixed effects and 0.79% and 0.34% with fixed effects, achieving significance at the 1% (Columns 1 and 3) and 10% (Column 3) levels. Elevated put open interest suggests greater hedging or uncertainty, leading to higher forecasted volatility.

A surge in VC leads to higher volatility on the next option initiation day, increasing by 0.361% without fixed effects and 0.49% and 0.39% with fixed effects, significant at the 1% level in Columns 1 and 3, and the 5% level in Column 2. Higher call option volume suggests speculative trading and expectations of price movement, contributing to increased forecasted volatility. Conversely, an increase in VP is associated with reduced volatility, decreasing by 0.14% without fixed effects and 0.86% and 0.49% with fixed effects, significant at the 1% level in Columns 1 and 3, and 5% in Column 2. Higher put option volume indicates downside risk protection, potentially leading to lower forecasted volatility. These findings support Donaldson and Kamstra (2005), highlighting trading volume's role in predicting volatility.

The S&P 500 volatility and VIX show a significant positive relationship with forecasted volatility, indicating that higher market volatility and increased fear lead to greater stock volatility. This suggests that broader market trends and investor reactions to market uncertainty influence individual stock volatility. Additionally, Amihud's illiquidity, gross profit margin, and 20-day moving average (MA20) exhibit significant relationships with forecasted volatility. A negative association with Amihud's illiquidity indicates that less liquid stocks experience less price fluctuation. The negative relationship with MA20 implies that upward price trends are associated with lower volatility forecasts, suggesting more stable market conditions. A negative relationship between gross profit margin and forecasted volatility indicates that higher profit margins signal investor confidence and lower anticipated volatility, reflecting expectations of stable financial performance.

4.5 Robustness Check for Volatility Forecasting Using GARCH Model

To validate the robustness of our conditional return volatility forecasting model, we implement a GARCH model to capture the time-varying nature of volatility. Specifically, we employ a GARCH(1,1) model to account for volatility clustering and leverage effects. Using Equation 5, we specify the GARCH model, where the error term ε_{it} follows a GARCH(1,1) process:

$$\mathrm{Var}(\varepsilon_{it}) \text{ or } \sigma_{it}^2 = \alpha + \beta\varepsilon_{it-1}^2 + \omega\, \sigma_{it-1}^2 \tag{9}$$

Here, α is the constant term in the GARCH model, β is the coefficient for the lagged squared residual term, and ω is the coefficient for the lagged conditional variance term. The results are shown in Table 7. The β coefficient, with an estimate of 0.0476, captures the short-term effects of past shocks on current volatility, while ω, with an estimate of 0.9524 reflects the long-term persistence of volatility. Variables such as lagged returns, OIC, OIP, VC, and VP have statistically significant coefficients, suggesting they play a crucial role in explaining volatility dynamics. The high significance of the GARCH terms (p-values < 0.0001) suggests that the GARCH(1,1) model is appropriately capturing the volatility clustering observed in the data. Overall, the GARCH model results validate our original forecasts and provide confidence in the robustness of our findings[5].

[Table 7 here]

[5] The residual plot from the GARCH model shows a bell-shaped distribution, suggests that the model captures the volatility clustering effect effectively. This was confirmed by the residual analysis, which indicated no significant patterns or remaining heteroscedasticity. This indicates that the variance of residuals is consistent over time, suggesting that the GARCH model is effectively modeling the time-varying volatility.

5. Trading Strategy based on predicted returns

We allocate an approximate investment of $10,000 to each Magnificent 7 stock, SPY, and the S&P500 in our portfolio. At the close of trade initiation day, labeled as t, we establish positions based on the predicted return for Magnificent 7 and SPY from the previous day, $t-1$. This estimation is grounded in a detailed examination of the distribution of open interests and the volume of call and put options, all reaching maturity on the same date, T. For S&P500, we establish a position based on the actual return from the previous day. We maintain consistency in our methodology for each expiration day, T, for our weekly options dataset. Creating a binary variable, R_t^Z, we assign the value 1 to signify a positive estimated return and -1 for a negative estimated return on $(t-1)$. A positive estimate signals a potential buy (long position) at the ask price, while a negative estimate suggests a sell (short position) at the bid price. This method is consistently applied for each expiration day (T) in our weekly options dataset.

Positions are initiated and maintained for a one-week holding period, consistent with modern market dynamics and the need for agile decision-making. The cumulative return starts at 1, with an initial portfolio value of $10,000. Transaction costs are factored in by considering the bid-ask spread for both entering and exiting positions. Each week, we calculate the portfolio value for each stock and SPY based on the established positions and transaction costs on the expiration day.

In the case of a long position (buy), the portfolio value experiences an increase; conversely, for a short position (sell), it undergoes a decrease. When $R_t^Z = 1$, a long position is initiated. The portfolio value at time T is then determined by:

$$Portfolio\ value\ =\ initial\ investment\ \times\ (1\ +\ (contemporary\ stock\ return_{t-1} - transaction\ cost_{t-1})) \tag{10}$$

If $R_t^Z = -1$, a short position is taken. The portfolio value at time T is:

$$Portfolio\ value\ =\ initial\ investment\ \times\ \left(1-\ (contemporary\ stock\ return_{t-1} +\ transaction\ cost_{t-1})\right)$$

(11)

We also calculate the cumulative return of the portfolio utilizing the following formula:

$$Cumulative\ return_T = Cumulative\ return_{T-1} \times \frac{(portfolio\ value\ _T - portfolio\ value_{T-1})}{portfolio\ value_{T-1}} \quad (12)$$

A 2% stop-loss mechanism is implemented for our short-term predictions. For long positions, if the stock return falls below 98% of the estimated return, or for short positions, if the return exceeds 102% of the estimated return, the position is closed to limit losses.

The portfolio return on each expiration day is calculated by measuring the percentage change in portfolio value relative to the initial value. After processing all expiration days, any remaining open positions are closed, accounting for transaction costs. This ensures the final portfolio value accurately reflects all trading decisions and represents the performance of the simulated strategy over the specified period.

Figure 2 shows the weekly strategic returns for each Magnificent 7 stock and SPY compared to the S&P 500 trading strategy from 2013 to 2022. Our strategy dynamically adjusts positions in the SPDR S&P 500 ETF based on the previous period's actual returns: taking a long position for positive returns and a short position for negative returns. The figure reveals that portfolios of the Magnificent 7 stocks and SPY consistently outperform the S&P 500 strategy, except for GOOG, which shows notable returns in certain weeks of 2021. This suggests that the return estimates from open interest and volume can form a high-yielding strategy relative to the S&P 500. Our results support Bhuyan and Chaudhury (2005), indicating that open interest-based trading strategies can outperform S&P 500 returns.

[Figure 2]

We systematically evaluate our strategy's effectiveness using both absolute and risk-adjusted performance metrics for each stock and SPY. The Sharpe ratio is calculated by subtracting the risk-free rate from the portfolio return and dividing it by the portfolio's standard deviation. This provides a measure of risk-adjusted returns, with higher Sharpe ratios indicating better performance relative to risk. We apply the same calculation for the S&P 500 for comparison. Additionally, we assess the volatility and coefficient of variation of our portfolios based on weekly strategic returns. By comparing these metrics to those of the benchmark S&P 500 active trading strategy, we gain insights into how our approach performs in varying market conditions.

Given the large volume of observations, weekly data is not presented in tabular form. Instead, we aggregate the monthly summaries of portfolio return, Sharpe ratio, and volatility for the Magnificent 7 stocks and SPY portfolios. These are compared to the corresponding monthly summaries of the S&P 500 active trading strategy. The results are presented in Table 8.

[Table 8 here]

In early 2013, the Magnificent 7 and SPY portfolios outperformed the S&P 500, with notable gains in January and March. This trend continued in the second quarter, showing resilience despite a dip in April 2014. The third and fourth quarters highlighted a significant performance boost for the Magnificent 7 and SPY, demonstrating their ability to capitalize on favorable market conditions and consistently surpass the S&P 500. In 2014 and 2015, the Magnificent 7 and SPY portfolios consistently outperformed the S&P 500, despite occasional dips, highlighting their strong strategic performance. The years 2016 and 2017 showed mixed results with some declines, but the portfolios demonstrated resilience with notable recoveries, indicating their ability to rebound from challenges and maintain strong performance overall.

In late 2018 and 2019, while facing occasional challenges, the Magnificent 7 and SPY portfolios showed remarkable recovery and adaptability, maintaining positive returns. In 2020 and 2021, despite volatility, these portfolios continued to perform strongly, with notable positive returns amidst market uncertainties. Recent data indicates that the Magnificent 7 and SPY remain resilient, displaying consistent outperformance despite short-term fluctuations.

Recent months have seen substantial shifts in S&P500 active trading returns and predictive returns for SPY and the Magnificent 7 stocks. This volatility can be attributed to the COVID-19 pandemic and significant events like nationwide lockdowns, rising inflation, increasing interest rates, and geopolitical tensions, such as the Russia-Ukraine war, which occurred after trade initiation and before option expiration. These factors intensified information asymmetry, bid-ask spreads, and order flow imbalances, leading to increased stock price volatility and erratic returns. Major news events often cause significant deviations from recent trends, which can lead to substantial discrepancies between actual stock returns and predictions based on open interest and volume. For instance, negative news may lead to unexpected price movements even if previous trends and predictors suggest otherwise.

6. Out-of-Sample Analysis

In this section, we conduct our out-of-sample analysis utilizing options data obtained from Option Metrics from the month of January to August 2023.[6] During this period, we analyzed 37 weekly options expiration dates, including three from September 2023. Using a shorter timeframe for robustness checks enables a more focused analysis, capturing variations or anomalies that longer periods might miss. This approach helps assess the stability and consistency of our results, strengthening the robustness of our findings.

Once again, we calculate OIC, OIP, VC, and VP for three consecutive option weeks for each stock, SPY, and each option initiation day. Additionally, we introduce the NASDAQ 100-based ETF, Invesco QQQ Trust, which we denote as "QQQ", and forecast its return on each option initiation date. To further ensure robustness, we use various sets of control variables in predicting stock returns. The dynamic panel regression equation incorporating firm-fixed effects and time-fixed effects selected for this analysis is as follows:

[6] As of the current date, OptionMetrics has not provided data updates beyond August 2023, and CRSP has not released daily data for the same period. Considering this, we compute stock returns using closing prices from the Compustat database for January-August of 2023. The Fama-French daily 5-Factors with Momentum has been sourced from WRDS.

$$return_{it} = \alpha + b_1\, return_{it-1} + b_2\, RMRF_{it} + b_3\, SMB_{it} + b_4\, HML_{it} + b_5\, RMW_{it} + b_6\, CMA_{it} + b_7\, OIC_{it} + b_8\, VC_{it} + b_9\, OIP_{it} + b_{10}\, VP_{it} + b_{11}\, OIC_{it-1} + b_{12}\, OIP_{it-1} + b_{13}\, VC_{it-1} + b_{14}\, VP_{it-1} + b_{15}\, Momentum_{it} + \lambda + \zeta + \varepsilon_{it} \quad (13)$$

In Equation 12, RMRF denotes the market risk premium, HML represents the value factor (high minus low), SMB indicates the size factor (small minus big), CMA refers to the investment factor (conservative minus aggressive), and RMW stands for the profitability factor (robust minus weak). The Fama-French 5-factor model, used to explain stock returns, incorporates these factors to assess how our options open interest and volume predictors impact stock returns within the context of broader market factors. Results are detailed in Table 9.

[Table 9 here]

The results align with patterns from Tables 3 and 4. OIC and OIP show a negative relationship with returns, whereas VP and VC are positively associated. Lagged OIC, OIP, VC, and VP also significantly impact returns. In the Fama-French 5-factor model, RMRF, HML, and RMW are positively linked to stock returns, indicating that higher market risk exposure, a high book-to-market ratio, and strong profitability are associated with better returns. Conversely, SMB and CMA are negatively related, suggesting that smaller firm size and conservative accounting may lead to lower returns. Consistent with earlier tables, momentum exhibits a negative relationship, suggesting that stocks with recent strong performance might face lower returns due to mean reversion.

We employ a parallel methodology as delineated in Section 5 to devise a trading strategy harnessing the predicted returns generated from Equation 5 for both the Magnificent 7 stocks, SPDR S&P 500 ETF, and Invesco QQQ Trust ETF.[7] Utilizing the forecasted returns as our guiding principle, we enter positions, opting for a long position when the predicted returns are positive and a short position when they are negative. We also generate benchmarks for the S&P 500 Index, the

[7] To streamline our discussion, we designate the portfolio constructed for the SPDR S&P 500 ETF based on the predicted returns as "SPY" and the portfolio constructed for the Invesco QQQ Trust ETF based on the predicted returns as "QQQ".

NASDAQ 100 Index (referred to as "NASDAQ 100" in this paper, which involves taking positions in the NASDAQ 100 Index using the ticker symbol "NDX" based on its actual return), and an aggregated Magnificent 7 active trading strategy. The portfolio value is subsequently generated, adhering to the methodology elucidated in Section 5, contingent upon the current position's direction. A portfolio return is computed for each stock, SPY, and QQQ, along with the S&P 500, and NASDAQ 100 indexes, and aggregated Magnificent 7 active trading strategies on every expiration day. Moreover, we calculate the Sharpe ratio which is determined using the method outlined in Section 5. It's worth noting that we implement a stop-loss mechanism in this context as well, adding a layer of risk management to the trading strategy.

Table 10 shows that the aggregated risk-adjusted performance, as measured by the Sharpe ratio, of the Magnificent 7 stocks, QQQ, and SPY exceeds that of the S&P 500 and NASDAQ 100 active trading strategies. The Magnificent 7 portfolio outperforms the S&P 500 active trading strategy on 35 out of 37 expiration days and the aggregated Magnificent 7 active trading strategy on 31 out of 37 expiration days. This consistent superiority underscores the effectiveness of our predictive model and highlights the value of using options market data for improving risk-adjusted returns.

[Table 10 here]

Panel A of Table 11 shows that the Magnificent 7 portfolio outperformed the S&P 500 active trading strategy 69.29% of the time, with 792 out of 1143 expiration weeks being superior in the case of within-sample options data. The SPY portfolio outperformed the S&P 500 57.79% of the time, achieving superiority in 661 out of 1143 expiration weeks. For out-of-sample weekly options data, the Magnificent 7 portfolio outperformed the S&P 500 active trading strategy 94.59% of the time, excelling in 35 out of 37 expiration weeks. The SPY portfolio also showed strong performance, outperforming the S&P 500 91.89% of the time, or in 34 out of 37 expiration weeks. When examining aggregated option data monthly, the Magnificent 7 portfolio outperformed the S&P 500 active trading strategy 58.33% of the time, or in 70 out of 120 months. The SPY portfolio showed even greater performance, surpassing the S&P 500 66.67% of the time, or in 80 out of 120 months. These findings highlight the consistent outperformance of our predictive model-based portfolios compared to the traditional active trading strategy across different timeframes and scenarios.

In Panel B, we compare the weekly risk-adjusted aggregated trading performance of the Magnificent 7 portfolio, based on predicted returns, with the aggregated Magnificent 7 active trading strategy. For within-sample data, the Magnificent 7 portfolio outperforms the active trading strategy 85.71% of the time (980 out of 1143 weeks). For out-of-sample data, it surpasses the active trading strategy in 31 out of 37 weeks, achieving an 83.78% success rate.

Panel C reveals that the Magnificent 7 portfolio outperformed the NASDAQ 100 active trading strategy 94.59% of the time, or in 35 out of 37 expiration weeks for out-of-sample options data. Similarly, the QQQ portfolio surpassed the NASDAQ 100 strategy 91.89% of the time, achieving superior performance in 34 out of 37 weeks. These findings underscore the effectiveness of the Magnificent 7 portfolio and predictive trading strategy in delivering higher returns compared to conventional active trading strategies across the observed periods.

[Table 11 here]

7. Conclusion

In conclusion, this study provides a comprehensive analysis of options trading by leveraging weekly open interest and volume-based predictors to forecast short-term stock returns for the Magnificent 7 stocks and SPY. Our findings highlight the critical role of options market dynamics in predicting stock performance, corroborating Goyenko and Zhang's (2022) assertion on the importance of option characteristics as predictors, especially for prominent market players.

Across diverse market conditions and years, our analysis consistently reveals that the Magnificent 7 stocks and SPY outperform the widely tracked S&P 500 active trading strategy across varying market scenarios. The robustness of our predictors- open interest and volume- is evident across both weekly expiration and monthly-aggregated expiration periods, highlighting their capability to generate superior returns compared to benchmark indexes. This highlights the strategic value of options market indicators in enhancing investment performance and optimizing trading strategies.

Out-of-sample tests reinforce the reliability of our predictors, showing their consistent ability to generate returns for the Magnificent 7, SPY, and QQQ that surpass those of the S&P 500 and NASDAQ 100 indexes, as well as the aggregated Magnificent 7 active trading strategies. This empirical validation confirms the effectiveness of our trading strategy as a valuable tool for achieving superior returns in complex financial markets.

The application of the Fama-French 5-factor model further enriches our analysis, showing the enduring relevance of established variables while emphasizing the unique predictive power of our indicators. Our results validate the predictive significance of lagged predictors like OIC and OIP, contrasting with prior findings and reinforcing their efficacy when appropriate controls are applied. The predictive power of non-price indicators holds during unprecedented market conditions as well.

Expanding beyond stock returns, we explore return volatility forecasting by integrating our open interest and volume-based predictors, along with company-specific variables, and exponential moving averages. We validate the effectiveness of these predictors in forecasting return volatility through GARCH(1,1) modeling, confirming their robust performance in capturing volatility dynamics.

The consistent outperformance of the Magnificent 7 stocks, SPY, and QQQ highlights the robust predictive capabilities of options market indicators. Looking ahead, future research could explore advanced machine-learning techniques and sophisticated theoretical frameworks. Potential directions include developing an information-theoretic, multi-period Bayesian model for dynamic portfolio optimization under asymmetric information, innovative approaches to expected utility maximization within non-linear stochastic systems and expanding the sample to include a broader range of stocks across different sectors and market capitalizations to enhance the generalizability and robustness of the results. These avenues promise to further refine and enhance trading strategies, advancing the field.

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Table 1: Summary statistics for options open interest and volume-based predictors for Magnificent 7 and SPY

Ticker	*Statistics*	*Return*	*OIC*	*VC*	*OIP*	*VP*
AAPL	N	13448	13376	13376	12790	12790
AAPL	Minimum	-0.13	74.62	87.43	80	77.52
AAPL	Maximum	0.12	650.24	671.27	650.98	643.46
AAPL	Mean	0.00104	177.27	182.52	175.36	171.43
AAPL	Std. Dev	0.02	101.64	103.97	96.29	95.4
AMZN	N	10256	9828	9838	8240	8248
AMZN	Minimum	-0.14	81.66	83.68	69.96	67.04
AMZN	Maximum	0.14	4600	4600	3745.02	3700
AMZN	Mean	0.00095	1470.55	1495.48	1343.09	1326.18
AMZN	Std. Dev	0.02	1158.16	1184.53	1113.64	1098.49
GOOG	N	6968	6578	6584	4024	4032
GOOG	Minimum	-0.06	84	84	75	75
GOOG	Maximum	0.14	3110.71	3130.67	3000	3000
GOOG	Mean	0.0029	1162.19	1170.22	1032.06	1026.53
GOOG	Std. Dev	0.02	743.49	751.9	726.07	721.72
META	N	14116	13902	13904	12174	12182
META	Minimum	-0.26	22.49	23	22.72	21.3
META	Maximum	0.3	400	400	382.17	380
META	Mean	0.0012	155.8	160.08	152.91	150.08
META	Std. Dev	0.02	84.02	87	81.99	80.42
MSFT	N	12670	12164	12214	10506	10552
MSFT	Minimum	-0.15	25.17	26.47	26.5	26.16
MSFT	Maximum	0.14	351.49	356.46	375	375
MSFT	Mean	0.0011	133.63	135.41	131.87	129.62
MSFT	Std. Dev	0.02	92.33	94.18	90.93	89.12
NVDA	N	9470	8870	8894	7312	7342
NVDA	Minimum	-0.19	10.21	9.83	11.97	11.5
NVDA	Maximum	0.3	900	900	815.54	812.53
NVDA	Mean	0.0024	228.34	233.65	222.12	217.01
NVDA	Std. Dev	0.0314	161.64	166.16	148.15	146.64
SPY	N	31792	30316	30406	30780	30856
SPY	Minimum	-0.11	129.78	145	141.12	138.34
SPY	Maximum	0.09	540	540	487.75	487.32
SPY	Mean	0.00044	303.17	306.73	300.01	294.81
SPY	Std. Dev	0.01	86.49	87.54	84.51	83.15
TSLA	N	11690	11232	11242	10398	10404
TSLA	Minimum	-0.21	25	25	32.84	32.64
TSLA	Maximum	0.24	3000	3196.98	2271.72	2188.61
TSLA	Mean	0.0021	441.24	467.88	417.19	396.65
TSLA	Std. Dev	0.04	321.88	359.38	288.74	270.22

Summary Statistics for S&P500 Actual Returns

	N	**Minimum**	**Maximum**	**Mean**	**Std. Dev.**	**Median**
S&P 500	2518	-0.1198	0.0938	0.0005	0.0111	0.0006

Summary Statistics for NASDAQ100 Actual Returns (Jan-Aug 2023)

	N	**Minimum**	**Maximum**	**Mean**	**Std. Dev.**	**Median**
NASDAQ 100	167	-0.0227	0.0276	0.0021	0.011	0.0009

Table 1 provides a comprehensive overview of the main predictors- open interest and volume- for each of the Magnificent 7 stocks, SPY and **S**&P500. The summary statistics are derived from weekly option data spanning from 2013 to 2022. The raw values of OIC, OIP, VP, and VC are presented, showcasing their variation over the specified time frame. Here, N is the number of observations. The mean, standard deviation (Std. Dev), minimum, and maximum stats are shown in the table for each Magnificent 7 stock, SPY, along with S&P500.

Table 2: Person's correlation between predictors and stock return

Pearson's Correlation Coefficients					
	OIC	**OIP**	**VC**	**VP**	**Stock return**
OIC	1.00	-0.0564	0.5449	-0.0835	-0.0361
		(<.0001)	(<.0001)	(0.8735)	(<.0001)
OIP	-0.0564	1.00	-0.0504	0.5782	-0.0581
	(<.0001)		(0.0809)	(<.0001)	(<.0001)
VC	0.5449	-0.0504	1.00	-0.0709	0.0198
	(<.0001)	(0.0809)		(0.8072)	(<.0001)
VP	-0.0835	0.5782	-0.0709	1.00	0.0454
	(0.8735)	(<.0001)	(0.8072)		(<.0001)
Return	-0.0361	-0.0581	0.0198	0.0454	1.00
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	

Table 2 shows the Pearson correlation coefficients between predictors and stock return. The p-values are in parentheses. Despite utilizing open interest calls in their computation, the correlation between VC and OIC remains relatively low at 0.54. Similarly, the correlation between OIP and VP is 0.57. These values suggest that multicollinearity is not a significant concern in the model. Generally, correlations below 0.7 or 0.8 are considered acceptable to indicate that multicollinearity is not severe.

Table 3: Return of Magnificent 7 stocks and SPY using options open interest and volume-based predictors.

Parameter	*Coefficients*	*Coefficients*	*Coefficients*	*Coefficients*
	(1)	*(2)*	*(3)*	*(4)*
return $_{t-1}$	0.6254**	0.632***	0.3878***	0.6154***
	(2.05)	(270.03)	(161.83)	(236.17)
OIC	-0.0077***	-0.0062***	-0.0072***	-0.0071***
	(-5.29)	(-5.89)	(-7.66)	(-6.32)
OIC $_{t-1}$		0.0021**	0.0012***	0.0019**
		(1.98)	(2.34)	(2.17)
OIP	-0.0121***	-0.0098***	-0.0124***	-0.0061***
	(-8.21)	(-9.14)	(-12.81)	(-5.12)
OIP $_{t-1}$		-0.0039***	-0.0064***	-0.0013**
		(-3.69)	(-6.7)	(2.1)
VC	0.0056***	0.0044***	0.0064***	0.0048***
	(3.91)	(4.27)	(6.88)	(4.33)
VC $_{t-1}$		-0.0018*	-0.0027**	-0.0022**
		(-1.78)	(-2.22)	(-2.2)
VP	0.0104***	0.0082***	0.0113***	0.0038***
	(6.77)	(7.51)	(11.32)	(3.22)
VP $_{t-1}$		0.0045***	0.0071***	0.0051*
		(4.11)	(7.18)	(1.73)
momentum			-8.7647	-0.0131***
			(0.005)	(-2.57)
VIX			-0.0086	-0.0001***
			(0.03)	(-15.32)
Amihud's_illiquidity			-0.06597	-0.1064
			(-0.46)	(-0.67)
Adj. R^2	0.3989	0.6891	0.6376	0.6918
Firm-fixed effect	Yes	No	No	Yes
Time-fixed effect	Yes	No	No	Yes
Number of observations	78,840	78,840	78,840	78,840

Table 3 shows the results of dynamic panel regression on stock return and various independent and control variables. The independent and the control variables are lagged by one option initiation day. The standard errors have been congregated at the firm level and fitted for heteroskedasticity. The coefficients of estimations are presented with ***, **, and * which show statistical significance at 1%, 5%, and 10% levels, respectively. The t-statistics are reported in parentheses and are adjusted for both heteroskedasticity and within correlations.

Table 4: Robustness check for return of Magnificent 7 stocks and SPY using options open interest and volume-based predictors.

Parameter	***Coefficients***	***Coefficients***
	(1)	***(2)***
return $_{t-1}$	0.6715***	0.4419***
	(189.85)	(142.43)
OIC	-0.0067***	-0.0058***
	(-4.69)	(-4.59)
OIC_{t-1}	0.0061***	0.0034***
	(4.16)	(2.7)
OIP	-0.0105***	-0.0142***
	(-7.35)	(-11.39)
OIP_{t-1}	-0.0018	-0.0049***
	(-1.3)	(-3.98)
VC	0.0039***	0.0045***
	(2.75)	(3.62)
VC_{t-1}	-0.0062***	-0.0027**
	(-4.37)	(-2.13)
VP	0.0091***	0.0141***
	(6.16)	(10.97)
VP_{t-1}	0.0024*	0.0058***
	(1.66)	(4.61)
MA10	0.6185***	0.6623***
	(62.74)	(60.98)
BM_ratio	-0.0015**	-0.0001
	(-2.02)	(-0.19)
return $_{t-2}$	-0.1374***	-0.0678***
	(-32.42)	(-19.14)
return $_{t-3}$	-0.1261***	-0.0405***
	(-35.81)	(-12.57)
Adj. R^2	0.438	0.6426
Firm-fixed effect	No	Yes
Time-fixed effect	No	Yes
Number of observations	78,840	78,840

Table 4 shows the results of the robustness check for the dynamic panel regression on stock return and various independent and control variables. The independent and the control variables are lagged by one option initiation day. The standard errors have been congregated at the firm level and fitted for heteroskedasticity. The coefficients of estimations are presented with ***, **, and * which show statistical significance at 1%, 5%, and 10% level. The t-statistics are reported in parentheses and are adjusted for both heteroskedasticity and within correlations.

Table 5: Subsample analyses of return prediction for Magnificent 7 stocks and SPY using options open interest and volume-based predictors.

Parameters	Pre-pandemic period (2013-2019)			Pandemic period (2020-2021)		
	Coefficients *(1)*	*Coefficients* *(2)*	*Coefficients* *(3)*	*Coefficients* *(4)*	*Coefficients* *(5)*	*Coefficients* *(6)*
return $_{t-1}$	0.5347***	0.5357***	0.5058***	0.5848***	0.5818***	0.5715***
	(112.01)	(111.73)	(95.61)	(80.12)	(78.92)	(74.31)
OIC	-0.0015***	-0.0016***	-0.0017***	-0.0022***	-0.002***	-0.0021***
	(-9.75)	(-9.94)	(-10.12)	(-3.74)	(-3.55)	(-3.32)
OIC $_{t-1}$	0.0014***	0.0015***	0.0015***	0.0042***	0.0039***	0.0037***
	(11.35)	(11.35)	(10.85)	(6.24)	(5.74)	(5.33)
OIP	-0.0016***	-0.0017***	-0.0019***	-0.0026***	-0.0028***	-0.0028***
	(-10.04)	(-10.11)	(-10.79)	(-5.39)	(-5.36)	(-5.19)
OIP $_{t-1}$	-0.0013***	-0.0012***	-0.0014***	-0.0039***	-0.0033***	-0.0029***
	(-10.98)	(-11.12)	(-10.44)	(-6.22)	(-5.24)	(-4.66)
VC		0.0027**	0.0043**		0.0035**	0.0072**
		(2.13)	(2.14)		(2.08)	(2.15)
VC $_{t-1}$		-0.0017*	-0.0066***		-0.0218***	-0.0107*
		(-1.98)	(-2.78)		(-4.2)	(-1.98)
VP		0.0058**	0.0047*		0.0227***	0.0116**
		(2.26)	(1.98)		(4.28)	(2.1)
VP $_{t-1}$		0.0019**	0.0059**		0.0073**	0.0022**
		(2.09)	(2.03)		(2.16)	(2.18)
momentum			-0.1661***			0.1881***
			(-10.77)			(14.09)
VIX			-0.0037***			-0.0015***
			(-12.78)			(-7.11)
Amihud's Illiquidity			-1.173***			-0.4679***
			(-14.65)			(-2.42)
Adj. R^2	0.596	0.775	0.5882	0.5644	0.7526	0.7387
Firm-fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Time-fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	55,220	55,220	55,220	14,862	14,862	14,862

Table 6: Return volatility forecast for Magnificent 7 stocks and SPY using options open interest and volume-based predictors.

Parameter	Coefficient	Coefficient	Coefficient
	(1)	**(2)**	**(3)**
$volatility_t$	0.0207***	0.0066	0.0037***
	(51.04)	(0.43)	(51.27)
OIC_t	-0.0063***	-0.0051***	-0.0032***
	(-2.82)	(-2.7)	(-9.31)
OIP_t	0.0079***	0.0034*	0.0012***
	(3.59)	(1.75)	(3.44)
VC_t	0.0049**	0.0038**	0.0036***
	(2.19)	(2.03)	(10.4)
VP_t	-0.0086***	-0.0049**	-0.0014***
	(-3.8)	(-2.01)	(-3.83)
$S\&P500\_volatility_t$		1.012***	0.9913***
		(138.31)	(126.37)
$MA10_t$		-0.0015	-0.0039
		(-0.68)	(-1.24)
VIX_t		0.0002***	0.0003***
		(2.43)	(4.85)
$Amihud's\_illiquidity_t$		-0.0029	-0.2315***
		(-0.13)	(-5.97)
$momentum_t$		0.5936	-0.0002
		(1.41)	(0.005)
gpm_t		-0.0008	-0.0004***
		(-0.31)	(-4.07)
$MA20_t$		-0.0021	-0.0183***
		(0.66)	(-4.05)
Adj. R^2	0.6634	0.9259	0.8765
Firm-fixed effect	Yes	Yes	No
Time-fixed effect	Yes	Yes	No
Number of observations	78840	78840	78840

Table 6 shows the results of the dynamic panel regression on stock volatility forecast for time t+1 and various independent and control variables. The independent and the control variables are on option initiation day in time t. The standard errors have been congregated at the firm level and fitted for heteroskedasticity. The coefficients of estimations are presented with ***, **, and * which show statistical significance at 1%, 5%, and 10% level. The t-statistics are reported in parentheses and are adjusted for both heteroskedasticity and within correlations.

Table 7: GARCH model estimate for return volatility forecast.

Parameter	Coefficients
α	0.0017***
	(50.87)
β	0.0476***
	(164.14)
ω	0.9524***
	(309.6)
return $_{t-1}$	0.633***
	(361.91)
OIC	-0.0015***
	(-5.96)
OIC $_{t-1}$	0.0069***
	(2.6)
OIP	-0.0042**
	(-14.47)
OIP $_{t-1}$	-0.0453***
	(-3.8)
VC	0.0318***
	(12.71)
VC $_{t-1}$	-0.0015***
	(-2.44)
VP	0.0254***
	(9.64)
VP $_{t-1}$	0.0338*
	(1.99)
momentum	-0.0048*
	(-1.96)
VIX	-0.0008***
	(-24.93)
Amihud's_illiquidity	-0.1244
	(-0.78)
Adj. R^2	0.573
Normality test: Pr > ChiSq	0.619
Log Likelihood	130641.758
AIC	-261251.52
BIC	-261112.28
HQC	-261207.66
Number of observations	78,840

Table 7 presents the GARCH(1,1) model estimation results for forecasting volatility. Standard errors are clustered at the firm level and adjusted for heteroskedasticity. Coefficients marked with ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively. T-statistics, shown in parentheses, are adjusted for heteroskedasticity and within-firm correlations. The p-value for the normality test is 0.619, indicating that the GARCH model residuals are normally distributed. Log Likelihood measures model fit, with higher values suggesting a better fit. AIC, BIC, and HQC balance model fit and complexity, with lower values preferred. AIC has the least penalty for the number of parameters, followed by HQC, and then BIC, which penalizes the most. Despite large absolute values due to the large sample size, the relative values of AIC, BIC, and HQC indicate the balance between fit and complexity. Lower values suggest a better model fit.

Table 8: Monthly aggregated trading strategy performance of Magnificent 7 stocks and SPY vs. S&P500 active trading strategy.

Month	Return	Cum. return	σ	Sharpe ratio	Return	Cum. return	σ	Sharpe ratio	Month	Return	Cum. return	σ	Sharpe ratio	Return	Cum. return	σ	Sharpe ratio
	SPY				Magnificent 7 Stocks					SPY				Magnificent 7 Stocks			
Jan13	0.00327	0.01121	0.00248	1.32123	0.00461	0.0205	0.0047	0.9723	**Jan18**	0.00211	-0.0014	0.00219	0.96115	0.00428	-0.0275	0.0025	1.7058
Feb13	0.00114	0.00036	0.00227	0.50463	0.00028	0.0149	0.0049	0.0562	**Feb18**	-0.00051	0.0251	0.00541	-0.09502	0.00188	-0.0181	0.0111	0.1695
Mar13	0.00123	0.00491	0.00266	0.46338	0.00020	0.0077	0.0022	0.0924	**Mar18**	0.00017	0.0093	0.00512	0.03343	0.00087	-0.0033	0.0050	0.1738
Apr13	0.00071	0.01219	0.00282	0.25222	0.00243	0.0158	0.0038	0.64405	**Apr18**	0.00005	0.0117	0.00448	0.01013	-0.00162	0.0025	0.0104	-0.155
May13	0.00161	0.0049	0.00306	0.52520	0.00531	0.0253	0.0031	1.7138	**May18**	0.00113	0.0026	0.00303	0.37354	0.00318	-0.0102	0.0052	0.6132
Jun13	-0.0003	0.00978	0.00460	-0.0727	0.00143	0.0032	0.0028	0.5207	**Jun18**	0.00074	0.0062	0.00427	0.17305	0.00163	0.0086	0.0029	0.5625
Jul 13	0.00201	0.00386	0.00264	0.76125	0.00342	0.0111	0.0029	1.19313	**Jul 18**	0.00094	0.0024	0.00282	0.33390	0.00204	-0.0148	0.0070	0.2897
Aug13	-0.0001	0.00344	0.00277	-0.0343	0.00378	0.2821	0.0015	2.5578	**Aug18**	0.00096	0.0025	0.00231	0.41603	0.00078	0.0050	0.0051	0.1551
Sep13	0.00122	0.00338	0.00256	0.47645	0.00274	0.0005	0.0030	0.9068	**Sep18**	0.00081	0.0014	0.00179	0.45085	0.00009	0.0068	0.0067	0.0130
Oct13	0.00116	0.00905	0.00286	0.40674	0.00256	0.0019	0.0035	0.7227	**Oct18**	-0.00141	0.0117	0.00303	-0.46458	-0.00055	-0.0141	0.0030	-0.182
Nov13	0.00142	0.00233	0.00251	0.56424	0.00050	0.0019	0.0006	0.8399	**Nov18**	0.00023	0.0166	0.00668	0.03514	0.00033	-0.0022	0.0131	0.0252
Dec13	0.00081	0.0041	0.00225	0.35863	0.00232	0.0095	0.0041	0.5675	**Dec18**	-0.00188	0.0223	0.00560	-0.33557	-0.00068	0.0333	0.0115	-0.058
Jan14	0.00034	0.00493	0.00315	0.10776	0.00120	0.0142	0.0023	0.5344	**Jan19**	0.00244	0.0267	0.00444	0.55116	0.00299	0.0524	0.0072	0.4175
Feb14	0.00122	0.01085	0.00463	0.26355	0.00332	0.0119	0.0033	1.0161	**Feb19**	0.00201	0.0048	0.00395	0.50813	0.00086	0.0500	0.0077	0.1116
Mar14	0.00057	0.00392	0.00324	0.17486	0.00072	-0.0019	0.0049	0.1461	**Mar19**	0.00087	0.0045	0.00326	0.26640	0.00105	0.0079	0.0041	0.2536
Apr14	0.00033	0.00804	0.00229	0.14519	-0.0017	0.0211	0.0031	-0.5632	**Apr19**	0.00148	0.0039	0.00212	0.69819	0.00180	0.0190	0.0089	0.2035
May14	0.00118	-0.0003	0.00276	0.42960	0.00023	0.0104	0.0027	0.08716	**May19**	-0.00042	0.0047	0.00270	-0.15426	-0.00020	0.0219	0.0131	-0.015
Jun14	0.00119	-0.0025	0.00243	0.49160	0.00252	0.0024	0.0032	0.7781	**Jun19**	0.00138	0.0111	0.00362	0.38258	0.00242	0.0287	0.0123	0.1977
Jul 14	0.00082	-0.0008	0.00229	0.35652	0.00110	0.0094	0.0009	1.1882	**Jul 19**	0.00120	0.0004	0.00196	0.61182	0.00156	0.0205	0.0055	0.2863
Aug14	0.00055	0.00647	0.00365	0.14964	0.00172	-0.0012	0.0029	0.58393	**Aug19**	-0.00062	0.0172	0.00309	-0.20118	-0.00162	0.0262	0.0112	-0.145
Sep14	0.00052	0.00335	0.00366	0.14216	0.00124	0.0091	0.0030	0.41235	**Sep19**	0.00153	0.0073	0.00420	0.36486	0.00252	0.0058	0.0058	0.4340
Oct14	-0.0003	0.01517	0.00694	-0.0041	0.00074	0.003	0.0001	5.15445	**Oct19**	0.00054	0.0062	0.00429	0.12533	0.00575	0.0153	0.0096	0.6012
Nov14	0.00207	0.00084	0.00189	1.09360	0.00346	0.0093	0.0043	0.80838	**Nov19**	0.00162	-0.0013	0.00326	0.49652	0.00618	0.0107	0.0075	0.8245
Dec14	0.00056	0.01029	0.00216	0.25858	0.00027	0.0135	0.0028	0.09571	**Dec19**	0.00130	-0.0012	0.00338	0.38534	0.00561	0.0101	0.0037	1.5281
Jan15	0.00004	0.00963	0.00498	0.00883	-0.0002	0.0036	0.0054	-0.0397	**Jan20**	0.00118	0.0015	0.00497	0.23837	0.00418	0.0207	0.0117	0.3573
Feb15	0.00179	0.00377	0.00474	0.37653	0.00242	0.0264	0.0050	0.48622	**Feb20**	0.00026	0.0105	0.00283	0.09332	0.00390	0.0527	0.0131	0.2966
Mar15	0.00018	0.00481	0.00437	0.04021	0.00131	0.0072	0.0030	0.44277	**Mar20**	-0.00658	0.1301	0.01417	-0.46449	-0.00315	0.0892	0.0208	-0.151
Apr15	0.00077	0.00326	0.00303	0.25479	0.00209	0.0041	0.0028	0.74355	**Apr20**	0.00466	0.0908	0.00924	0.50475	0.00632	0.0540	0.0141	0.4491
May15	0.00067	0.00201	0.00335	0.20036	0.00244	0.0127	0.0057	0.42990	**May20**	0.00170	0.0195	0.00918	0.18533	0.00297	0.0065	0.0206	0.1443
Jun15	0.00016	0.00547	0.00334	0.04804	0.00166	0.0052	0.0029	0.57481	**Jun20**	0.00180	0.0373	0.00969	0.18618	0.00177	0.0049	0.0285	0.0623
Jul 15	0.00039	0.00838	0.00429	0.09089	0.00219	0.0070	0.0025	0.86477	**Jul20**	0.00190	0.0121	0.00486	0.39013	0.00372	0.0078	0.0364	0.1024
Aug15	-0.0008	0.01213	0.00428	-0.1949	0.00179	0.0187	0.0036	0.50107	**Aug20**	0.00208	0.0034	0.00329	0.63322	0.00584	-0.0679	0.0237	0.2462
Sep15	-0.0004	0.02237	0.00714	-0.0618	0.00103	0.0131	0.0038	0.26779	**Sep20**	-0.00056	0.0206	0.00478	-0.11671	-0.00034	0.0543	0.0160	-0.021
Oct15	0.00187	0.01201	0.00559	0.33473	0.00298	0.0098	0.0057	0.52265	**Oct20**	0.00127	0.0111	0.00505	0.25207	0.00314	0.0117	0.0172	0.1828
Nov15	0.00053	0.00565	0.00477	0.11204	0.00440	0.0184	0.0048	0.92443	**Nov20**	0.00170	0.0169	0.00399	0.42702	0.00384	0.0146	0.0106	0.3612
Dec15	0.00009	0.00876	0.00600	0.01433	-0.0007	-0.002	0.0042	-0.1798	**Dec20**	0.00123	0.0048	0.00380	0.32375	0.00360	0.0056	0.0258	0.1395
Jan16	-0.0017	0.0147	0.00646	-0.2682	-0.0036	0.0172	0.0049	-0.7348	**Jan-21**	0.00133	0.0046	0.00347	0.38308	0.00217	0.0054	0.0241	0.0901
Feb16	0.00054	0.0125	0.00797	0.06821	-0.0007	0.0266	0.0090	-0.0808	**Feb-21**	0.00133	0.0114	0.00382	0.34897	0.00094	0.0134	0.0098	0.0959
Mar16	0.00243	0.01056	0.00465	0.52326	0.00410	0.0072	0.0063	0.65414	**Mar-21**	0.00084	0.0116	0.00410	0.20473	0.00125	0.0461	0.0174	0.0718
Apr16	0.00098	0.00105	0.00293	0.33402	0.00174	-0.017	0.0019	0.89455	**Apr-21**	0.00206	0.0065	0.00429	0.48056	0.00267	0.0148	0.0106	0.2516
May16	0.00026	0.00211	0.00456	0.05749	0.00108	-0.0008	0.0059	0.18258	**May21**	0.00034	0.0098	0.00391	0.08797	0.00239	0.0120	0.0126	0.1890
Jun16	0.00043	0.00757	0.00319	0.13323	0.00259	0.0045	0.0041	0.62474	**Jun21**	0.00099	0.0033	0.00228	0.43606	0.00123	0.0170	0.0068	0.1805
Jul 16	0.00175	0.01261	0.00210	0.83389	0.00894	-0.0120	0.0050	1.80667	**Jul21**	0.00135	0.0037	0.00301	0.44838	0.00198	0.0065	0.0091	0.2178
Aug16	0.00058	-0.0005	0.00170	0.34458	0.00127	-0.0072	0.0028	0.44844	**Aug21**	0.00105	0.0032	0.00361	0.29177	0.00035	0.0116	0.0138	0.0255
Sep16	0.00013	0.00876	0.00172	0.07451	0.00051	-0.0102	0.0022	0.23449	**Sep21**	-0.00001	0.0057	0.00268	-0.00346	0.00161	0.0051	0.0118	0.1364
Oct16	0.00013	0.00227	0.00290	0.04383	0.00136	-0.0059	0.0052	0.26308	**Oct21**	0.00076	0.0175	0.00406	0.18776	0.00324	0.0096	0.0100	0.3241
Nov16	0.00120	0.00719	0.00197	0.60752	0.00281	0.0174	0.0053	0.53097	**Nov21**	0.00151	0.0003	0.00399	0.37987	0.00889	0.0362	0.0236	0.3774
Dec16	0.00129	0.00082	0.00214	0.60027	0.00297	0.0022	0.0042	0.71166	**Dec21**	0.00058	0.0100	0.00449	0.12802	0.00210	0.0070	0.0469	0.0447
Jan17	0.00084	0.00116	0.00327	0.25688	0.00342	-0.0099	0.0047	0.72400	**Jan22**	-0.00089	0.0091	0.00607	-0.14629	-0.00058	0.0081	0.0362	-0.016
Feb17	0.00134	-0.0009	0.00203	0.66034	0.00204	-0.0006	0.0052	0.39233	**Feb22**	-0.00044	0.0278	0.00579	-0.07648	-0.00170	0.0453	0.0351	-0.048
Mar17	0.00071	0.00274	0.00205	0.34756	0.00132	-0.0035	0.0050	0.26247	**Mar22**	0.00097	0.0165	0.00624	0.15536	0.00152	0.0154	0.0281	0.0542
Apr17	0.00029	-0.0005	0.00097	0.30072	0.00099	-0.0144	0.0016	0.63182	**Apr22**	-0.0003	0.0140	0.00567	-0.05225	0.00072	0.0324	0.0244	0.0294
May17	0.00085	0.00399	0.00273	0.30981	0.00302	-0.0018	0.0052	0.58328	**May22**	-0.00168	0.0207	0.01272	-0.13182	-0.00123	0.0616	0.0282	-0.043
Jun17	0.00095	0.00374	0.00289	0.32964	0.00290	-0.0242	0.0063	0.45776	**Jun22**	-0.00113	0.0251	0.00980	-0.11551	-0.00060	0.0454	0.0169	-0.035
Jul 17	0.00082	0.00167	0.00306	0.26706	0.00404	-0.0043	0.0063	0.64183	**Jul22**	0.00133	0.0229	0.00798	0.16650	0.00255	0.0347	0.0170	0.1503
Aug17	0.00020	0.00254	0.00102	0.19575	0.00263	0.0015	0.0034	0.78500	**Aug22**	0.00198	0.0203	0.00676	0.29263	0.00232	0.0364	0.0143	0.1623
Sep17	0.00113	0.00175	0.00297	0.37892	0.00131	-0.0019	0.0026	0.51086	**Sep22**	-0.00217	0.0298	0.00956	-0.22660	-0.00261	0.0537	0.0156	-0.166
Oct17	0.00116	-0.0043	0.00145	0.80067	0.00228	-0.0056	0.0050	0.45876	**Oct22**	0.00003	0.0210	0.00944	0.00302	0.00154	0.0469	0.0191	0.0807
Nov17	0.00076	-0.0015	0.00203	0.37432	0.00245	-0.0132	0.0031	0.78635	**Nov22**	0.00178	0.0328	0.00350	0.50926	0.00419	0.0862	0.0218	0.192
Dec17	0.00137	0.00365	0.00258	0.53019	0.00097	-0.0276	0.0054	0.18160	**Dec22**	-0.00068	0.0182	0.00610	-0.11155	-0.00230	0.0358	0.0125	-0.184
									Jan-23	0.00102	0.0063	0.00602	0.16996	-0.00331	0.0212	0.0128	-0.257

Table 8 shows the aggregate monthly trading performance of the Magnificent 7 stocks and SPY portfolio against the S&P500 active trading portfolio. As indicators of aggregated performance in each month, we show mean returns, volatility, and Sharpe ratios for S&P active trading and the Magnificent 7 stock portfolios. "Cum. Return" is the cumulative return, return is the portfolio return, and σ is the volatility of the portfolio. In almost every month, the Magnificent 7 and SPY portfolios outperform the S&P active trading portfolios.

Table 8: Monthly aggregated trading strategy performance of Magnificent 7 stocks and SPY vs. S&P500 active trading (Continued).

S&P500 Active Trading Strategy									
Month	**Return**	**σ**	**Cum.Ret**	**Sharpe**	**Month**	**Return**	**σ**	**Cum.Ret**	**Sharpe**
Jan-13	0.0031	0.0066	0.0912	0.4697	**Jan-18**	0.004	0.0043	0.6364	0.9302
Feb-13	0.0005	0.0065	0.1613	0.0769	**Feb-18**	-0.0022	0.0167	-0.5500	-0.1317
Mar-13	0.0015	0.0065	0.3050	0.2308	**Mar-18**	-0.0016	0.0125	0.7273	-0.1280
Apr-13	0.0005	0.0092	0.3333	0.0543	**Apr-18**	0.0006	0.011	-0.3750	0.0545
May-13	0.0013	0.0067	0.6000	0.1940	**May-18**	0.0011	0.0058	0.6667	0.1724
Jun-13	-0.0007	0.0109	-0.5385	-0.0642	**Jun-18**	0.0000	0.0065	0.0000	0.0000
Jul-13	0.0027	0.0044	-3.8571	0.6136	**Jul-18**	0.0019	0.0054	0.0000	0.3519
Aug-13	-0.0014	0.0062	-0.5185	-0.2258	**Aug-18**	0.0012	0.0045	0.6316	0.2667
Sep-13	0.0019	0.0054	-1.3571	0.3519	**Sep-18**	0.0002	0.0036	0.1667	0.0556
Oct-13	0.002	0.0083	1.0526	0.2410	**Oct-18**	-0.0045	0.0141	-0.1134	-0.3191
Nov-13	0.0011	0.0055	0.5500	0.2000	**Nov-18**	0.0016	0.0118	-0.3556	0.1356
Dec-13	0.001	0.0063	0.9091	0.1587	**Dec-18**	-0.0056	0.019	-3.5000	-0.2947
Jan-14	-0.0014	0.0076	-1.4000	-0.1842	**Jan-19**	0.0039	0.0119	-0.6964	0.3277
Feb-14	0.0023	0.008	-1.6429	0.2875	**Feb-19**	0.0025	0.0066	0.6410	0.3788
Mar-14	0	0.0065	0.0000	0.0000	**Mar-19**	0.0006	0.0068	0.2400	0.0882
Apr-14	0.0002	0.0088	0.0000	0.0227	**Apr-19**	0.0019	0.0041	3.1667	0.4634
May-14	0.0013	0.0049	6.5000	0.2653	**May-19**	-0.0027	0.0085	-1.4211	-0.3176
Jun-14	0.001	0.0037	0.7692	0.2703	**Jun-19**	0.0034	0.0066	-1.2593	0.5152
Jul-14	0.0005	0.0054	0.5000	0.0926	**Jul-19**	0.0015	0.0048	0.4412	0.3125
Aug-14	0.0005	0.0063	0.0542	0.0794	**Aug-19**	-0.0012	0.0136	-0.8000	-0.0882
Sep-14	-0.0005	0.0062	-1.0000	-0.0806	**Sep-19**	0.0006	0.0056	-0.5000	0.1071
Oct-14	0.0008	0.0111	-1.6000	0.0721	**Oct-19**	0.0011	0.0088	1.8333	0.1250
Nov-14	0.0013	0.0026	1.6250	0.5000	**Nov-19**	0.0016	0.0036	1.4545	0.4444
Dec-14	0.0006	0.0102	0.4615	0.0588	**Dec-19**	0.0016	0.0048	1.0000	0.3333
Jan-15	-0.0019	0.0102	-3.1667	-0.1863	**Jan-20**	-0.0002	0.0073	-0.1250	-0.0274
Feb-15	0.0028	0.0061	-1.4737	0.4590	**Feb-20**	-0.0045	0.0156	0.5220	-0.2885
Mar-15	-0.001	0.0088	-0.3571	-0.1136	**Mar-20**	-0.0057	0.0612	1.2667	-0.0931
Apr-15	0.0014	0.0059	-1.4000	0.2373	**Apr-20**	0.0062	0.0278	-1.0877	0.2230
May-15	-0.0002	0.0067	-0.1429	-0.0299	**May-20**	0.003	0.0146	0.4839	0.2055
Jun-15	-0.0001	0.0057	0.5000	-0.0175	**Jun-20**	-0.0004	0.0189	-0.1333	-0.0212
Jul-15	0.0001	0.0083	-1.0000	0.0120	**Jul-20**	0.0035	0.0088	-8.7500	0.3977
Aug-15	-0.0027	0.0172	-2.0000	-0.1570	**Aug-20**	0.0035	0.0051	0.1533	0.6863
Sep-15	-0.0015	0.013	0.5556	-0.1154	**Sep-20**	-0.0031	0.0156	-0.8857	-0.1987
Oct-15	0.003	0.01	-2.0000	0.3000	**Oct-20**	-0.0003	0.0129	0.0968	-0.0233
Nov-15	0.0003	0.0078	0.1000	0.0385	**Nov-20**	0.0057	0.0102	-0.1900	0.5588
Dec-15	-0.0009	0.0114	-3.0000	-0.0789	**Dec-20**	0.0014	0.0055	0.2456	0.2545
Jan-16	-0.0026	0.0152	2.8889	-0.1711	**Jan-21**	-0.0005	0.0107	-0.3571	-0.0467
Feb-16	0.0003	0.0119	-0.1154	0.0252	**Feb-21**	0.0014	0.009	-2.8000	0.1556
Mar-16	0.0024	0.0079	0.8088	0.3038	**Mar-21**	0.0022	0.0111	1.5714	0.1982
Apr-16	0.0006	0.0062	0.2500	0.0968	**Apr-21**	0.0021	0.0065	0.9545	0.3231
May-16	0.0008	0.0072	0.1333	0.1111	**May-21**	0.0003	0.0089	0.1429	0.0337
Jun-16	-0.0015	0.0097	-1.8750	-0.1546	**Jun-21**	0.001	0.0057	0.3333	0.1754
Jul-16	0.0027	0.0078	-1.8000	0.3462	**Jul-21**	0.0011	0.0069	0.1000	0.1594
Aug-16	-0.0001	0.0036	-0.0370	-0.0278	**Aug-21**	0.0013	0.0054	0.1818	0.2407
Sep-16	0.0000	0.0086	0.0000	0.0000	**Sep-21**	-0.0006	0.0068	-0.4615	-0.0882
Oct-16	-0.001	0.0043	0.0000	-0.2326	**Oct-21**	0.0014	0.0083	-2.3333	0.1687
Nov-16	0.0021	0.0068	-2.1000	0.3088	**Nov-21**	-0.0001	0.0066	-0.0714	-0.0152
Dec-16	0.0005	0.0049	0.2381	0.1020	**Dec-21**	0.0016	0.0114	-0.1600	0.1404
Jan-17	0.0014	0.0039	0.8200	0.3590	**Jan-22**	-0.0038	0.0109	-2.3750	-0.3486
Feb-17	0.0016	0.0033	0.1429	0.4848	**Feb-22**	-0.0005	0.015	0.1316	-0.0333
Mar-17	-0.0001	0.0049	-0.0625	-0.0204	**Mar-22**	0.0019	0.0149	-3.8000	0.1275
Apr-17	0.0005	0.0046	-5.0000	0.1087	**Apr-22**	-0.0038	0.0148	-2.0000	-0.2568
May-17	0.0007	0.0051	0.1400	0.1373	**May-22**	0.0005	0.0202	-0.1316	0.0248
Jun-17	0.0001	0.0044	0.1429	0.0227	**Jun-22**	-0.0032	0.0197	-6.4000	-0.1624
Jul-17	0.0011	0.0036	0.0210	0.3056	**Jul-22**	0.0023	0.0124	-0.7188	0.1855
Aug-17	-0.0006	0.006	-0.5455	-0.1000	**Aug-22**	-0.0008	0.0128	-0.3478	-0.0625
Sep-17	0.0013	0.0034	-2.1667	0.3824	**Sep-22**	-0.005	0.0141	6.2500	-0.3546
Oct-17	0.0012	0.0031	0.9231	0.3871	**Oct-22**	0.0044	0.0179	-0.8800	0.2458
Nov-17	0.0004	0.0033	0.3333	0.1212	**Nov-22**	0.0018	0.0169	0.4091	0.1065
Dec-17	0.0011	0.0041	0.7500	0.2683	**Dec-22**	-0.0019	0.0129	-1.0556	-0.1473

Table 9: Return prediction for Magnificent 7 and SPY using open interest and volume-based predictors using out-of-sample data.

Parameter	*Coefficients (1)*	*Coefficients (2)*	*Coefficients (3)*	*Coefficients (4)*
return $_{t-1}$	0.6823***	0.0097	0.0131*	0.0055**
	(3.88)	(1.39)	(1.72)	(2.25)
OIC	-0.0043**	-0.0057***	-0.0044***	-0.0042***
	(-2.31)	(-3.19)	(-2.43)	(-2.92)
OIP	-0.0096**	-0.0015***	-0.0015*	-0.0015***
	(-2.14)	(-2.75)	(-1.86)	(-2.86)
VC	0.0035**	0.0054***	0.0055***	0.0041**
	(2.15)	(3.16)	(3.09)	(2.16)
VP	0.0097**	0.0014**	0.0013**	0.0018***
	(2.28)	(2.17)	(2.13)	(2.54)
OIP_{t-1}		-0.0086***	-0.0164*	-0.0043**
		(-3.8)	(-1.68)	(-2.04)
OIC_{t-1}		0.0029**	0.0129***	0.0029***
		(2.32)	(2.55)	(2.33)
VP_{t-1}		0.004**	0.0109**	0.0045***
		(2.04)	(2.08)	(2.43)
VC_{t-1}		-0.0081***	-0.0068***	-0.0061***
		(-2.71)	(-2.65)	(-2.54)
Momentum			-0.1515	-1.459
			(-0.89)	(-0.64)
RMRF			0.6338***	0.5685***
			(4.74)	(6.28)
SMB			-0.4759*	-0.2626
			(-1.83)	(-1.33)
HML			1.622***	0.9067***
			(4.17)	(3.29)
RMW			0.371*	0.2432
			(1.72)	(1.12)
CMA			-2.5061***	-1.431***
			(-5.17)	(-3.87)
Adj. R^2	0.4859	0.5826	0.5026	0.554
Firm-fixed effect	Yes	Yes	Yes	No
Time-fixed effect	Yes	Yes	Yes	No
Number of observations	5334	5334	5334	5334

Table 9 shows the results of the dynamic panel regression on stock return for time t and various independent and control variables. The standard errors have been congregated at the firm level and fitted for heteroskedasticity. The coefficients of estimations are presented with ***, **, and * which show statistical significance at 1%, 5%, and 10% level. The t-statistics are reported in parentheses and are adjusted for both heteroskedasticity and within correlation.

Table 10: Comparison of the weekly risk-adjusted trading strategy performance of Magnificent 7 stocks, QQQ, and SPY based on predicted returns over the S&P500, NASDAQ 100, and aggregated Magnificent 7 active trading (AT) strategy for out-of-sample data.

Expiration date	Magnificent 7	SPY	QQQ	S&P 500	NASDAQ 100	Magnificent 7: AT
6-Jan-23	-0.2784	0.0145	0.0378	0.0048	0.0278	-0.0487
13-Jan-23	0.1985	0.0065	0.0088	-0.0015	0.0071	0.2203
20-Jan-23	0.2066	0.0085	0.0367	-0.0018	0.0286	0.0601
27-Jan-23	0.3890	0.0050	0.0137	-0.0051	0.0096	0.1732
3-Feb-23	0.3051	0.0075	0.0024	-0.0067	-0.0179	0.2254
10-Feb-23	0.4193	0.0066	0.0002	-0.0060	-0.0062	0.3301
17-Feb-23	0.0910	0.0116	0.0006	-0.0085	-0.0068	0.3816
24-Feb-23	0.1774	-0.0184	-0.0167	-0.0076	-0.0017	0.0664
3-Mar-23	0.6888	0.0760	0.0555	0.0161	0.0204	0.2664
10-Mar-23	-0.0022	-0.0081	-0.0307	-0.0145	-0.0138	-0.1386
17-Mar-23	0.0460	0.0235	0.1456	-0.0110	-0.0049	0.2008
24-Mar-23	0.0107	0.0216	0.1158	0.0056	0.0030	0.0018
31-Mar-23	0.1469	0.1793	0.2884	0.0144	0.0168	0.0495
6-Apr-23	0.1625	0.1070	0.0656	0.0036	0.0074	0.1616
14-Apr-23	0.0062	0.1228	0.1087	-0.0021	-0.0023	0.0023
21-Apr-23	0.0213	0.0220	0.0124	0.0009	0.0011	-0.0972
28-Apr-23	0.0302	0.0465	0.0716	0.0083	0.0065	0.0078
5-May-23	0.0810	0.0364	0.0086	0.0185	0.0213	0.0794
12-May-23	0.0771	0.0118	0.0958	-0.0016	-0.0037	0.0211
19-May-23	0.1536	0.0623	0.1530	-0.0014	-0.0023	0.0705
26-May-23	0.2252	0.0430	0.1436	0.0130	0.0258	0.2164
2-Jun-23	0.0523	0.1012	0.2468	0.0145	0.0073	0.0369
9-Jun-23	0.0702	0.0974	0.1215	0.0011	0.0030	0.0254
16-Jun-23	0.0652	0.2107	0.5480	-0.0037	-0.0067	0.3275
23-Jun-23	-0.0279	0.0720	0.1011	-0.0077	-0.0100	-0.0102
30-Jun-23	0.2924	0.9565	0.0996	0.0123	0.0160	0.2020
7-Jul-23	0.0506	-0.0098	0.0117	-0.0029	-0.0035	0.0622
14-Jul-23	0.2154	0.1573	0.1647	-0.0010	-0.0004	0.1891
21-Jul-23	0.2647	0.0688	0.0177	0.0003	-0.0026	0.0415
28-Jul-23	0.1641	0.0637	0.1019	0.0099	0.0185	0.1537
4-Aug-23	-0.0022	0.0016	-0.0016	-0.0053	-0.0051	-0.0056
11-Aug-23	0.0614	0.0188	0.0085	-0.0011	-0.0067	-0.0500
18-Aug-23	-0.0973	-0.0730	-0.1113	-0.0001	-0.0014	-0.0315
25-Aug-23	0.0982	0.0602	0.0541	0.0067	0.0085	-0.0717
1-Sep-23	0.1060	0.0215	0.0762	0.0018	-0.0007	0.1036
8-Sep-23	0.3808	0.0953	0.1614	0.0014	0.0014	0.1274
15-Sep-23	0.1928	0.0433	0.1947	-0.0122	-0.0175	0.0859

Table 10 shows the percentage of time the weekly and monthly trading performance of the Magnificent 7 stock portfolio, SPY, and QQQ outperformed the S&P 500 (INX) and NASDAQ 100 (NDX) active trading portfolio on each expiration date for the out-of-sample dataset. The positions in the trading of SPY, QQQ, and Magnificent 7 portfolios are based on the estimated return using our main predictors. Almost every week, the Magnificent 7 portfolios, QQQ, and SPY portfolios outperform the S&P500 and NDX active trading strategy as well as the Magnificent 7 active trading strategy.

Table 11: Comparison of the weekly and monthly trading strategy performance of aggregated Magnificent 7 stocks, QQQ, and SPY based on predicted returns over the S&P500, NASDAQ 100, and aggregated Magnificent 7 active trading (AT) strategy for in-sample and out-of-sample data.

Panel A Risk-adjusted trading performance outperforming S&P500 active trading strategy (in percentage)		
	Aggregated Magnificent 7 portfolio	**SPY portfolio**
Within-sample (Weekly)	69.29% (792 out of 1143 option expiration weeks)	57.79% (661 out of 1143 option expiration weeks)
Within-sample (Monthly)	58.33% (70 out of 120 option expiration months)	66.67% (80 out of 120 option expiration months)
Out-of-sample (Weekly)	94.59% (35 out of 37 option expiration weeks)	91.89% (34 out of 37 option expiration weeks)
Panel B Risk-adjusted trading performance outperforming Magnificent 7 active trading strategy (in percentage)		
	Within-sample	**Out-of-sample**
Aggregated Magnificent 7	85.71% (980 out of 1143 option expiration weeks)	83.78% (31 out of 37 option expiration weeks)
Panel C Risk-adjusted trading performance outperforming NASDAQ 100 active trading strategy (in percentage)		
	Aggregated Magnificent 7 portfolio	**QQQ portfolio**
Out-of-sample	94.59% (35 out of 37 option expiration weeks)	91.89% (34 out of 37 option expiration weeks)

In Panel A of Table 11, we present the percentage of time the aggregated Magnificent 7 portfolio and SPY portfolio outperform the S&P 500 and Magnificent 7 (aggregated) active trading strategy on a weekly and monthly basis for in-sample and out-of-sample datasets. Panel B illustrates the percentage of time the weekly risk-adjusted aggregated trading performance of the Magnificent 7 portfolio outperforms the aggregated Magnificent 7 active trading strategy. This comparison spans both within-sample and out-of-sample data, evaluated for each expiration week. In Panel C, we show the percentage by which the weekly risk-adjusted aggregated trading performance of the Magnificent 7 portfolio and QQQ portfolio outperforms the NASDAQ 100 active trading strategy. This comparison spans only the out-of-sample data, evaluated for each expiration week.

Figure 1: Histograms of the distribution of the returns against the distribution of OIC, OIP, VC, and VP of the Magnificent 7 stock and SPY for each trade initiation day of the weekly options.

Figure 1 displays histograms illustrating the distribution of returns in comparison to the distributions of OIC, OIP, VC, and VP for the Magnificent 7 stocks and SPY on each trade initiation day. Additionally, normality curves for both the predictors and returns are depicted. Across all four histograms, a discernible bell-shaped pattern is observed for the predictors.

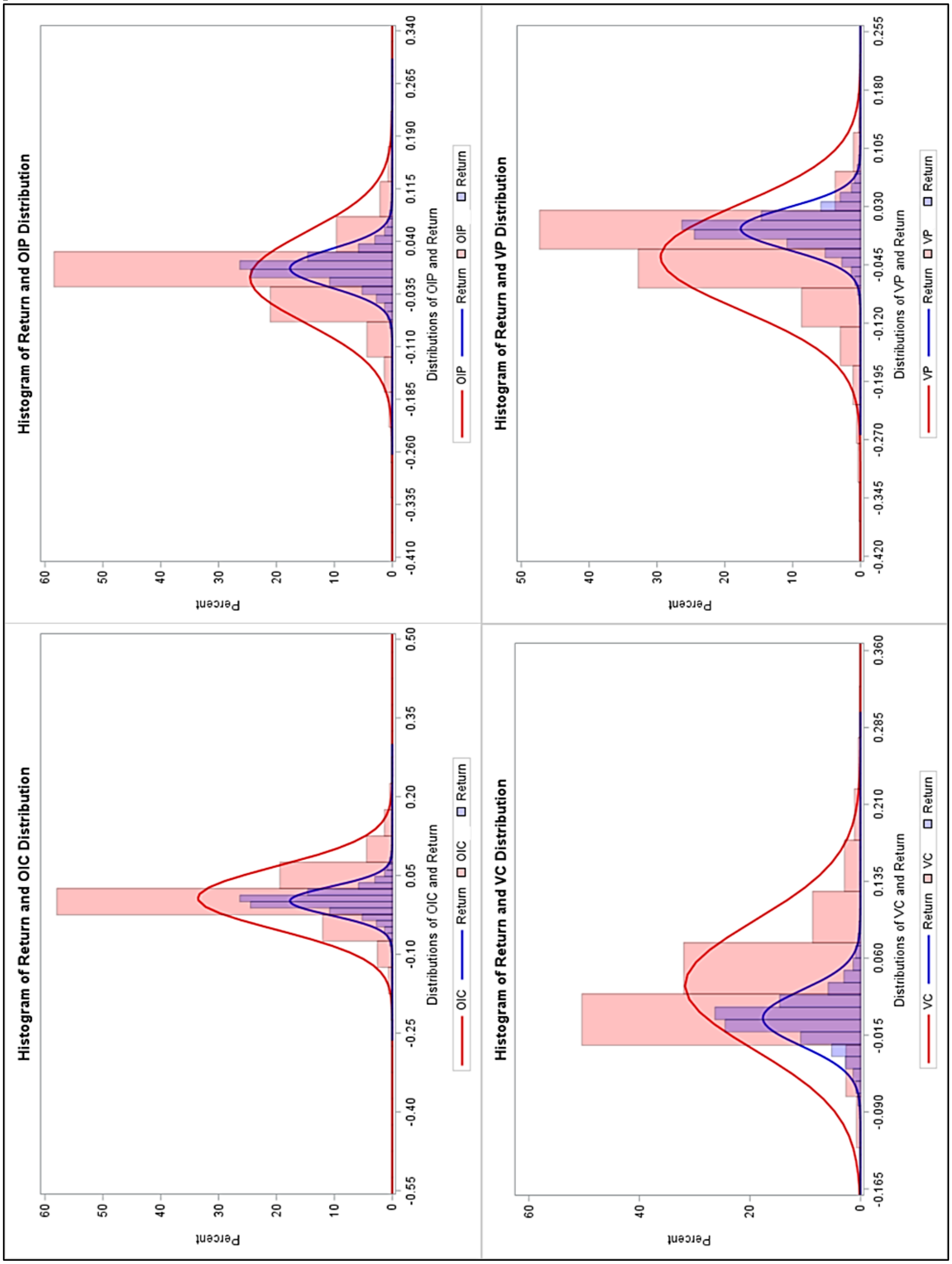
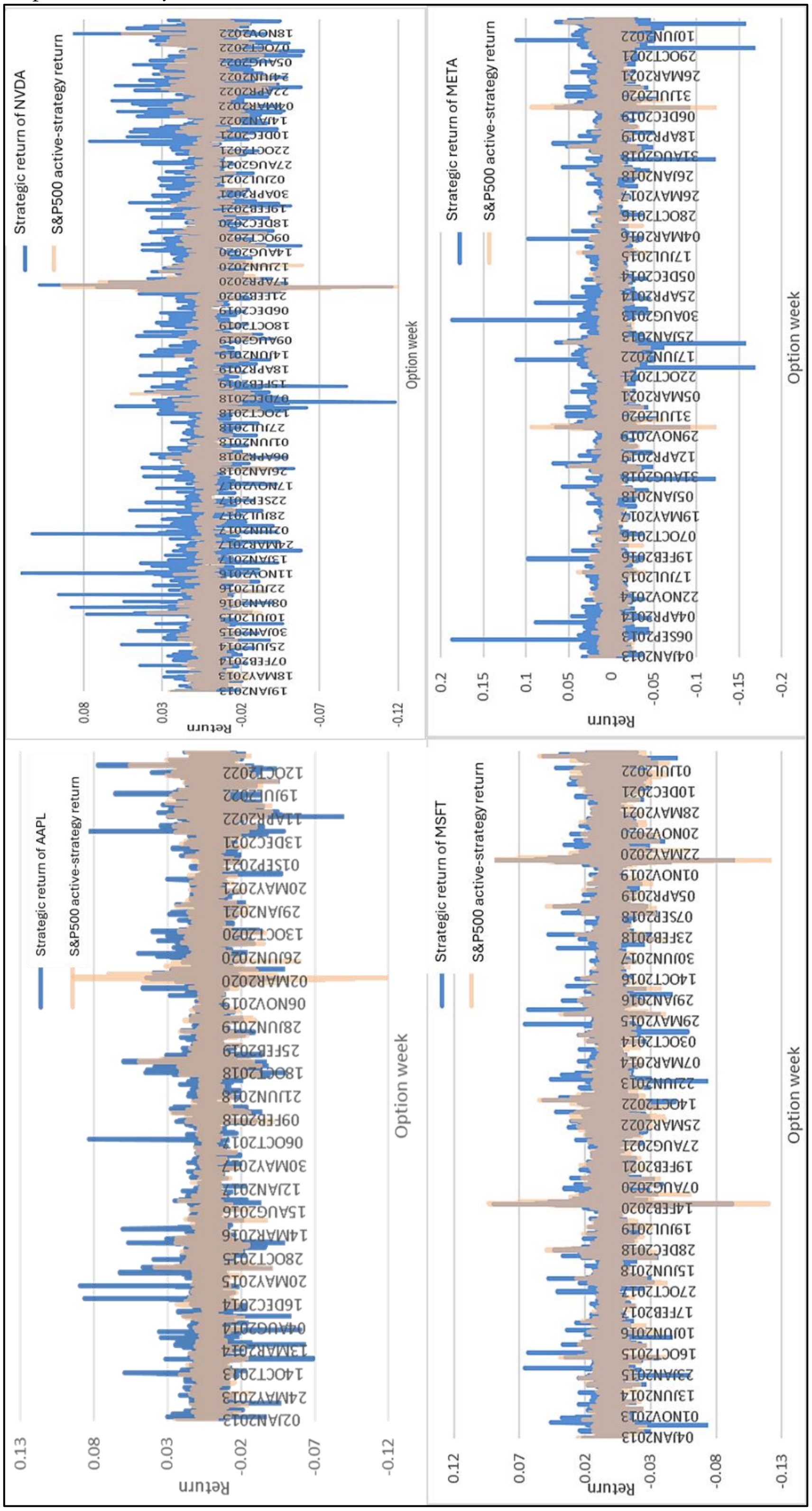


Figure 2: Weekly strategic return for Magnificent 7 and SPY portfolios compared to S&P500 active trading portfolio on each expiration day.

Figure 2 shows weekly strategic returns from the portfolios for Magnificent 7 and SPY and a comparison of them with the S&P 500 active trading strategy portfolio. The positions in the strategies are undertaken based on the estimated returns, which are generated using open interest and volume-based predictors. The x-axis shows the weekly strategic returns and the y-axis shows the option maturity dates.



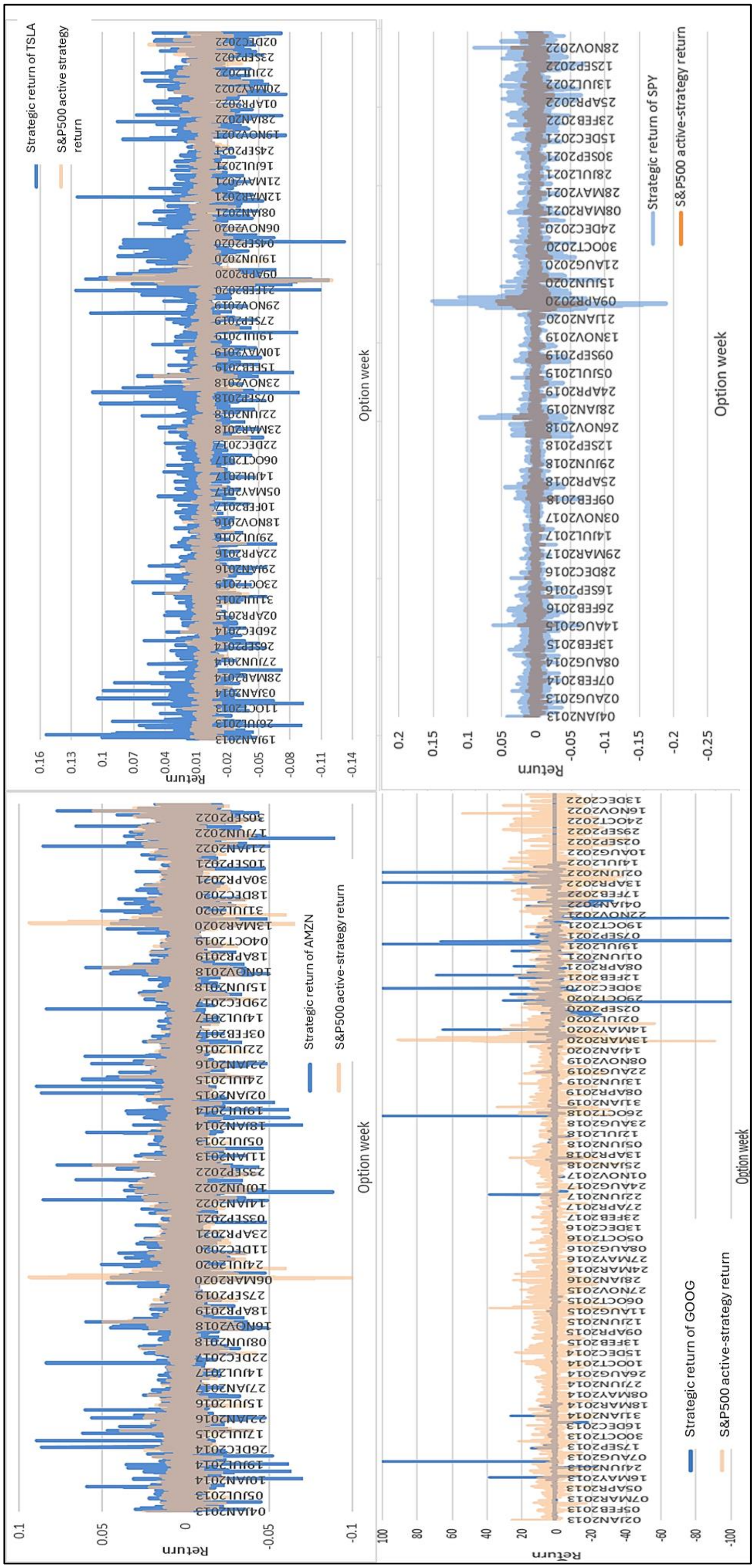


Figure 2: Weekly strategic return for Magnificent 7 and SPY portfolios compared to S&P500 active trading portfolio on each expiration day (Continued).