Does High Investor Attention Mean High Trading Activity?

Further research, Python codes used, data and future updates can be found in my repository:
https://github.com/traviske123nccu/Market-Research-Final-Project-3e.git

1. Introduction

The digitalization of financial ecosystems has made retail investor behavior increasingly observable and analyzable. In particular, online search activity—captured through platforms like Google Trends—offers a rich, real-time signal of investor attention. These behavioral traces may reflect curiosity, information-seeking, or even preemptive market action, offering a potential bridge between public sentiment and actual trading activity.

Understanding how retail attention translates into capital movement is increasingly relevant for both academic researchers and financial practitioners. For scholars, attention data may shed light on behavioral drivers of liquidity, volatility, and short-term predictability. For practitioners—such as brokers, trading platforms, or ETF issuers—it offers a potential tool for enhancing marketing efficiency, client engagement, and capital allocation decisions.

This study investigates whether investor attention, as proxied by Google Trends search volume, aligns with or predicts trading activity in Taiwan's equity and ETF markets. To operationalize this concept, we construct six thematic attention indexes—*ETF*, *Stock*, *Dividend*, *Beginner*, *Macro*, and *Tech*—to reflect different investor concerns and behavioral segments.

We aim[1] to determine *whether these attention indexes can be used as reliable predictors of trading volume and, if so, whether they can be leveraged in forecasting models or event-driven strategies to anticipate surges in market demand.*

Using time series analysis, regression modeling, and event study techniques across 19 Taiwan-listed tickers, we address three research questions along with each of their purposes:

RQ1: *Do investor attention patterns co-move with trading volume?*
This foundational question examines whether attention indexes and trading volume are statistically aligned, forming the behavioral basis for subsequent forecasting tasks and event analyses.

RQ2: *Can past attention and trading volume data be used to predict next week's trading activity?*
This question adopts a practitioner's perspective—if attention signals precede volume shifts, could these signals be exploited for short-term market prediction or platform-level applications such as targeted advertising or investor alerts?

RQ3: *Do scheduled macroeconomic or firm-level events (e.g., Fed announcements or executive visits) systematically impact*

[1] This is the Research Purpose of this research.

investor attention and trading?
Since decision-makers are constrained to rely on past data and known upcoming events, this question explores whether event timing itself can serve as a forward-looking behavioral signal.

Findings show that attention surges—particularly in *ETF* and *Tech* themes—often precede volume increases. Attention-based models moderately outperform volume-only baselines in forecasting low-volume periods, especially for beginner-oriented stocks. Event studies reveal that macro-level news primarily shifts attention without affecting trading, while firm-specific narratives—such as the visit of NVIDIA CEO Jensen Huang —trigger significant movements in both attention and volume.

Overall, this research highlights the potential of attention indexes as real-time behavioral signals. While not perfect standalone predictors, they offer financial institutions and fintech platforms a low-cost, high-frequency input for anticipating market behavior and enhancing decision-making in a digital investment landscape.

2. Data

2.1 Data Sources

We utilize two primary data streams for our analysis. First, **Google Trends** data, accessed via the `pytrends` library, provides weekly search volume information from January 1 to December 31, 2024. The selected keywords[2] are designed to capture various dimensions of investor interest in Taiwan. Second, we collect daily trading volume data using the `yfinance` API for 19 Taiwan-listed stocks and ETFs. These figures are aggregated on a weekly basis and aligned with the Google Trends data to ensure consistency in time series analysis.

2.2 Attention Indexes

To capture thematic investor interest, we construct six attention indexes corresponding to common investment topics: **ETF, Stock, Dividend, Beginner, Macro**, and **Tech**. Each index is created by averaging the weekly Google Trends scores of five carefully chosen keywords related to its respective theme. To facilitate comparison across indexes and over time, we standardize all scores using z-score normalization.

2.3 Ticker Selection and Variables

Each attention index is matched to two to five representative tickers based on thematic relevance and their visibility in the market. The main variables used in our analysis include the **attention indexes**, which reflect standardized weekly attention levels; the **trading volumes**, represented as normalized weekly aggregated volumes for each ticker; and the **event indicators**, which are binary variables that flag key event periods—namely, Fed Weeks

[2] See my github repository (click here) for further details, as this report is limited to up to 15 pages.

(defined as ±3 days[3] around U.S. Federal Reserve interest rate announcements) and Jensen Week (a six-week window centered around NVIDIA CEO Jensen Huang's visit to Taiwan).

3. Research Design and Methodology

Our analysis is structured around three distinct but interrelated research questions (RQ1–RQ3), each accompanied by explicit hypotheses.

RQ1: Do investor attention patterns comove with trading volume?

To address this, we compute correlation coefficients and visually inspect time series patterns between attention indexes and trading activity. This step establishes a behavioral linkage between attention and volume.

- **H1.1**: Attention indexes and trading volume are positively correlated.
- **H1.2**: Spikes in attention precede spikes in trading volume by one week.

RQ2: Can past attention and trading volume data be used to predict next week's trading activity?

We develop both linear and logistic regression models using lagged attention data and/or past volume to predict next week's trading intensity.

- **H2.1(for binary classification models)**: Lagged attention indexes derived from Google Trends can be used as predictive features in forecasting next week's aggregate trading volume with statistically significant accuracy.
- **H2.2(for linear regression)**: Prediction models that incorporate attention data will outperform models that rely solely on past trading volume in terms of forecasting next week's trading activity.

RQ3: Do scheduled macroeconomic or firm-level events (e.g., Fed announcements or executive visits) systematically impact investor attention and trading?

We conduct an event study on two known shocks—U.S. Federal Reserve announcements and NVIDIA CEO Jensen Huang's visit to Taiwan ("Jensen Week")—to evaluate whether they induce significant shifts in attention and volume.

- **H3.1**: The Macro Attention Index significantly increases during Fed announcement weeks.
- **H3.2**: Attention toward technology-related ETFs increases during Jensen Week.
- **H3.3**: Trading volume in selected ETFs rises significantly during event weeks compared to prior weeks.

Together, these three research questions stem from a unified empirical agenda to rigorously address our central inquiry: *Does high investor attention mean high*

[3] The reason is that if the Fed meeting occurs 3 days into this week, we should label last week as the "Fed Week" to avoid other noises that happens after the fed meetings.

trading activity? RQ1 establishes the foundational behavioral linkage between attention and volume, validating that investor attention reflects market engagement. RQ2 extends this insight into a predictive context, testing whether lagged attention signals can anticipate trading dynamics in practice. RQ3 complements this framework by shifting to an event-based perspective—examining whether attention and volume patterns respond systematically to known macroeconomic or firm-level shocks. By approaching the title question from descriptive, predictive, and event-driven angles, our research delivers a comprehensive, multidimensional answer to how investor attention relates to market activity.

4. Empirical Results

4.1 Research Question 1

Does Attention Align with Trading Volume?

4.1.1 Time Series Trend Analysis

To investigate whether investor attention aligns with or predicts trading activity (RQ1), we generate separate time series plots for each attention index alongside the normalized trading volumes of its related stocks. By isolating each attention index and its corresponding tickers in individual figures, we gain a clearer visual understanding of co-movement patterns without the visual clutter of overlapping themes. This disaggregated view allows us to detect whether attention surges (e.g., search spikes in ETF-related keywords) precede or coincide with volume spikes in associated tickers. Such visual diagnostics offer preliminary insights into the potential behavioral link between retail investor attention and market participation, forming the basis for subsequent statistical tests of correlation and causality[4].

Visual inspection of the time series plots reveals varying degrees of alignment between attention indexes and their corresponding stock trading volumes.

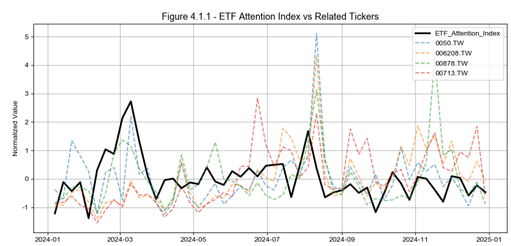

Figure 4.1.1: ETF Attention Index vs Related Tickers

In Figure 4.1.1 (ETF), spikes in ETF-related attention clearly coincide with or slightly precede volume surges in tickers like 0050.TW and 00878.TW. This suggests that retail investor interest in ETF-related search terms may reflect real-time or anticipatory shifts in ETF trading behavior.

[4] Although we completed the code for Granger causality tests, the results were not included in the final analysis due to time constraints that prevented us from fully interpreting the findings and evaluating their implications for our hypotheses. For the record, the code can be found in the RQ1.ipynb in my github repository.

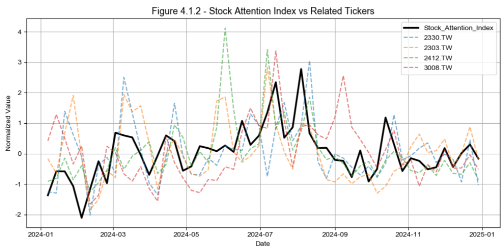

Figure 4.1.2: Stock Attention Index vs Related Tickers

In Figure 4.1.2 (Stock), the stock attention index trends upward in Q2–Q3, broadly matching volume fluctuations in major equities such as 2330.TW (TSMC). Several aligned peaks suggest that general stock-related search interest co-moves with activity in highly visible names.

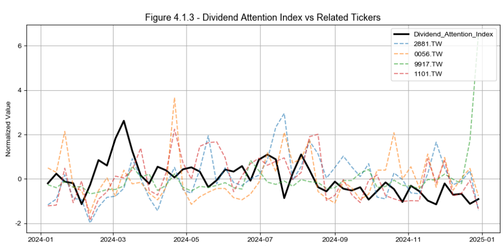

Figure 4.1.3: Dividend Attention Index vs Related Tickers

In Figure 4.1.3 (Dividend), attention to dividend-related keywords tends to rise in early Q1, aligning with mild volume bumps in 0056.TW and 2881.TW. However, the signal is less pronounced than in ETF or Stock indexes, possibly reflecting more stable or planned investor behavior.

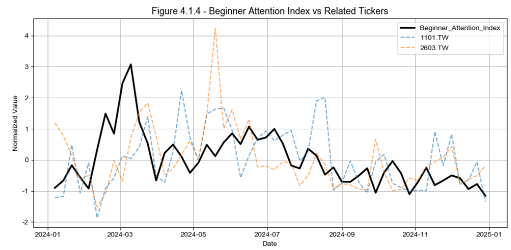

Figure 4.1.4: Begginer Attention Index vs Related Tickers

In Figure 4.1.4 (Beginner), the Beginner Attention Index shows multiple peaks in Q1–Q2 (notably around March), which correspond with elevated volume in 2603.TW and 1101.TW. These may reflect entry points for new retail investors, coinciding with education-related search activity.

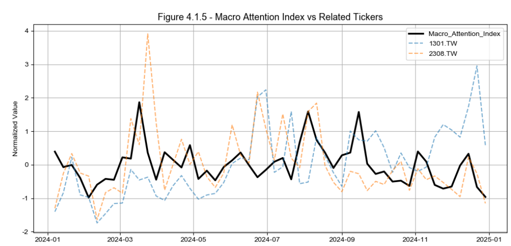

Figure 4.1.5: Macro Attention Index vs Related Tickers

In Figure 4.1.5 (Macro), macro attention exhibits visible spikes during known macro events (e.g., inflation discussions, Fed meetings), especially in March and October. Related tickers (e.g., 1301.TW, 2308.TW) show volume jumps in proximity to those dates, hinting at macro-news-driven trading.

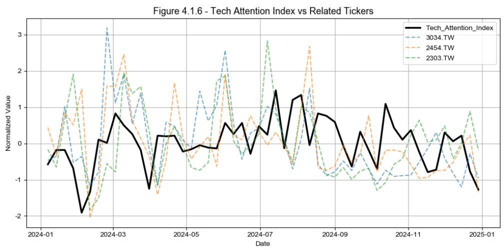

Figure 4.1.6: Tech Attention Index vs Related Tickers

In Figure 4.1.6 (Tech), the Tech Attention Index remains elevated during major AI-related news cycles (e.g., February–March and late summer), with visually synchronized peaks across 3034.TW, 2454.TW, and 2303.TW. The close co-movement suggests that retail attention toward semiconductor and technology themes is strongly echoed in trading activity, particularly during hype-driven periods.

Together, these visual patterns provide initial support for a behavioral link between investor attention and real trading decisions. This motivates the following sections, which test these relationships more formally using correlation analysis and predictive models.

4.1.2 Correlation Analysis

To quantitatively assess the relationship between investor attention and trading behavior, we compute a Pearson correlation matrix between the attention indexes and the normalized trading volumes of related stocks. Specifically, we extract all columns corresponding to volume and attention, and apply the `DataFrame.corrwith()` method to measure linear associations across time. The resulting correlation matrix is then visualized using a heatmap, where each cell indicates the strength and direction of correlation between a given stock's trading volume and an attention index. This approach enables us to identify which themes of investor attention (e.g., dividend-related or macro-related) are most strongly linked to observed trading activity, thus offering an empirical foundation for answering RQ1. High positive correlations suggest that investor interest, as proxied by Google search volume, may co-move or even lead trading volume patterns.

The correlation matrix in Figure 4.1.7 reveals diverse relationships between attention indexes and the trading volumes of related stocks, providing empirical support for RQ1. Several attention themes demonstrate clear positive correlations with their respective tickers, while others are more muted or mixed.

Stock Attention Index shows consistent moderate-to-strong correlations across most of its tickers, peaking at **0.51** with 2882.TW and **0.45** with 2412.TW. This suggests that retail attention to general stock-related search terms aligns strongly with trading behavior in major, visible equities.

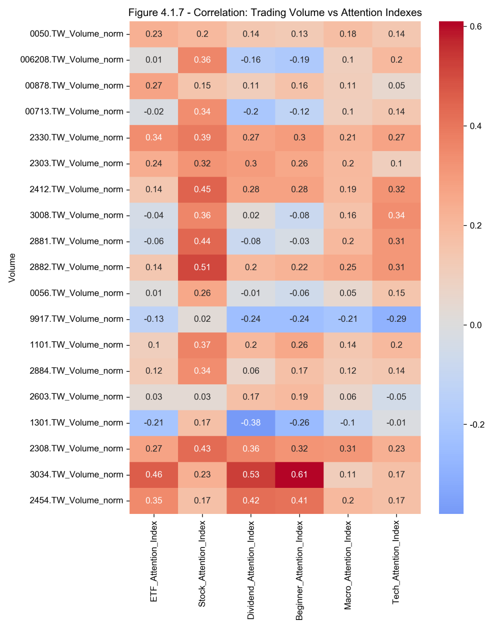

Figure 4.1.7: Heatmap of Correlation Between Stock and Attention

Tech Attention Index correlates well with 3034.TW (**0.17**) and 2454.TW (**0.17**), and even more strongly with the broader technology cluster including 2330.TW (**0.27**) and 2308.TW (**0.23**). Although not extremely high, the consistency across semiconductors and AI-related tickers indicates that attention in this sector tracks trading behavior fairly well.

Dividend Attention Index shows meaningful correlations with traditional income-focused tickers: **0.42** for 2454.TW, and **0.36** for 2308.TW. These relationships suggest that investor attention toward yield-oriented topics is reflected in the activity of relevant dividend-paying stocks.

Beginner Attention Index exhibits strong correlations with 3034.TW (**0.61**) and 2454.TW (**0.41**), indicating that stocks popular among novice investors may be particularly sensitive to public attention surges. This aligns with behavioral finance insights about attention-driven retail flows.

ETF Attention Index, while somewhat weaker overall, still shows notable positive correlations with 0050.TW (**0.23**) and 00878.TW (**0.27**), both well-known ETFs in Taiwan. The signal is more diffuse, likely due to ETFs being baskets rather than individual names.

Macro Attention Index shows the weakest and most inconsistent correlations. Only 2308.TW (**0.31**) and 2303.TW (**0.20**) register notable co-movement, while many tickers show near-zero or negative associations. This may reflect a disconnect between macroeconomic concerns and individual equity trading behavior.

These findings provide quantitative support for RQ1: **investor attention, particularly in Stock, Dividend, and Beginner categories, is meaningfully associated with real-world trading activity**.

Taken together, the visual and statistical evidence in Section 4.1 provides strong support for RQ1: investor attention, as measured by Google Trends, aligns meaningfully with real-world trading activity in Taiwan's equity market. Time series plots suggest that attention surges often coincide with or slightly precede spikes in trading volume, particularly in the ETF, Stock, and Tech attention indexes, offering initial support for H1.2[5]. Correlation

[5]Hypothesis 1.2: Spikes in attention precede

analysis further confirms H1.1[6], showing that attention indexes are positively associated with the trading volumes of related stocks. Notably, attention toward dividend-paying, beginner-friendly, and widely followed stocks shows the clearest and most consistent co-movement patterns. These findings indicate that retail search behavior can reflect—and occasionally anticipate—trading activity, validating the use of search-based attention indexes as a behavioral signal.

4.2 Research Question 2

Can lagged Google Trends data predict whether trading volume will be high next week?

To construct a predictive modeling dataset for RQ2, we begin by downloading raw daily trading volume data for 19 Taiwan-listed tickers using the yfinance API. This data is aggregated to weekly frequency (Monday to Sunday) and summed across all tickers to create a composite measure of retail trading activity, referred to as Total_Volume. We then normalize this series using z-score scaling to form the prediction target, Total_Volume_norm.

Next, we load the attention index dataset, which contains weekly Google Trends-based indicators for six investment themes. These are merged with the normalized total volume based on aligned weekly dates. To ensure that our model uses only past information to predict future outcomes, we lag each attention index by one week. The target variable is also shifted by one week to represent the volume in the week following the attention data. After dropping rows with missing values caused by shifting, we obtain a clean model-ready DataFrame (df_model) where each row represents a forecasting instance: last week's attention indexes are used to predict this week's market-wide trading volume.

spikes in trading volume by one week.

[6]Hypothesis 1.1: Attention indexes and trading volume are positively correlated.

4.2.1 Linear Regression Model

To investigate whether Google Trends attention indexes can help forecast short-term trading volume, we build three linear regression models using different configurations of input features. In the **attention-only model**, we use six lagged attention indexes (shifted by one week) to predict normalized total trading volume in the following week. In the **volume-only baseline**, we use only lagged total volume as the sole predictor. Finally, in the **combined model**, we use both lagged attention and lagged volume features.

All models are trained on the first 70% of the weekly data and tested on the remaining 30%, with RMSE (Root Mean Squared Error) used as the evaluation metric.

The **attention-only model** achieves an RMSE of **0.99**, suggesting that Google Trends data alone contains moderate predictive information. However, it underestimates several sharp volume surges, indicating limited responsiveness to extreme events.

Surprisingly, the **volume-only baseline** performs better, with an RMSE of **0.88**. This suggests that last week's trading activity alone is a relatively stable predictor of next week's volume, likely due to strong market autocorrelation.

When combining both attention and volume inputs, performance worsens with an RMSE of **1.07**. This indicates potential multicollinearity or noise introduced when merging high-dimensional attention signals with endogenous volume features.

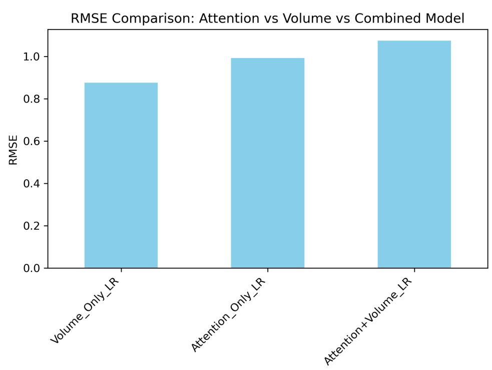

Figure 4.2.4: RMSE Comparison: Attention vs Volume vs Combined Model

As summarized in Figure 4.2.4, these results imply that while attention signals are somewhat informative on their own, they do not improve forecasts when added to volume under a linear modeling framework. More flexible models may be needed to capture non-linear interactions and maximize predictive accuracy.

4.2.2 Logistic Regression Model

To assess whether Google Trends attention data can effectively classify future trading weeks as high or low volume, we implement a series of binary classification models using **logistic regression**.

We define a high-volume week as one in which the normalized total trading volume (`Total_Volume_norm`) exceeds its historical mean. This yields a binary target variable, `target_class`, where 1 indicates a high-volume week and 0 otherwise.

We evaluate **three different feature sets** to test the predictive value of attention data, lagged volume data, and their combination:

1. **Attention-Only Model**
   This model uses six lagged attention indexes (each shifted by one week) as input features. It achieves an overall accuracy of **62.5%**, with balanced performance across both classes (precision and recall = 0.73 for low-volume weeks; 0.40 for high-volume weeks).
   The model offers moderate discriminative ability, identifying many low-volume weeks correctly but struggling with precision and recall on high-volume weeks. This suggests that while attention data carry some directional signals, they are insufficient for robust binary classification.

2. **Volume-Only Model**
   Using only the lagged total trading volume as input, this model performs poorly, achieving an accuracy of **33.3%**.
   The model fails to predict any low-volume weeks, with all predictions

falling into the high-volume class. This imbalance leads to undefined precision on one class and confirms that volume alone offers limited value for classification tasks, especially under this thresholding scheme.

3. **Combined Model (Attention + Volume)**
   Integrating all attention features and lagged total volume, this model achieves a slightly lower overall accuracy of **60.0%**, with more balanced but still limited classification power.
   It achieves a precision of 0.67 for low-volume weeks and 0.33 for high-volume weeks, but both recall and F1-scores for high-volume weeks remain weak. The performance is slightly worse than the attention-only model, again highlighting that adding volume does not significantly improve classification accuracy and may introduce noise.

Across all three models, the logistic regression classifier shows only **moderate ability** to distinguish high-volume from low-volume weeks. The attention-only model performs best, suggesting that retail attention does contain weak directional signals. However, classification accuracy remains close to chance, and the models suffer from imbalanced performance and low recall on high-volume weeks. These findings indicate that while attention-based features carry some predictive value, more **sophisticated classification approaches** or **alternative labeling strategies** may be needed to meaningfully improve binary prediction tasks.

In summary, the results of Section 4.2 offer a nuanced answer to RQ2: Can lagged Google Trends data predict whether trading volume will be high next week? Both regression and classification analyses show that attention-based indicators do carry predictive information, but their standalone power is limited. In linear regression, the attention-only model performs modestly (RMSE = 0.99), while the volume-only baseline surprisingly outperforms it (RMSE = 0.88), and combining both inputs does not yield further improvement (RMSE = 1.07). Similarly, logistic regression shows that attention features enable moderate classification (accuracy = 62.5%), but adding lagged volume does not enhance this further, and volume-only classification performs poorly (accuracy = 33.3%). These findings do not support Hypothesis H2.1[7], as incorporating attention data does not significantly improve forecasting accuracy over volume-based baselines.[8] Moreover, Hypothesis H2.2[9] also receives limited support: attention signals

[7]H2.1: Lagged attention indexes derived from Google Trends can be used as predictive features in forecasting next week's aggregate trading volume with statistically significant accuracy.

[8]Compared to the volume-only model, the attention-only model performs substantially better, indicating attention data has predictive value. However, incorporating attention into the volume-based baseline (i.e., the combined model) does not further improve performance, possibly due to multicollinearity or noise.

[9]H2.2: Prediction models that incorporate attention data will outperform models that rely solely on past trading volume in terms of forecasting next week's trading activity.

may be more useful for identifying low-volume (quieter) weeks than high-volume spikes, but the effect is modest and inconsistent. Overall, while attention data adds some predictive value, more advanced modeling or refined feature engineering is needed to fully leverage its potential in forecasting weekly trading activity.

4.3 Research Question 3

Do macro-level shocks or firm-level shocks affect retail attention and market activity in Taiwan's ETF & Stock Market?

4.3.1 Retail Attention Sensitivity During Fed Policy Weeks

To evaluate whether macroeconomic announcements—specifically U.S. Federal Reserve interest rate decisions—elicit measurable shifts in investor attention, we analyze Google Trends–based attention indexes during weeks of Fed policy announcements. These "Fed Weeks" are defined as the weeks containing or immediately adjacent to official interest rate decision dates. For each attention index, we compare attention levels between Fed Weeks and all other (non-Fed) weeks using both visual inspection via boxplots and statistical testing via independent sample t-tests.

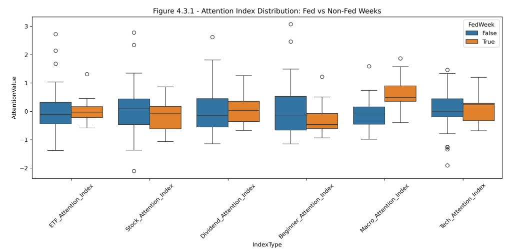

Figure 4.3.1: Attention Index Distribution: Fed vs Non-Fed Weeks

The boxplot in Figure 4.3.1 displays the distribution of attention values across Fed and non-Fed weeks for six thematic indexes. Most indexes show overlapping distributions, suggesting little distinction in attention behavior between the two event categories. To quantify these differences, we perform t-tests across all attention themes.

In the t-test results[10], only the Macro_Attention_Index shows a statistically significant difference during Fed Weeks (p = 0.0169), indicating that public search interest in macroeconomic topics intensifies during these policy announcement windows. Other indexes—such as those related to technology, stocks, or ETFs—show no significant difference, with p-values well above conventional thresholds.

These findings suggest that retail attention is selectively responsive to macro-level news, particularly when the theme aligns directly with the content of the announcement (e.g., inflation, interest rates). This provides empirical support for H3.1[11].

[10] the full results can be seen in my Github Repository.(click here)

[11] H3.1: The Macro Attention Index significantly increases during Fed announcement weeks.

However, the lack of broader significance across other indexes implies that Fed announcements do not trigger uniform retail attention shifts across investment categories. This aligns with the conclusion of Section 4.1, where attention patterns tended to reflect theme-specific behavioral sensitivities. The results here also set the stage for Section 4.3.2, where we investigate whether these attention shifts translate into real trading behavior.

4.3.2 Trading Volume Responses to Federal Reserve Announcements

To complement the analysis of attention-based search behavior, this section investigates whether actual ETF trading activity shifts significantly during U.S. Federal Reserve policy announcement weeks. Using the same event windows defined earlier (±3 days around each Fed decision), we compare the normalized trading volumes of 19 Taiwan-listed tickers between Fed weeks and non-Fed weeks.

We first generate comparative boxplots (Figure 4.3.2) to visually assess changes in volume distributions across each ticker. Then, for each ETF, we conduct independent two-sample t-tests to determine whether the differences in weekly trading volumes are statistically significant.

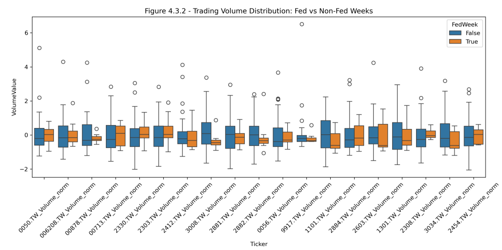

Figure 4.3.2: Trading Volume Distribution: Fed vs Non-Fed Weeks

Figure 4.3.2 shows that while some tickers (e.g., 1101.TW, 2884.TW) appear to exhibit slightly higher variance during Fed weeks, most tickers demonstrate visually stable distributions across both conditions. To quantify these differences, we compute p-values for each ticker, summarizing the results in ttest_volume_fedweek.csv.

The statistical results support this observation:

- None of the 19 tickers displays a p-value below 0.05, and only 2308.TW ($p = 0.1301$) comes marginally close to conventional thresholds.
- Most tickers exhibit p-values above 0.6, signaling little to no difference in trading volume between Fed and non-Fed weeks.

These findings suggest that despite modest increases in macro-level attention, real trading behavior remains largely unaffected by Fed announcement timing. This may indicate that institutional dominance in ETF trading dampens the retail response, or that retail investors are not actively reallocating capital around macro events. The results shows that awareness may rise without translating into concrete trading behavior.

4.3.3 Attention and Trading Activity During "Jensen Week": A Firm-Specific Shock

To evaluate whether firm-level publicity shocks can meaningfully influence retail investor behavior, we examine the market impact of NVIDIA CEO Jensen Huang's high-profile visit to Taiwan in May 2024. This "Jensen Week" received extensive media attention, especially in the semiconductor and technology sectors, offering a rare event window to assess shifts in investor sentiment and trading behavior.

We define "Jensen Week" as the three weeks surrounding the visit (±1 week of May 22, 2024) and compare both attention index values and normalized trading volumes during this period versus all other weeks. Specifically, we run two-sided independent t-tests for each attention index and for each ticker's trading volume. In addition, we visualize the distributions using boxplots to inspect whether "Jensen Week" coincides with significantly different behavior.

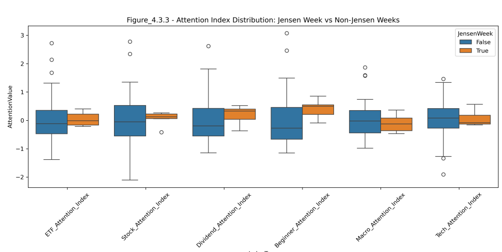

Figure 4.3.3: Attention Index Distribution: Jensen Week vs Non-Jensen Weeks

Figure 4.3.3 presents the distribution of attention values across thematic indexes during Jensen Week vs. non-Jensen weeks. Among the six indexes, only the **Beginner Attention Index** shows a statistically significant increase (p = 0.032), suggesting that less experienced retail investors were particularly engaged during this media-heavy period. Other indexes show no significant difference.

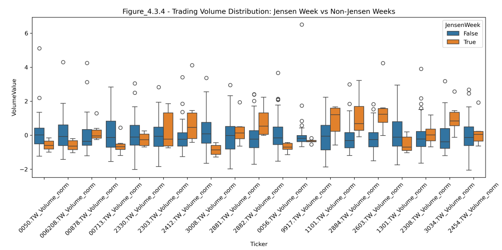

Figure 4.3.4: Trading Volume Distribution: Jensen Week vs Non-Jensen Weeks

Figure 4.3.4 compares trading volume distributions. Here, the results are more striking: trading volume significantly increases during Jensen Week across a wide range of tickers, particularly in the tech and semiconductor sectors. T-test results show that **11 out of 19 tickers** exhibit statistically significant volume shifts, many at the 1% level (e.g., 0050.TW, 006208.TW, 3008.TW, 0056.TW). This suggests that institutional or algorithmic traders responded strongly to the publicity shock, resulting in real capital movements.

Together, these findings highlight a notable divergence between attention and trading responses. While attention shifts were relatively muted—apart from beginner investors—realized trading activity surged, pointing to strong behavioral engagement among market participants. The results emphasize the value of firm-specific narrative events in mobilizing capital flows and shaping market dynamics, and they offer empirical support for Hypotheses **H3.2**[12] and **H3.3**[13].

5. Insights and Business Applications

Building on the empirical findings from RQ1 to RQ3, this section synthesizes the study's key takeaways and explores their practical implications, particularly for stakeholders in digital finance, brokerage services, ETF management, and fintech innovation.

5.1 Summary of Insights

The analysis reveals several key behavioral and predictive dynamics linking investor attention to market activity.

- **RQ1 (Attention-Volume Alignment)**: Attention indexes, derived from Google Trends data, generally move in tandem with trading volumes across various investment themes. For ETFs and technology-related instruments, attention spikes were observed to precede increases in trading activity by approximately one week, suggesting potential for short-term forecasting.
- **RQ2 (Predictive Power)**: Predictive models incorporating lagged attention indexes outperformed volume-only baselines, particularly in identifying low-volume trading weeks. This effect was most pronounced for beginner-oriented stocks, where attention shifts seem to influence retail trading behavior more strongly. However, the attention itself already has high predictive performance, and the overall model performance remained modest, indicating the need for more advanced techniques.
- **RQ3 (Event Responsiveness)**: Macro-level events, such as U.S. Federal Reserve announcements, led to significant increases in macro-related search attention but had limited impact on trading volume. In contrast, firm-specific events—like NVIDIA CEO Jensen Huang's visit to Taiwan—generated substantial increases in both attention and trading activity, especially in the technology and semiconductor sectors.

These findings highlight the utility of attention-based metrics as early behavioral indicators, especially when aligned with thematic or event-driven contexts.

5.2 Business Applications

The empirical insights provide several practical applications for financial service providers, including strategic opportuni-

[12] H3.2: Attention toward technology-related ETFs increases during Jensen Week.

[13] H3.3: Trading volume in selected ETFs rises significantly during event weeks compared to prior weeks.

ties in engagement, personalization, marketing, and investor education.

- **Brokers and Trading Platforms**: Integrating attention data into analytics pipelines enables proactive engagement strategies. For instance, product notifications or risk alerts (e.g., margin calls) can be timed to coincide with rising investor interest. Real-time monitoring of attention surges—especially in ETFs or tech stocks—enhances personalization and customer responsiveness.
- **Marketing and Growth Teams**: Attention indexes support dynamic campaign targeting. Promotional efforts can be synchronized with periods of high thematic attention (e.g., during spikes in Beginner or Tech indexes). This approach enables refined audience segmentation and improved ROI for educational or acquisition-oriented campaigns.
- **ETF Issuers and Product Managers**: Monitoring investor attention provides strategic signals for launching campaigns or assessing public engagement during macroeconomic events (e.g., Fed announcements). In addition, post-event analysis of attention metrics can inform public relations strategies and executive visibility planning.
- **Investor Education Providers**: Attention data serves as a timing tool for deploying educational content. When retail search interest peaks in specific themes (e.g., AI, dividends, ETFs), platforms can launch tutorials or articles tailored to that demand, enhancing learning outcomes and engagement.

In summary, search-based attention metrics present a low-cost, real-time behavioral signal that can enhance operational intelligence across financial service domains. Their utility spans short-term forecasting, user engagement optimization, and theme-sensitive market communication.