Research Questions & Analysis

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1 Does investor attention (from Google Trends) align with trading volume?

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 thematic 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.

1.2 Time Series Comparison Between Attention Indexes and Trading Volume of Related Stocks

The figure above illustrates the temporal relationship between six thematic Attention Indexes (constructed from Google Trends) and the normalized trading volumes of associated TWSE-listed stocks throughout 2024. Each subplot corresponds to a different investment theme—ETFs, individual stocks, dividends, beginner-friendly picks, macro-sensitive sectors, and technology. In each case, the black solid line represents the attention index, while dashed colored lines depict the weekly normalized trading volumes of 2–5 related tickers.

Visual inspection reveals several instances of alignment between attention spikes and volume surges, particularly for the ETF and stock-related panels, suggesting that increases in search interest may precede or coincide with trading activity. Notably, attention peaks in March and July often correspond to volume spikes across multiple tickers, supporting the hypothesis that investor attention may be a leading indicator of trading behavior. This preliminary observation motivates further statistical testing for lagged correlation or causal influence, as posed in Research Question 1.

1.3 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.

1.4 Interpreting the Link Between Retail Attention and Trading Volume: Evidence from Correlation Patterns

The correlation heatmap reveals varying degrees of association between thematic attention indexes and the normalized trading volumes of corresponding TWSE-listed stocks. Notably, the Beginner Attention Index exhibits the strongest positive correlations, particularly with 3034.TW ($r = 0.61$), 2454.TW ($r = 0.41$), and 00878.TW ($r = 0.16$), suggesting that spikes in beginner-related search interest may coincide with or lead to increased trading activity in these stocks. Similarly, the Stock Attention Index shows moderate-to-strong positive correlations across several stocks, with 2412.TW ($r = 0.45$), 2882.TW ($r = 0.51$), and 2881.TW ($r = 0.44$) standing out, supporting the idea that general retail attention to "stock" topics aligns with actual market behavior. On the other hand, attention indexes tied to macro and tech topics display weaker and more dispersed correlations, implying that these themes may not drive immediate trading volume to the same extent. The observed heterogeneity across themes and tickers highlights the need for further temporal analysis, such as lagged correlations or Granger causality, to better understand whether attention truly precedes volume changes or merely reflects them.

1.5 Causality Analysis

To test for predictive relationships between investor attention and trading activity, we conduct a series of Granger causality tests using each attention index and its associated stock trading volumes. Specifically, we examine whether past values of each attention index help forecast current trading volume, controlling for up to two lags. For each attention–volume pair, we extract p-values from the Chi-squared test statistics at multiple lags and assess significance at the 5% level. The results are compiled into a structured summary table that highlights statistically significant causal relationships, helping us determine not just correlation but potential directional influence. This approach is essential for addressing RQ1 from a causal inference perspective, identifying which types of retail attention may serve as leading indicators of trading activity. All outputs are displayed in Jupyter and exported for further review or reporting.

1.6 Granger Causality Reveals Predictive Power of Investor Attention on Trading Activity

Based on the Granger causality test results summarized in the table, several attention indexes exhibit statistically significant predictive power over corresponding trading volumes, particularly at lag lengths of 1 and 2 weeks. For example, the ETF Attention Index significantly Granger-causes the trading volumes of 0050.TW and 006208.TW at both lag levels ($p < 0.01$), suggesting that increased public interest in ETFs—as measured by Google search trends—can help forecast short-term fluctuations in ETF trading activity. Similar patterns emerge in the Stock Attention Index, which shows strong predictive effects on blue-chip tickers like 2330.TW and 2412.TW. These findings support the hypothesis that investor attention contains informational content that precedes market behavior. However, not all attention–volume pairs yield significant results, indicating that the predictive power of attention may be theme- or stock-specific. This highlights the importance of tailoring attention-based forecasting models to the characteristics of specific asset classes or investor segments.

1.7 Reverse Causality

To evaluate the possibility of reverse causality—namely, whether changes in trading volume can predict shifts in investor attention—we perform a series of Granger causality tests in the direction of volume $\rightarrow$ attention. For each attention index and a selected subset of key tickers (e.g., 0050.TW and 2330.TW), we test whether past values of trading volume can help forecast attention levels over one- and two-week lags. The results are summarized into a table containing p-values and significance flags for each pair. This analysis helps distinguish whether investor attention is purely reactive or whether it may be shaped by preceding market activity, thereby providing a more complete view of the dynamic interaction between behavioral and transactional signals.

1.8 Reverse Causality Evidence: Trading Volume as a Predictor of Investor Attention

The results of the reverse Granger causality tests indicate that changes in trading volume can significantly predict future shifts in investor attention across different thematic indexes. Remarkably, the results reveal consistently low p-values (all < 0.02), with the strongest predictive signals observed for 2330.TW across multiple attention themes. For instance, trading volume in 2330.TW significantly Granger-causes attention shifts in the Stock, ETF, and Dividend Attention Indexes ($p = 0.00000$ to 0.0002), suggesting that heightened trading activity in Taiwan's most prominent semiconductor stock may precede and possibly drive broader public search behavior. Even for 0050.TW, a passive ETF, the pattern holds: volume fluctuations appear to significantly influence attention across nearly all categories tested. These findings challenge the conventional assumption that attention always leads volume, suggesting instead a potentially bidirectional feedback loop between market activity and retail interest.

1.9 Conclusion for Research Question 1, Does Investor Attention (from Google Trends) Align with Trading Volume?

The empirical results for RQ1 reveal a complex yet compelling relationship between investor attention—proxied by Google search activity—and actual trading behavior in the Taiwanese stock market. Through time series visualization, we observe that surges in attention index values frequently coincide with, or slightly precede, notable increases in trading volume for thematically related tickers. This qualitative signal is reinforced by the correlation analysis, which uncovers moderate to strong positive associations between several attention indexes and the trading volumes of representative stocks, particularly in beginner-friendly, stock-focused, and ETF-related themes.

To move beyond association and probe causality, we implement Granger causality tests in both directions. The forward-direction tests (attention $\rightarrow$ volume) confirm that investor attention often holds predictive power over subsequent trading activity. For example, the ETF and Stock Attention Indexes significantly Granger-cause volume fluctuations in well-known tickers such as 0050.TW, 2330.TW, and 2412.TW, particularly at 1- to 2-week lags. These findings support the behavioral finance hypothesis that retail search behavior reflects emerging market sentiment that may precede action, offering potential utility in short-term forecasting models.

Conversely, reverse-direction tests (volume $\rightarrow$ attention) suggest that trading activity itself can also serve as a predictor of future shifts in attention, especially for highly visible or systemically important stocks like 2330.TW. This implies that investor attention is not purely a leading indicator, but also a reactive one, shaped by market movements. The bidirectional causality highlights the feedback loop between behavioral signals and transactional outcomes: attention can influence market participation, and market events, in turn, drive shifts in attention.

Overall, the evidence suggests that Google Trends-based attention indexes are not only correlated with trading volume but may also contain valuable predictive information. However, the strength and direction of this relationship are not uniform—it varies by theme, asset type, and lag structure. This underscores the importance of contextualizing attention metrics rather than applying them indiscriminately. For practitioners and researchers alike, attention data holds promise as a complementary input to traditional financial models, especially when calibrated to the characteristics of specific investor segments or market regimes.

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

To address Research Question 2, we investigate whether investor attention—quantified through Google Trends search volume indexes—can be used to predict short-term fluctuations in stock trading activity. Specifically, we test whether current or lagged values of attention indexes improve the accuracy of next-week trading volume forecasts across different types of stocks, including ETFs, large-cap firms, and beginner-targeted equities. Our approach involves constructing a supervised learning framework where lagged attention variables serve as predictors, and normalized trading volume in the following week is the target. We evaluate predictive performance using standard forecasting metrics such as Mean Squared Error (MSE) for continuous models, and optionally classification accuracy or AUC if trading volume is discretized into high/low categories. To contextualize the value of attention data, we compare its performance against traditional autoregressive baselines that rely only on past volume data. This setup allows us to determine not only whether attention contains forward-looking information, but also whether that information adds measurable forecasting power relative to historical price-and-volume-only models.

2.1 Linear Regression Model

To evaluate the predictive power of attention-based features in forecasting next-week trading volume, we begin with a linear regression framework. This model treats trading volume as a continuous variable and estimates its magnitude based on three sets of predictors: lagged trading volume (baseline), attention indexes derived from Google Trends (attention-only), and a combination of both. Linear regression provides a simple and interpretable benchmark for understanding how well attention signals explain variations in future volume relative to market-based indicators. Model performance is assessed using Root Mean Squared Error (RMSE) on a time-based test split.

2.1.1 Linear Regression Model Comparison and Interpretation

The RMSE comparison reveals that the model using only lagged trading volume achieves the best predictive performance, with an RMSE of approximately 0.756. In contrast, the attention-only model performs worse, with an RMSE of 0.834, indicating that while investor attention data captures some relevant signals, it is less effective than historical volume data for forecasting next-week trading activity. Surprisingly, the combined model, which integrates both lagged attention and volume features, does not outperform the volume-only baseline—it produces an RMSE of 0.835, slightly worse than using attention alone. This suggests that the attention signals may introduce noise or multicollinearity when added alongside volume data, rather than offering additive predictive value in this linear setting. These results highlight the importance of benchmarking attention-based models against simple baselines and caution against assuming that more features always improve forecasting accuracy. Further exploration using nonlinear models or feature selection may help clarify whether attention data can enhance predictive power when used more selectively or interactively.

While linear regression offers insight into how attention signals explain continuous variation in trading volume, it does not capture whether these signals can accurately classify upcoming periods of heightened trading activity. To examine the directional predictability of attention-based features, we next reframe the task as a binary classification problem and assess model performance using logistic regression.

2.2 Logistic Regression Model

To assess whether attention data can classify future trading activity into high or low volume categories, we implement logistic regression models. This approach transforms the regression target into a binary outcome and allows us to evaluate the directional forecasting ability of different feature sets. We compare three specifications: a volume-only model using lagged volume, an attention-only model using six thematic attention indexes, and a combined model. Each is evaluated using AUC, accuracy, and confusion matrices. Logistic regression serves as a baseline classification method for testing whether attention signals meaningfully distinguish between high and low volume periods.

2.2.1 Interpretation: Classification Models for Predicting High Trading Volume

The classification analysis reveals mixed performance across models, with none achieving particularly strong predictive power. Among the three logistic regression classifiers, the Attention-Only and Combined Attention+Volume models performed similarly, both reaching an AUC of 0.444 and an accuracy of 0.4667. This is only slightly above random guessing (accuracy = 0.5, AUC = 0.5) and indicates limited but slightly better-than-chance discriminative power.

In contrast, the Volume-Only model exhibited an AUC of 0.2963 and lower accuracy of 0.40, suggesting that recent volume movements alone may not be helpful—indeed, even counterproductive—for predicting next-week volume direction in this binary setting. This is further supported by its confusion matrix, which shows extreme imbalance: the model predicted almost all outcomes as "high volume" regardless of actual labels, failing to distinguish between classes.

The confusion matrices for both the Attention-Only and Combined classifiers show some variance in prediction but still struggle with false negatives—frequently misclassifying high-volume weeks as low. Notably, the Combined model did not improve upon the Attention-Only model, which implies that in a linear classification setting, attention data alone captures most of the weak predictive signal available.

Overall, these results indicate that while attention-related data may contain some marginally useful information for forecasting volume direction, its predictive power remains limited and fragile. Traditional features like lagged volume do not help much in this classification context and might even degrade model performance. This highlights the potential need for more complex models (e.g., nonlinear classifiers), longer lags, or alternative feature engineering to extract stronger signals.

Although logistic regression offers a useful linear benchmark, it may fail to capture nonlinear relationships or interactions between attention indexes and trading volume. To address this limitation, we extend the analysis using Random Forest classifiers, which allow for more flexible modeling of complex, non-additive patterns in the data.

2.3 Nonlinear Classification Model - Random Forest

To explore potential nonlinear relationships and interactions between attention and volume features, we extend our classification analysis using Random Forest classifiers. Random Forests are well-suited for capturing complex patterns and can help reveal whether attention indexes contribute predictive value beyond what linear models detect. We apply the same three model structures—volume-only, attention-only, and combined—and evaluate their performance using AUC, accuracy, and confusion matrix visualizations. This analysis tests whether nonlinear modeling unlocks additional forecasting power from attention-based inputs, particularly in low-signal, small-sample settings.

2.3.1 Random Forest vs Logistic Regression: Classification Model Comparison

The application of Random Forest classifiers in this study reveals a more nuanced landscape of predictive performance compared to the earlier linear models. Among the Random Forest models, the Volume-Only model achieves the highest performance with an AUC of 0.6481 and accuracy of 0.5333, outperforming both the Attention-Only and Combined models. This is a notable reversal from the logistic regression results, where the attention-based mode ls performed marginally better than volume-based predictions.

The improved AUC in the Volume-Only RF model suggests that Random Forest is better able to capture nonlinear relationships and threshold effects within historical volume patterns that linear models could not exploit. Its confusion matrix also reflects a more balanced classification across both classes, avoiding the extreme bias seen in the volume-only logistic regression.

In contrast, the Attention-Only Random Forest model reaches an AUC of 0.3889, which is slightly worse than its linear counterpart (AUC = 0.4444). Similarly, the Combined model (Attention + Volume) fails to improve performance, with an AUC of 0.3611, suggesting that attention data, when added to volume, may introduce noise or overfitting in a small-sample nonlinear setting.

Importantly, despite the Random Forest's theoretical ability to model interactions, the Combined model again fails to outperform simpler alternatives, indicating that the predictive value of attention data may be too weak or unstable in this context. The fact that volume data alone shows the greatest gains when passed through a nonlinear model also underscores that volume patterns may carry richer latent signals than attention scores—at least for predicting the direction of next-week trading activity.

2.3.2 Feature Importance Interpretation: Random Forest Models

The Random Forest feature importance plots offer insight into which variables were most influential in predicting next-week trading volume direction. In the Attention-Only RF model, the most predictive feature was the Macro Attention Index, followed closely by Tech and Stock Attention Indexes. This indicates that investors' search interest in macroeconomic and sector-specific themes may contain relatively stronger signals about future trading activity than general or retail-oriented themes (like beginner or dividend attention), which were less influential.

Interestingly, when we include lagged volume in the Combined Attention + Volume RF model, the attention features continue to dominate the top importance rankings. Macro Attention Index again ranks first, with Tech and Stock Attention Indexes retaining high importance. The lagged volume feature, while somewhat informative, only ranks fourth—suggesting that Random Forest did not find substantial nonlinear patterns in volume alone strong enough to outweigh thematic attention data.

However, this relative ranking should be viewed in light of the overall weak predictive performance of the combined model (AUC = 0.3611). Although attention features appear important within the model structure, the final classification accuracy and AUC remained low. This may reflect overfitting or that no single feature set provided consistently strong signal in the limited-sample, noisy classification context.

In sum, Macro and Tech attention dominate in terms of feature contribution, but their standalone predictive utility remains modest. Their relative prominence suggests potential value in attention segmentation—but also highlights the need for richer or more targeted features to achieve reliable prediction.

2.4 Conclusion: RQ2 – Can Google Trends Data Predict Whether Trading Volume Will Be High Next Week?

The analysis of RQ2 aimed to evaluate whether attention-based signals from Google Trends could predict next-week trading volume direction in financial markets. Across both linear (logistic regression) and nonlinear (random forest) classifiers, the results consistently showed that while attention-related features provided marginal improvements over random guessing, they lacked strong predictive power. In logistic regression, attention-only and combined models achieved modest AUCs (both ~0.44), while volume-only models underperformed (AUC = 0.30), suggesting some linear signal in thematic search interest. However, in the random forest models, the situation reversed: volume-only features performed best (AUC = 0.65), while attention signals failed to add value or even diluted model accuracy.

Feature importance analysis confirmed that certain attention categories—especially macroeconomic and tech-related keywords—held relatively more importance within models, yet this did not translate into meaningful classification gains. The models' consistently low accuracies and shallow ROC curves underscore the difficulty of using short-lag attention data alone to anticipate directional shifts in trading activity on a week-ahead basis.

In sum, while thematic Google search trends may reflect latent investor sentiment, they do not offer reliable standalone signals for binary prediction of volume surges in the short term. Attention-based data may still hold potential when combined with richer market features, more granular time horizons, or in regression-based frameworks that forecast magnitudes rather than direction. Further research could explore higher-frequency attention dynamics, multi-lag temporal stacking, or hybrid deep learning models to better capture the behavioral-financial linkage.

3 Do macro-level shocks (e.g., Fed decisions) or firm-level shocks affect retail attention and market activity in Taiwan's ETF sector?

As part of our market research project, we explore whether macro-level events—such as U.S. Federal Reserve policy announcements and high-profile public appearances (e.g., NVIDIA CEO Jensen Huang's visit to Taiwan)—lead to detectable changes in retail investor behavior. Specifically, we investigate whether such events trigger shifts in retail search interest (proxied by thematic Google Trends attention indexes) and trading activity in selected ETFs or sectors. By comparing periods before, during, and after each event, we aim to uncover systematic behavioral responses in both attention and market participation. These insights can help clarify whether external shocks reliably activate retail investor engagement—valuable knowledge for media strategy, investor relations, and anticipating retail sentiment dynamics.

3.1 Analyzing Attention Shifts During Fed Announcement Weeks

To evaluate whether U.S. Federal Reserve policy announcements meaningfully shift investor attention, we analyze Google Trends–based attention indexes during weeks that coincide with Fed interest rate decisions. By comparing these attention levels across Fed and non-Fed weeks, we assess whether such macroeconomic events lead to observable increases in public search behavior across thematic investment categories. We use boxplots for visual distributional comparison and independent t-tests to identify statistically significant differences. This analysis helps clarify whether central bank signals draw heightened retail awareness, providing insight into the sensitivity of retail sentiment to macro-level monetary policy events.

The results show mixed evidence regarding attention shifts during Fed announcement weeks. Among the six thematic attention indexes, only the Macro_Attention_Index demonstrates a statistically significant increase during Fed weeks ($p = 0.0169$), suggesting that investors may indeed become more focused on macroeconomic themes in anticipation of central bank policy changes. Other indexes, including those related to ETFs, stocks, dividends, and technology, show no statistically significant changes. This implies that while macro-level monetary signals may capture investor interest on broad economic topics, they do not consistently influence sector-specific attention. These findings highlight the selective nature of retail attention responses and underscore the importance of using multiple indicators when assessing investor sentiment toward macroeconomic events.

3.2 Trading Volume Behavior Around Fed Announcement Weeks

To investigate whether actual trading activity mirrors investor attention in response to macroeconomic news, we analyze ETF trading volume patterns around Federal Reserve policy announcement weeks. Building on our earlier examination of attention index movements, we now assess whether shifts in trading behavior occur during the same event windows. By comparing normalized trading volumes during Fed weeks and non-Fed weeks, and applying statistical tests to evaluate their differences, this analysis helps determine whether retail trading activity exhibits measurable sensitivity to macro-level policy signals. This approach offers a more grounded perspective on market reactions—tracking not just what investors are searching for, but what they actually do.

The analysis of trading volume around Federal Reserve announcement weeks reveals limited evidence of statistically significant changes across the ETF universe. None of the examined tickers exhibit a p-value below the conventional 5% threshold, and most exceed even more relaxed significance levels. These results suggest that, unlike attention-based signals which showed more noticeable shifts, actual trading activity during Fed weeks remains relatively stable. This may indicate that retail investors are not reacting in aggregate through trade execution, or that institutional participants dominate volume to a degree that masks any attention-induced behavioral shifts. Overall, this finding underscores the importance of distinguishing between expressed interest (e.g., search activity) and realized market behavior, and highlights the limits of macro policy events in triggering broad-based volume responses in Taiwan's ETF market.

3.3 Investigating Retail Investor Behavior During "Jensen Week": A Firm-Specific Event Lens

To extend our macro-level analysis, we next examine a major firm-specific event: NVIDIA CEO Jensen Huang's high-profile visit to Taiwan. Garnering extensive media coverage, the event may have influenced investor attention and trading behavior—especially within tech-oriented and semiconductor-related ETFs. This section investigates whether retail sentiment (captured via Google Trends–based attention indexes) and actual trading volumes exhibited notable shifts during the three-week window surrounding the visit. By comparing pre-event, event-week, and post-event activity, we aim to detect whether publicity-driven firm exposure can significantly shape investor engagement. This helps assess the market's sensitivity to corporate presence and firm-specific narrative momentum, providing insight into how publicity events impact both sentiment signals and real capital flows.

The results from Jensen Week analysis reveal a notable divergence between attention shifts and trading activity. While most attention indexes did not exhibit statistically significant changes, the Beginner_Attention_Index stands out with a meaningful increase, indicating that less experienced investors may have been particularly responsive to the media coverage surrounding Jensen Huang's visit. On the other hand, trading volume data shows a broader and more consistent pattern of significant increases across a wide range of ETF tickers, especially those related to semiconductors and technology. This suggests that market participants—possibly institutional or algorithmic—acted decisively in response to perceived signals during the event window. The discrepancy between attention and trading responses emphasizes the value of analyzing both sentiment and behavior: attention signals can reveal where interest is concentrated, while volume changes reflect concrete market engagement. Together, they provide a more complete view of how macro-level publicity events shape retail market dynamics.

3.4 Conclusion - Synthesizing Insights Across Macro and Firm-Level Retail Investor Responses

Our investigation into retail investor behavior surrounding macroeconomic shocks and firm-specific events reveals important nuances in how attention and trading activity respond to external signals. At the macro level, U.S. Federal Reserve announcement weeks show limited influence on aggregate trading behavior and only marginal shifts in attention—primarily in broad macroeconomic indexes—suggesting that retail investors may not consistently reorient their focus or adjust their trades in response to central bank policy timing. This points to a selective sensitivity in sentiment, where awareness may rise without translating into actionable changes in market activity.

In contrast, the firm-specific "Jensen Week" event—centered on NVIDIA CEO Jensen Huang's high-profile visit to Taiwan—demonstrates a more pronounced effect, particularly among less experienced retail investors. The Beginner_Attention_Index exhibited a statistically significant increase, and trading volume surged across a wide array of ETF tickers, especially those linked to semiconductors and technology. This indicates that media-driven firm narratives can evoke measurable behavioral responses, not only in attention but also in capital flow, likely amplified by institutional actors responding to retail cues or public sentiment.

Together, these findings underscore two key takeaways: first, the asymmetry between attention and trading signals highlights the importance of separating sentiment shifts from actual market impact; second, event type matters—while macro-level shocks offer diffuse and inconsistent behavioral cues, concrete firm-specific catalysts with strong media salience may exert a clearer influence. For policymakers, financial communicators, and ETF strategists, this dual-track sensitivity framework offers a more granular understanding of how and when retail investors engage with market-moving narratives.