

AI-Enabled Sentiment Monitoring for Human-Supervised Cross-Market Wealth Management between Mainland China and Hong Kong

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Abstract—The investor sentiment can amplify short-term risks and complicate wealth decisions, especially with global themes of rapid change and volatility. This paper presents an event-driven empirical proof-of-concept of AI-driven sentiment tracking as human-assisted wealth management in Mainland China and Hong Kong. A pre-trained Chinese financial sentiment classifier labels 70 dated A-Dame market-news headlines and 28 dated Hong Kong market-news reports as positive, neutral, or negative. Headline-level tone is aggregated into daily and event-window measures of everyday and event-time frame tone and compared to CSI300 and Hang Seng index. Three event-windows are studied: 2023 panic-and-recover window, 2024 sentiment-reward and high volatility window, and 2525 tech flair and trading on volatility window. Positive during 2023 window, and negative window in Hong Kong, both positive in 2024 sentiment-reward window, Hong Kong sentiment stronger, negative in 25 tech flair window in Hong Kong, neutral in mainland. Risks varied by event-windows. 2024 window was high volatility in both locations and the deepest average post-event drawdowns period, however, later-stage risks varied in profile. Rather, they support the use of AI-derived news signals as a structured prompt for human review of concentration, liquidity, and cross-market diversification decisions.

Keywords—AI sentiment analysis, wealth management, A-share market, Hong Kong market, investor sentiment

I. INTRODUCTION

Long-run investing not only concerns returns, but also involves concentration, liquidity, volatility, and behaviorally motivated trading. Investor sentiment matters therefore because investors' beliefs about fundamental cash-flows and risk might be different from fundamentals (Baker, & Wurgler, 2007). Behavioral models also demonstrate that investors might underreact to a signal on its own, but overreact to a sequence of good or bad news, resulting in price pressure and a risk of a crash (Barberis, Shleifer, & Vishny, 1998). Sentiment from online sources and trading data has been associated with volatility in China underlining the usefulness of online information for trading decisions (Gao, Zhao, Sun, & Zhao, 2022).

The Mainland China-Hong Kong context is appropriate for exploring these issues. The Cross-boundary Wealth Management Connect connects the qualified residents of the Greater Bay Area to a limited number of wealth-management products delivered via restricted channels (Hong Kong Monetary Authority, 2025). In a cross-market portfolio, a wealth manager may have to consider whether heightened awareness of a particular market or theme warrants a soft review versus a hard trade trigger. This recommendation is supported when market

behavior and financial data appear to support one another.

Textual market-data signals are becoming plentiful, while the available time for human review is scarce. Media sentiment has been linked to short-term market pressure and trading, whereas search attention can also proxy for such temporary demand pressure (Tetlock, 2007; Da, Engelberg, & Gao, 2011). However, rather little applied research has looked at how a transparent AI-assisted sentiment score methodology could be integrated into human wealth management decision-making mechanisms in Mainland China and in Hong Kong. This research fills the knowledge gap by employing an event-driven pilot program around public market sounding headlines and reports, AI-generated sentiment scores, and parallel-market-danger proxies. The research aims to explore if the combination of sentiment, volatility, drawdown, and A-share trading-crowding information could be helpful to discipline a human review-based process for cross-market wealth management.

II. LITERATURE REVIEW AND CONCEPTUAL FRAMEWORK

A. Investor Sentiment, Attention, and Trading Crowding

There are two ways that investor attitude can be expressed: the conviction and the visible trading patterns. The more attention investors pay to a limited number of stocks, sectors, or stories, the less they react to changes in the true value of long-term profitability and instead only to the most obvious headlines and past returns. According to Da *et al.*, (2011) search-based investor attention can cause short-term price changes in one direction, which are eventually followed by reversals. In the case of Barber and Odean, they reached the conclusion that individual investors who are fairly active in trading tend to obtain lower net returns, implying that frequent trading is more of a reflection of behavioral biases rather than superior information (Barber & Odean, 2000). On the other hand, for portfolio managers, it means that the information revealed with a high level of attention and strange activity is to be considered as an additional signal for review instead of just a buy-or-sell-command.

share market is suitable for analyzing crowding as trading volume and turnover can increase dramatically in attention-driven phases. Herding signals from Shanghai and Shenzhen A-shares indicate that investors may behave even more similarly when the market moves up or down (Chiang, Li, & Tan, 2010). This could exacerbate positive feedback buying in the uptrend or synchronized selling in the downtrend. Thus, the current analysis uses both abnormal volume and abnormal amount to capture the trading crowding. The signal does not try to pick the ultimate

turning point.

However, it serves as a useful reference to ensure that the portfolio is not overcrowded in a certain market story. Another explanation that is, in a similar way, given by prospect theory for why downside events can be hard to control is as follows. People often react more vehemently to losing than to winning an equivalent amount, which can result in value inconsistency when markets fluctuate rapidly (Kahneman & Tversky, 1979). Hence, such a system needs to be human-supervised and combine textual sentiment with market risk and client-level suitability considerations. This approach makes more sense than viewing an AI label as a stand-alone investment suggestion.

B. AI-Enabled Sentiment Monitoring

AI-powered sentiment analysis can help make sense of massive amounts of qualitative financial information that is tough to evaluate manually. FinBERT, as an example of a domain-specific language model, shows the effectiveness of financial text classification for the purpose of sentiment analysis (Araci, 2019). In the current research, a pre-trained Chinese financial sentiment classification model is applied to tag the dated market news headlines as positive, neutral, or negative. The classifier output is transformed into a signed headline-level score, then aggregated by market date and selected event window. The process's transparency is intentional. The AI model provides a signal of information, but the human wealth manager analyzes the client's suitability in terms of liquidity requirements, investment horizon, and compliance limitations.

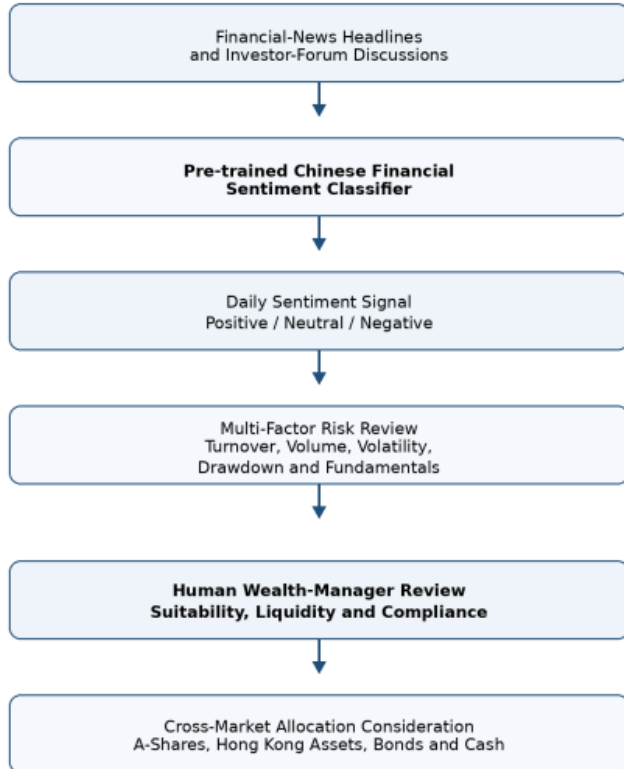


Fig. 1. AI-assisted sentiment monitoring and human-supervised cross-market allocation process.

The expected process is shown in Fig. 1. The news text generated from the public market is the first step in converting that text into AI-based sentiment signals, taking into account the market-typical indicators. For Mainland

China, the analysis is performed not only on trading crowding but also on volatility and subsequent drawdown. The study for Hong Kong employs similar measures of volatility and drawdown, taking the Hang Seng Index as a benchmark for comparison. In the last stage, a human review is carried out to find out whether cross-market diversification and cash buffers are to be given attention or whether concentration adjustments are needed.

C. Cross-Market Wealth-Management Relevance

Cross-market wealth management is not merely about picking the market with the best recent return. The same regional signal or technology theme can be presented differently in the Mainland and Hong Kong press, and the volatility (and thus subsequent drawdown) can also differ. Cross-market allocation should therefore be seen as a comparative between exposure, risk appetite, liquidity environment, and the extent to which news flow is either positively correlated or divergent across markets. The empirical pilot below looks at these differences but presents them in a descriptive format. It does not claim that mood influences future returns or test a deployable arbitrage method.

III. DATA AND METHODOLOGY

A. Event-Based News Samples

The empirical pilot uses two dated public news corpora. The Mainland China corpora have 70 A-share-market-news headlines aggregated to 31 unique news dates. The Hong Kong corpora have 28 Hong Kong market-new reports aggregated to 28 unique news dates. Each record has an associated market date, source, headline, and source url in the underlying audit files, including news sources such as Sina Finance, Xinhua News Agency, East Finance Network, Caixin, QQ News, and Cailian Press (Sina Finance, 2026; Xinhua News Agency, 2026; East Finance Network, 2026; Caixin, 2026; QQ News, 2026; Cailian Press, 2026). The records are purposive rather than random. They were chosen to sample three market contexts where sentiment and/or (perceived) risks were allegedly salient: the 2023 Market Stress and Rebound era, the 2024 Policy Rally and High Volatility era, and the 2025 Technology Themes and Active Trading era.

These two markets operate under different holiday calendars, publication schedules, and the number of available public reports. Consequently, the comparison is not a direct daily match, but a more event-window-aligned one. The data in this study can be compared in general terms of sentiment and risk, yet this design avoids the artificial assumption that the two news samples have an equal frequency. Therefore, the empirical conclusions are descriptive and should be seen as pilot evidence for wealth-management review, as opposed to universal market laws.

B. AI-Derived Sentiment Measure

The same pre-trained Chinese financial sentiment classifier is used in both corpora. Each headline is assigned one of three labels: positive, neutral, or negative, and a confidence score. The directional score is +1 for positive, 0 for neutral, -1 for negative. Headline-level sentiment value

is directional score X model confidence. A confident and positive headline will have a shelf value close to +1; a non-confident, negative headline will have a value close to -1; a neutral headline will have an adjusted value of 0.

In cases when several headlines are provided for a certain market date, headline-level values are averaged out to form a daily sentiment index. Daily composite values are calculated for each chosen event window. An initial hand-check on the A-share headlines generated 80% concordance between AI labels and the human evaluation. The second type of accuracy check is a validity check. It does not provide an absolute accuracy rate but a basic plausibility test of the classification process prior to aggregation of the event windows.

C. Market-Risk Measures

The CSI 300 Index for Mainland China and the Hang Seng Index for Hong Kong work as the market measures. Daily return is the change in daily percentage of the index value. The annualized volatility measure of 20-day is calculated by multiplying the standard deviation of the previous 20 daily returns by the square root of 252. The next ten trading days' maximum drawdown is computed as the current day index close minus the lowest next ten days' index close divided by the current index close, minus one. This, combined with the current closing value, ensures that the measure of drawdown cannot be a positive number.

For the A-share dataset, a trading-crowding measure is also computed. First, 20-day standardized scores are computed for daily turnover and turnover value, respectively. The crowding measure is the average of these two measures. It is not an intended cross-market comparison variable since fully comparable Hong Kong turnover and turnover value measures have not been constructed in this pilot. It is instead reported as a Mainland-specific risk signal in Fig. 3.

D. Analytical Design and Limits

The analysis proceeds in three distinct stages. First,

A-share news sentiment and A-Share crowding are contrasted on the three broad event windows. Second, Mainland China and Hong Kong sentiment are compared as per the same broad windows. Third, average volatility and subsequent drawdown are compared on CSI 300 and Hang Seng Index. No statistical significance testing or predictive trading backtest is presented as the sample is small, purposive and event-driven. The analysis therefore presents clear descriptive relationship and its implications for human supervised wealth-management practice.

IV. RESULTS

A. A-Share Sentiment and Trading Crowding

Table 1 lists the sentiment composition of the three A-share windows of events. The 2023 stress-and-rebound window consisted of 15 headlines on 7 reporting dates and posted the highest average daily sentiment score of 0.4519. Its positive news share was 52.38%, while negative news shares were 7.14%. This observation does not mean a uniformly good start to this period. Both stress on the loss of the 3000-point level and the following recovery event are covered by this window. So, the aggregate obviously includes the later sentiment warm-up together with the earlier stress.

The 2024 policy rally and high volatility period saw 33 headlines over fourteen news dates. Its average daily sentiment was slightly positive at 0.0875. The proportion of negative news reached 33.93% and was quite different from that in 2023. This combination was appropriate for a chapter involving a new, strong wave of policy-induced optimism and high intraperiod attention, followed by significant uncertainty. The 2025 technology theme period had 22 headlines on ten news dates. Its mean sentiment was precisely 0.0000, with equal shares of positive and negative news at 31.67%, indicating a more divided information landscape.

Table 1. AI-derived news sentiment indicators across selected event windows

Market	Event window	News	Days	Mean sentiment	Positive (%)	Negative (%)
A-Share	2023 Stress and Rebound	15	7	0.4519	52.38	7.14
A-Share	2024 Policy Rally and High Volatility	33	14	0.0875	42.26	33.93
A-Share	2025 Technology Themes and Active Trading	22	10	0.0000	31.67	31.67
Hong Kong HSI	2023 Stress and Rebound	6	6	-0.3309	33.33	66.67
Hong Kong HSI	2024 Policy Rally and High Volatility	13	13	0.2305	53.85	30.77
Hong Kong HSI	2025 Technology Themes and Active Trading	9	9	-0.3413	33.33	66.67

Note. Mean sentiment is the event-window average of daily AI-derived headline sentiment. Positive and negative shares are averages of daily headline-label proportions. The Hong Kong sample is event-window aligned rather than strictly one-to-one daily matched with the A-share sample.

Fig. 2 depicts A-Share sentiments in its graphical representation. As seen in Fig. 3, average A-share trading crowding was at its peak in the 2024 window at 1.4688, as compared to 0.9476 in 2023 and a low of 0.8727 in 2025. This is the most robust signal of mainland risk in the pilot. Crowding was at its height in the same window with rapid policy market movements and volatility. The conclusion for a wealth manager is not sell due to strong trading. It leads to closer scrutiny of specific concentrated positions, liquidity pressures within the material near term, and purchasing after rapid appreciation.

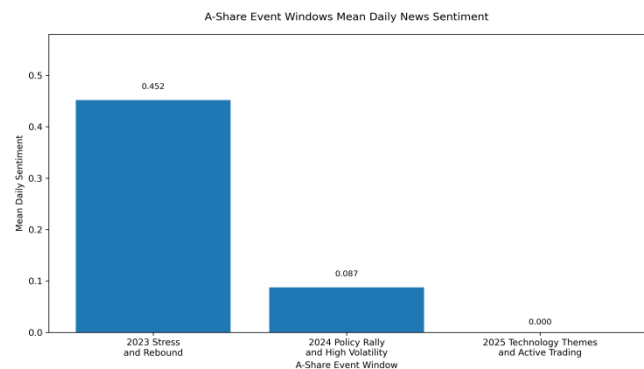


Fig. 2. A-share event windows mean daily news sentiments.

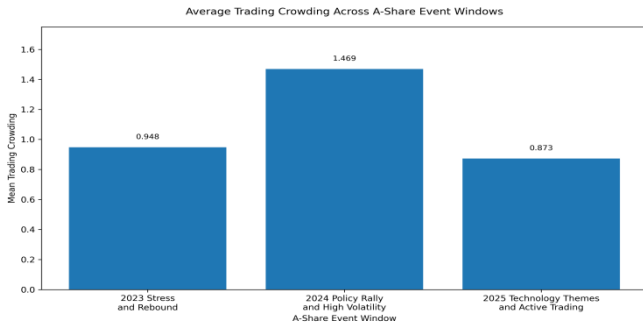


Fig. 3. Average trading crowding across a-share event windows.

B. Cross-Market Sentiment and Risk Comparison

Although the sentiment for the cross-markets due to news might not have been consistent across the two entities, that is, the mainland and Hong Kong, the border community. During the 2023 trial week, sentiment for the A-shares was mean positive at 0.4519, but mean negative for the Hong Kong sample, which was at -0.3309 . The latter result is in line with distinct sample compositions: In contrast, the main reason for the A-shares was the evident opinion demonstration, but that of the Hong Kong was more focused on the downside. For the latter half of 2024, both sentiment samples were mean positive, but the sentiment in Hong Kong was higher compared to that of A-shares, with a value of 0.2305 and 0.0875, respectively. Meanwhile, while Hong Kong sentiment in the 2025 technology-theme period was mean negative, with a score of -0.3413 , the A-share sample was near mean neutral. Fig. 4 shows the cross-market comparison of AI-generated news sentiment. It illustrates

that A-share and Hong Kong market sentiment did not always move in the same direction, especially in the 2023 and 2025 event windows.

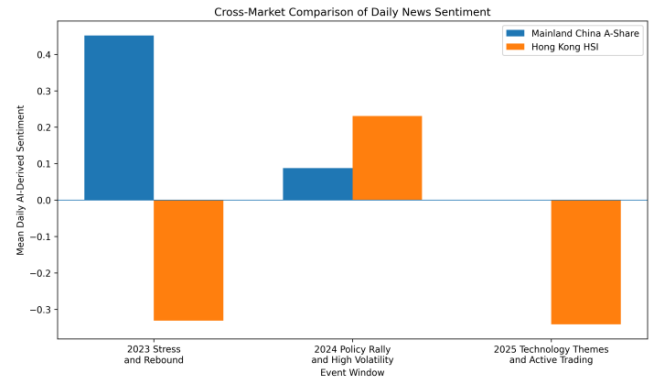


Fig. 4. Average daily cross-market AI-generated news sentiment over selected time periods.

Table 2 shows that the 2024 policy period with the low rally provides the highest average 20-day volatility for both markets of 39.84% and 38.89% for CSI 300 and Hong Kong Index as well, respectively. Fig. 5 presents the cross-market comparison of 20-day annualized volatility. It shows that both A-share and Hong Kong markets reached their highest volatility levels in the 2024 policy rally and high volatility window.

Table 2. Cross-market risk indicators for selected event windows

Market	Event window	20-day volatility (%)	Subsequent 10-day drawdown (%)
A-Share	2023 Stress and Rebound	13.70	-0.25
A-Share	2024 Policy Rally and High Volatility	39.84	-2.31
A-Share	2025 Technology Themes and Active Trading	12.18	-1.43
Hong Kong HSI	2023 Stress and Rebound	23.81	-0.50
Hong Kong HSI	2024 Policy Rally high volatility	38.89	-2.72
Hong Kong HSI	2025 Technology Themes and Active Trading	25.23	-1.25

Note. Volatility is annualized from the previous twenty daily index returns. The drawdown equals the average ten-day maximum post-event drawdown. Values are rounded to two decimal places.

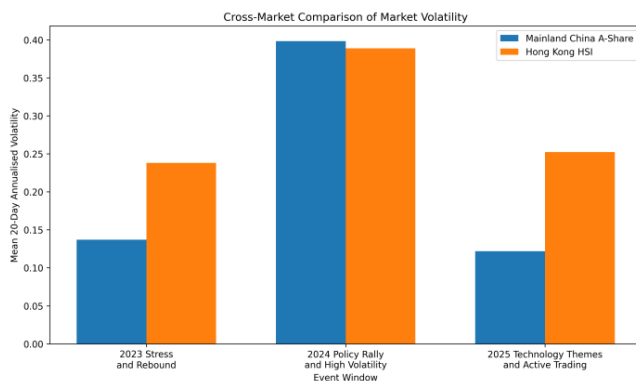


Fig. 5. Cross-market comparison of 20-day annual volatility means for selected event windows.

It not only has the highest medium-term follow-down draws, but also average values of around -2.31% and -2.72% , respectively. 2023 and 2025 frequency intervals are less typical for risk patterns. Moreover, the frequency of the intra-day swings for the Hong Kong market compared to the A-share market was much higher within these intervals, while in the most considerable drawdown rates in 2025

within the A-share sample. Therefore, to all appearances, it is possible to assume the cross-border investment approach by its name of the region that does not testify to the correlation in outlooks, volatility, or, respectively, follow-down losses. Fig. 6 shows the cross-market comparison of subsequent 10-trading-day drawdowns. It indicates that the 2024 window was associated with the deepest short-term downside risk in both markets.

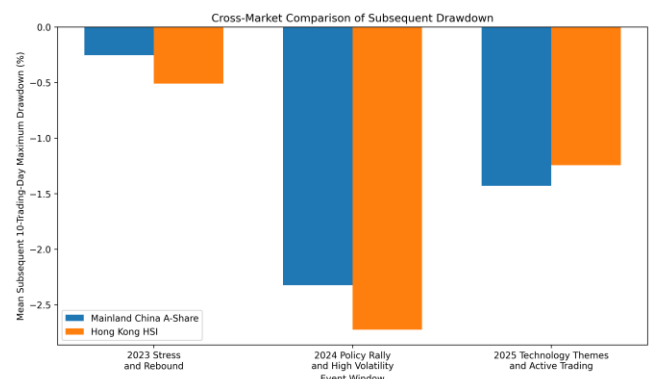


Fig. 6. Cross-market comparison of average subsequent 10-day highest drawdown across selected event windows.

V. DISCUSSION

Sentiment monitoring according to the practical interpretation is supported by the event-based evidence. First, the sentiment can be divided into two categories, those that are present in mainland and Hong Kong markets, when the major region environment is relatively the same. The windows of 2023 and 2025 are particularly revealing since the sentiment of A-shares positively or neutrally did not correspond with the sentiment of Hong Kong that was positive. Thus, a wealth manager who just monitors one market could not have a clear understanding of the situation, especially when a client is exposed to significant divergence in other markets. Second, sentiment should be read alongside market-risk measures. The 2024 window illustrates the folly of a straightforward “positive news means buy” strategy. The window is characterized by high average sentiment and by simultaneously having the most extreme volatility and the largest subsequent average drawdowns. In Chinese A shares, the crowding of trading was the highest. The prudent response isn’t a blanket sell suggestion; it’s a systematic discussion of whether the client’s allocation, liquidity buffer and risk tolerance are appropriate given the hyperactive market. Third, the paper demonstrates the importance of human oversight. While the AI classifier can transform a few hundred quickly-collated headlines into a uniform score on a scale of -1 to 1, it cannot know if an individual client should rebalance. Client-specific thresholds depend on investment timeframe, cashflow and liquidity requirements, concentration, tax, and compliance considerations. The signals generated by the AI classification are thus best seen as a systematic way to highlight focus areas for the wealth manager. There are many limitations. The samples are small, public, and deliberately selected around three market conditions. The news corpora differ in size and are not used in a fully matched day-by-day manner. There is no causal test, full-market backtest, firm-level fundamental data, or directly comparable Hong Kong crowding metric. These failings do not allow for claims of a market return-predicting system or assured diversification benefits, but they do not diminish the practical significance of this workflow as a starting point for more robust and systematic future work.

VI. CONCLUSION

This article creates a sentiment analysis approach prototype based on AI for a human-assisted cross-border wealth management between Hong Kong and Mainland China. A Chinese financial sentiment classifier pretrained on this technology was deployed on both 70 A-share market news headlines and 28 Hong Kong market news reports. Consequently, the labels at the headline level were transformed into daily or event-based sentiment indicators, as well as those of the CSI 300 and Hang Seng Index, which were treated as risk sources. Besides, the framework took into account a simpler, commonly used Mainland-specific valuation measure, which was also calculated based on the abnormal volume and transaction amount. In the first case, the news sentiment for Mainland and Hong Kong stocks often diverged: sentiment for A-shares was positive during the stress-and-rebound phase of 2023 when sentiment for

Hong Kong stocks was negative; sentiment for Hong Kong stocks was more upbeat during the policy rally of 2024, then was negative again during the technology theme of 2025 while sentiment for A-shares was around neutral. The second case illustrates that the top window for volatility for both markets was also the window that produced the greatest average subsequent declines. The third case shows that the greatest degree of crowding in A-share trading occurred in the 2024 window, confirming the utility of reviewing both traffic and sentiment signals together instead of judging either alone. The tenor given is applied to the word understating. The notion that AI sentiment does not substitute for the requirement of relevant investment decisions, client suitability tests, or due diligence seems unnecessary. It can warn wealth managers concerning clients that require special consideration: for instance, heterogeneous attention or trading patterns in a predominantly cross-market tranquil context. The future study can be designed to extend the time span, expand the language domain of the news database, enhance the parity with Hong Kong turnover comparisons, as well as to verify whether the signals added value beyond the common denominator market effect. The pilot, limited in scale, ensures a protocol that connects AI-based text mining with multi-directional asset management and includes a template to observe.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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