Betting Against the Crowd: Option Trading and Market Risk Premium*

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ABSTRACT

We examine time-series stock market excess return predictability by aggregate stock option order imbalance. While individual-level call order imbalance (CIB) captures informed trading and pos-itively predicts cross-sectional stock returns, we show that aggregate call order imbalance (ACIB) serves as a potent sentiment signal. Aggregation diversifies away firm-specific news, revealing a dominant sentiment component that negatively forecasts the U.S. market risk premium. This pre-dictability is driven by small-volume traders and is most pronounced during high-sentiment periods, underscoring the dual nature of option trading as both an informed-trading and sentiment-driven signal.

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1 Introduction

A well-established literature shows that option trading, driven by informed investors seeking leverage, predicts cross-sectional stock returns, see, for example, Easley, O'Hara, and Srinivas (1998), Cao, Chen, and Griffin (2005), Pan and Poteshman (2006), and Ge, Lin, and Pearson (2016). However, it remains an open question whether this predictive power extends to the time-series variation of the broader market. While recent work by Chordia, Kurov, Muravyev, and Subrahmanyam (2021) and Henderson, Pearson, and Wang (2023) explores specific index-level and structured derivative products, the rich predictive information embedded in the individual equity options for the broader market has been overlooked.

In this paper, we bridge the gap in the literature by presenting a comprehensive analysis of the information embedded in aggregate options trading in the context of market excess return predictability and find supporting evidence for a sentiment channel, capturing patterns of overreaction followed by subsequent corrections that explain the negative predictability of our predictors. First, we construct our predictor using the order imbalance of individual options and find that aggregate call order imbalance negatively predicts market excess returns. Second, we compare our predictor with all the existing stock- and option-based market excess return predictors in the literature and confirm that it is one of the strongest predictors for market risk premium. Third, we reconcile the cross-sectional and time-series evidence by showing how aggregation filters out firm news to leave sentiment. Our findings reveal that, in addition to informed trading, equity call option trading contains substantial information about sentiment.

To start, we construct two measures, ACIB and APIB, based on the aggregate order imbalance of individual call and put options, respectively. Bryzgalova, Pavlova, and Sikorskaya (2023) find that, in their sample, when it comes to buying decisions, retail investors strongly prefer call options to puts, and the call option trading accounts for 69% of their volume share. It suggests that retail investors are more likely to overreact to the upward movement of stock prices and lose money due to their irrational betting on the unsustainable trend. It also indicates that trading activity in individual call options is likely to be a richer source of sentiment-related information than put option activity.

Empirically, we investigate weekly market excess return predictability following Chordia et al. (2021) and Ge, Lin, and Pearson (2016). We find that ACIB strongly and negatively predicts future stock market excess returns. A one-standard-deviation increase in ACIB is associated with a 0.329% decline on average in the next-week stock market excess returns.[1] The forecasting power of ACIB remains robust to controlling for a number of factors, including prevalent sentiment indices, other option-based measures, and established predictors from the literature, highlighting that ACIB contains unique information about the market risk premium. In contrast, the aggregate equity put option order imbalance, APIB, shows no predictive power for market excess returns at any horizon.

The *negative* time-series (TS) market excess return predictability by ACIB could be surprising, particularly when we consider the role of option order imbalance in predicting the cross-sectional (CS) stock returns. A large body of literature documents that the CS variations in call and put option trading contain important news for future CS stock returns (e.g., Pan and Poteshman (2006), Johnson and So (2012), Hu (2014), and Ge, Lin, and Pearson

[1] To save space, the main empirical results are provided with weekly frequency, while daily and monthly results are provided in the Internet Appendix.

(2016)). We confirm these empirical findings in our sample using stock-level call order imbalance (CIB). Specifically, when sorting stocks into quintiles according to CIB, we document *positive* return predictability that stocks with high CIB outperform stocks with low CIB in the cross-section. It is important to note that a CS relationship does not necessarily imply TS predictability in the same direction. This is because cross-sectional analyses effectively neutralize the aggregate market effect, while aggregation diversifies away the idiosyncratic news of individual firms. Consequently, the resulting information extracted from the CS tests (e.g., high-minus-low portfolio sorting) could be different from that reflected in the TS tests (e.g., market return predictive regression).

To align the evidence from TS and CS analyses, we undertake two investigations. First, we demonstrate that the sentiment effect pervades the cross-section: ACIB negatively predicts returns for all individual CIB-sorted portfolios, though not the high-minus-low portfolio return. The latter effectively removes the common sentiment shock, preserving the differential (informed) signal. Second, we show that this sentiment effect is most salient in the aggregate TS analysis when firm-specific idiosyncratic information is diversified away—meaning that good and bad news are balanced and thus cancel each other out during aggregation. Therefore, our TS results are not inconsistent with CS evidence on informed trading. Instead, they underscore a critical distinction: option trading embeds both firm-specific informed signals, identifiable in the CS, and market-wide sentiment, which drives TS predictability.

We provide empirical evidence to support our explanation that ACIB captures investor sentiment. First, we show that ACIB is highly correlated with existing sentiment measures. For instance, it has a correlation of 50% with the BW sentiment of Baker and Wurgler (2007), a correlation of 33% with the SEP sentiment of Henderson, Pearson, and Wang (2023), which is constructed exclusively based on retail investors' trading activity, and a correlation of 37% with the AAII bullish sentiment from the survey data by the American Association of Individual Investors. Second, we decompose option orders by trade size and reconstruct ACIB for each group. Only the ACIB derived from small trades exhibits significant predictive power for market excess returns. This result precisely aligns with the fact that small-volume trades (including those from retail investors) are mainly driven by sentiment (Bryzgalova, Pavlova, and Sikorskaya (2023)).

Third, we examine whether the predictive power holds for market makers and professional customers, who are less prone to sentiment-driven trading. As hypothesized, the ACIB constructed from either group's trades shows no significant predictive power for the market risk premium. This null result not only reinforces the sentiment channel but also indicates that the predictability of the aggregate ACIB is from options' end-user demand instead of market-making activity.

Finally, we examine the predictability of ACIB conditional on the level of sentiment. Based on the insights from Stambaugh, Yu, and Yuan (2012), the sentiment effect from ACIB (i.e., the predictive power of ACIB) should be more salient when market participants are more optimistic in general. Using the SEP sentiment by Henderson, Pearson, and Wang (2023) and the AAII sentiment from the American Association of Individual Investors, we split our sample into two regimes based on the level of the two sentiment indices. We find that the predictability of ACIB is much stronger and significant only when SEP or AAII sentiment is high. The subperiod results based on SEP and AAII also support the view that our sentiment index extracted from equity call options likely reflects the sentiment of small-volume traders (including retail).

Our finding has important asset pricing implications, as ACIB can serve as a very robust predictor for market risk premium. We examine the predictive performance of ACIB in out-of-sample tests. The out-of-sample (OOS) R^2 reaches 0.756%, achieving the best performance among other weekly predictors. Economically, a mean-variance-utility investor who allocates wealth between the market portfolio and T-bill can obtain an annualized Sharpe ratio of 0.847 if she follows a weekly portfolio rebalancing strategy based on the predictive signal of ACIB. Furthermore, ACIB provides additional OOS forecasting power beyond all the existing predictors using partial least squares (PLS) regressions. We find the OOS R^2 of the weekly PLS aggregate predictor can be increased from 1.198% to 1.482% when combined with ACIB. The Sharpe ratio of a market-timing strategy based on PLS of all existing weekly predictors increases from 0.685 to 0.903.

Our analysis focuses on equity call options rather than index options, a distinction motivated by their differing investor clienteles. Extant literature documents that the market for individual equity options is largely driven by retail investors, whereas institutional traders dominate the index options market (Lemmon and Ni (2014)). This clientele difference is critical because retail investors are often posited as noise traders who are more susceptible to sentiment (Kumar and Lee (2006) and Lemmon and Portniaguina (2006)). We validate this premise by showing that our equity-based ACIB measure is significantly correlated with established sentiment indices, whereas the index-based call option imbalance (ICIB) is not. We therefore postulate and confirm that equity ACIB captures a potent sentiment mechanism with strong predictive power for market excess returns—a result starkly different from the weak and insignificant predictability we find for ICIB in Section 5.2.[2]

Our paper contributes to four strands of literature. First, it adds to the literature by highlighting that the information content extracted from option trading differs significantly between the cross-sectional portfolio sorting test and the time series predictive regression test. While most of the previous studies examine equity option trading through the cross-sectional test[3], we are the first one to study information content of aggregate individual stock option trading from a time-series perspective. More importantly, we demonstrate that the divergent CS and TS predictive power of CIB or ACIB can be reconciled by considering the distinct informational component isolated by each empirical design. In the cross-section, sentiment affects all stocks, so the long-short return difference primarily captures the informed trading component of the signal. In contrast, within the time series, firm-specific informed trading signals are diversified away at the aggregate level, allowing the more persistent and coherent sentiment component to become the dominant driver of the forecast capacity.

Second, our paper contributes to the literature by proposing a novel sentiment measure from equity options. Measuring investor sentiment is undeniably challenging.[4] Baker and Wurgler (2007) pioneered by constructing a stock market sentiment index. Recent literature aims to distinguish sentiment by different types of investors. Focusing on retail structured

[2]Another potential explanation for the insignificant sentiment effect of ICIB is the high salience of the index options market, which enables arbitrageurs to correct any sentiment-driven mispricing from noise traders.

[3]See, for example, Easley, O'Hara, and Srinivas (1998), Chan, Chung, and Fong (2002), Chakravarty, Gulen, and Mayhew (2004), Cao, Chen, and Griffin (2005), Pan and Poteshman (2006), Bali and Hovakimian (2009), Cremers and Weinbaum (2010), Xing, Zhang, and Zhao (2010), Johnson and So (2012), Grundy, Lim, and Verwijmeren (2012), An, Ang, Bali, and Cakici (2014), Hu (2014), Muravyev (2016), Ge, Lin, and Pearson (2016), and Ni, Pearson, Poteshman, and White (2021).

[4]As discussed in Baker and Wurgler (2007), "The question is no longer whether investor sentiment affects stock prices, but how to measure investor sentiment and quantify its effects."

equity product (SEP) issuance, Henderson, Pearson, and Wang (2023) construct the first retail sentiment measure for reference stocks. Different from previous studies, we are motivated by Bryzgalova, Pavlova, and Sikorskaya (2023) who find that retail investors prefer buying individual call options and suffer from big losses, and construct a sentiment measure from the order imbalance of individual equity call options. Compared with existing sentiment predictors, our measure can be easily constructed using exchange-traded equity options volume and is available at a higher frequency.

Third, our paper contributes to the recent important debate about market predictability. While Goyal and Welch (2008) find insignificant market return predictability for many common predictors in the literature, subsequent studies, such as Campbell and Thompson (2008), Rapach, Strauss, and Zhou (2010), Henkel, Martin, and Nardari (2011), Pettenuzzo, Timmermann, and Valkanov (2014), Colacito, Ghysels, Meng, and Siwasarit (2016), and Chen, Da, and Huang (2022), provide evidence to support market return predictability. In a recent study, Goyal, Welch, and Zafirov (2024) once again question the market predictability by examining the predictive power of a larger set of predictors published in top finance journals. We contribute to the debate by showing that ACIB is a unique and powerful predictor. The market predictability could be significantly improved when combining ACIB with existing predictors.

Fourth, our paper also contributes to the literature on asset pricing unity across asset classes. A growing literature demonstrates that information flows across the markets, and investors could make better decisions in one market by analyzing trading and price patterns in another market. For example, Easley, O'Hara, and Srinivas (1998), Pan and Poteshman

(2006), Bali and Hovakimian (2009), and Ge, Lin, and Pearson (2016) find that option-based characteristics predict the cross-section of stock returns. Cao and Han (2013), Christoffersen, Goyenko, Jacobs, and Karoui (2018), Zhan, Han, Cao, and Tong (2022), Bali, Beckmeyer, Moerke, and Weigert (2023), and Jeon, Kan, and Li (2025) show that the firm characteristics can predict stock option returns. In their comprehensive analysis, Chen, Roussanov, Wang, and Zou (2024) show that there are common risk factors that price a major set of asset classes, stocks, corporate bonds, and equity options. Complementing these studies, our paper provides new evidence that trading activity in the equity option market contains significant predictive information for the equity market risk premium.

The rest of the paper is organized as follows. Section 2 describes the construction of our predictors and other key variables. Section 3 presents time-series return predictability by ACIB and its difference from the cross-sectional return predictability. Section 4 provides evidence that ACIB captures investor sentiment. Section 5 provides robustness checks of the predictive power by ACIB and investigates the difference between index options and individual options. Section 6 concludes the paper.

2 Variable Construction

We measure equity option trading activity through *order imbalance* (IB). First, the signal IB is widely used in both practice and academia to measure trading activity in either option or stock markets.[5] Second, IB can be constructed using call or put volume separately, allowing us to identify the different trading effects from call and put options. Third, since

[5]See, for example, Chan and Fong (2000), Chordia, Roll, and Subrahmanyam (2002), Chordia and Subrahmanyam (2004), Hu (2014), Chen, Joslin, and Ni (2019), and Chordia et al. (2021)

the value of IB is bounded between -1 and $+1$, it can make a time series stationary. This is crucial for a time-series study because we need a stationary distribution of the predictor for regression analyses.

The option order imbalance is constructed using the equity options trading volume from CBOE, which covers the largest portion of option trading activity across all exchanges in the United States.[6] The CBOE open-close data documents detailed volume information for option trading activity on CBOE. The trading volume is aggregated and bucketed by origins, such as public customers, professional customers, and market makers. At the same time, it specifies and separates trading volume by buying/selling and opening/closing positions. The customer and professional customer volume can be further broken down into trading size buckets, including fewer than 100 contracts, 100-199 contracts, and greater than 199 contracts. The data on underlying stock prices is obtained from the Center for Research in Security Prices (CRSP). The target variable (i.e., market risk premium) is the value-weighted market excess return in logarithms (MKTRF) obtained from Kenneth French's website.

To construct the option trading order imbalance, we first collect all available trading volume data in the CBOE database from 2005 to 2020. Following Hu (2014), Chen, Joslin, and Ni (2019), and Chordia et al. (2021), we define the order imbalance of each individual equity option from end users on a certain day/week/month as the summation of total open buy trading volume less open sell trading volume divided by the sum of total trading volume

[6] We also construct our main predictors using another commonly used database, the Nasdaq International Securities Exchange (ISE), and find similar and robust results of the stock return predictability. The result is available in the Internet Appendix Section IA.4 and Table A8.

across all moneyness and time to maturities from public customers within that period:[7]

$$CIB_{i,t} = \frac{\sum_{s \in S} Open\ Buy^{Call}_{i,s,t} - \sum_{s \in S} Open\ Sell^{Call}_{i,s,t}}{\sum_{s \in S} Open\ Buy^{Call}_{i,s,t} + \sum_{s \in S} Open\ Sell^{Call}_{i,s,t}}, \tag{1}$$

$$PIB_{i,t} = \frac{\sum_{s \in S} Open\ Buy^{Put}_{i,s,t} - \sum_{s \in S} Open\ Sell^{Put}_{i,s,t}}{\sum_{s \in S} Open\ Buy^{Put}_{i,s,t} + \sum_{s \in S} Open\ Sell^{Put}_{i,s,t}}, \tag{2}$$

where s is a certain option contract for stock i each day across all traded equity call or put options in the CBOE database. Note that we exclude professional customers and only include option trading tagged by the "customer" category from CBOE in Equations (1) and (2).[8] A positive call (put) order imbalance, namely CIB (PIB), indicates that there is more buying pressure than selling pressure from call (put) option end users.

We use all traded option data from the CBOE database that is marked as "customer" to construct IB. In Section 4, we conduct a detailed decomposition of IB based on different trading sizes, and show that the predictive power of ACIB is mainly driven by public customers with small-size trading orders but not professional customers, implying that the predictive power of ACIB is more consistent with the sentiment explanation.

Correspondingly, the aggregate call (put) option order imbalance, i.e., ACIB (APIB), is the market-value weighted average of individual call (put) IB at each point of time:

$$ACIB_t = \sum_{i=1}^{N} w_{i,t} CIB_{i,t}, \ APIB_t = \sum_{i=1}^{N} w_{i,t} PIB_{i,t}, \tag{3}$$

[7] We use only open positions to construct CIB, as they better reflect the motivation of the option traders and are an unconstrained measure. A detailed discussion of using the closing positions is provided in Section 4.1.

[8] We thank the anonymous referee for pointing out the nuances of the CBOE "390 Rule". While the "customer" category is frequently used as a proxy for retail investors, it may include professional traders who place fewer than 390 orders per day on average in any month. Consequently, we adopt the more conservative interpretation of ACIB as a proxy for the sentiment of small-volume traders (including retail) rather than pure retail investors.

where $w_{i,t}$ is the weight by market capitalization for each option's underlying stock i, which is calculated by the underlying stock price multiplying the shares outstanding obtained from CRSP.[9] In general, one can think of ACIB (APIB) as the aggregate end-user demand for equity call (put) options in the market.

[Insert Figure 1]

Figure 1 shows that both ACIB and APIB have stationary distributions over time. ACIB (APIB) hits the bottom (top) during the 2008 financial crisis but rebounds quickly after the recession. The trading activities of call and put options do not always move oppositely to each other as commonly thought, suggesting that they embed distinct information when included together in predictive regressions. Moreover, investors trade more equity call options than equity put options in the recent period of Covid 19, consistent with Bryzgalova, Pavlova, and Sikorskaya (2023) who find that more people joined the option market to trade equity call options for speculation.

[Insert Table 1]

Table 1 summarizes some important statistics of our predictors. There are, on average, 2,053 (1,718) firms with options traded to construct ACIB (APIB) at weekly frequency. In the Internet Appendix Table A2, we further decompose option trading volume by trader classification (e.g., "customer", "professional customer", and "market maker"), trader size (e.g., small, medium, and large), and option type (e.g., index and individual equity options). We find that "customer" and "market maker" orders represent the majority of volume, ac-

[9] In the Internet Appendix Section IA.3 and Table A6, we show that the predictive power of ACIB is robust if we construct it using equal weights across all available stocks.

counting for 31% and 65% on average, respectively. The "professional customer" order only accounts for less than 2%, in line with the findings in Vasquez, Amaya, Pearson, and Garcia-Ares (2025). Index options trading features a higher proportion of large-size orders (13.27%) compared to equity options (9.09%), reflecting greater institutional activity in the index market. Conversely, equity options exhibit a higher proportion of small-size orders. Moreover, there are more put trading for index options than equity options. Within the "customer" segment for index options, we find that put trading (27.25%) slightly exceeds call trading (26.36%). In contrast, for individual equity options, call trading (35.34%) is higher than put trading (33.24%). The overall statistics are consistent with the literature, suggesting that index options are more frequently utilized for hedging or downside protection by sophisticated participants, while the preference for calls in equity options aligns with recent findings regarding retail-oriented trading behavior (Bryzgalova, Pavlova, and Sikorskaya (2023)).

The time-series averages for both ACIB and APIB are negative, implying that option traders are net sellers of both equity call and put options, similar to the findings by Lakonishok, Lee, Pearson, and Poteshman (2007). The fact that option investors are net sellers of equity options does not contradict our sentiment explanation. This is because the sentiment effect is primarily driven by buying behavior (Section 4.1), and we use the net order imbalance only to measure relative changes in this behavior.

When examining the correlations, we find that ACIB is strongly correlated with most of the other sentiment indices, such as the sentiment index by Baker and Wurgler (2007) with a correlation of 0.50, the SEP sentiment index by Henderson, Pearson, and Wang (2023) with a correlation of 0.33, GM sentiment by Gao and Martin (2021) with a correlation of 0.55, AAII sentiment with a correlation of 0.37, and the consumer sentiment index from University of Michigan with a correlation of 0.24. Given this anecdotal evidence and the high correlations with sentiment measures, we hypothesize that ACIB captures investor sentiment and negatively predicts market excess returns.

3 Aggregate Equity Option Order Imbalance and Stock Market Risk Premium

3.1 In-sample Predictive Regression

If ACIB captures investor sentiment, we expect that ACIB negatively forecasts future stock market excess returns. The most commonly used predictive regression follows Fama and French (1988, 1989):

$$r_{t,t+1} = a + b^C \times ACIB_t + \sum_{j=1}^{J} b_j X_{j,t} + \epsilon_{t,t+1}, \tag{4}$$

where r_{t+1} is MKTRF at time $t+1$ defined in Section 2; we examine one-week ahead and one-month ahead market excess returns.[10] $X_{j,t}$ specifies the control variable j. In particular, we classify other predictors into three categories: 1) *option-based predictors*, including aggregate put option order imbalance (APIB), variance risk premium (VRP, Bollerslev, Tauchen, and Zhou (2009)), index call IB and index put IB (ICIB and IPIB, Chordia et al. (2021)), aggregate implied volatility spread (IVS, Han and Li (2021)), aggregate risk neutral skewness (BKM Skew, Bakshi, Kapadia, and Madan (2003)), and deep out-of-the-money index put

[10]In the Internet Appendix Tables A3-A6, we show that our findings are robust for daily/weekly/monthly multiple forecast horizons and if we forecast equal-weighted stock market excess returns.

options IB (PNBO, Chen, Joslin, and Ni (2019));[11] 2) *sentiment measures*, such as the AAII bullish sentiment from the American Association of Individual Investors, SEP sentiment (Henderson, Pearson, and Wang (2023)), BW sentiment (Baker and Wurgler (2006)), GM sentiment (Gao and Martin (2021)), manager sentiment (Jiang, Lee, Martin, and Zhou (2019)), consumer survey sentiment from the University of Michigan, and PLS sentiment (Huang, Jiang, Tu, and Zhou (2015)); 3) *stock-based predictors*, including average skewness (JZZ Skew, Jondeau, Zhang, and Zhu (2019)), aggregate disagreement index (HLW Disp, Huang, Li, and Wang (2021)), and those classic predictors from Goyal and Welch (2008).[12] Note that some control variables are only available at the monthly level, so the regressions are done at different frequencies.

We then run the multiple predictive regressions to forecast one-period-ahead (weekly or monthly) market excess returns. The t-stat is corrected for the serial correlation and conditional heteroscedasticity based on Newey and West (1987). The Newey-West t-stat formula is provided in the Internet Appendix Section IA.1. To make the coefficients comparable, we standardize all independent variables to have a zero mean and unit standard deviation.

[Insert Table 2]

Table 2 provides evidence that ACIB is a strong and contrarian predictor for future market excess returns at both weekly and monthly frequencies. For example, a one-standard-deviation increase in ACIB forecasts an average decrease in stock market excess returns of 0.329% (1.358%) next week (month), with a t-stat of -2.37 (-2.81). More importantly,

[11] We compute the firm-level measures and aggregate them to the market level using a market-capitalization weighting scheme to obtain the "BKM Skew" predictor.

[12] Following Rapach, Ringgenberg, and Zhou (2016), we extract and include the principal component of the 22 predictors collected from Amit Goyal's website as a single predictor (GW PCA).

Table 2 demonstrates that ACIB is a strong and new predictor which could not be explained by other existing predictors. ACIB outperforms all the other existing predictors, not only because it has the highest t-stat and coefficient magnitude among all the predictors in most cases, but also because ACIB's forecasting capacity holds consistently in both weekly and monthly horizons.

In contrast, APIB does not significantly predict future market excess returns. We posit that this is due to distinct motivations behind trading call and put options. The sentiment effect, which drives negative return predictability, is primarily channeled through lottery-like call options due to their unlimited payoff potential, especially among unsophisticated traders (Byun and Kim (2016)). Consequently, sentiment is more strongly reflected in call option demand, a trend further evidenced by the recent influx of participants speculating in equity call options (Bryzgalova, Pavlova, and Sikorskaya (2023)).

It is worth noting that the predictive power of ACIB lasts for months. Empirically, the reversal horizon fluctuates over time, ranging from a few weeks to several months. As prior literature notes, mispricing driven by sentiment does not always correct immediately, in part because future shifts in investor sentiment are unpredictable. Our finding of persistent predictability aligns with studies documenting that the effects of sentiment can endure for months rather than reversing instantly, see for example, Baker and Wurgler (2006), Huang et al. (2015), Jiang et al. (2019), Gao and Martin (2021), and Henderson, Pearson, and Wang (2023).

3.2 Different Patterns between Cross-sectional and Time-series Analyses

Our conclusion that options trading volume conveys investor sentiment seems to stand in tension with prior research establishing its role in informed trading (Pan and Poteshman (2006), Johnson and So (2012), Hu (2014), and Ge, Lin, and Pearson (2016)). However, rather than contradicting these findings, our study offers a crucial refinement. We show that option trading activity is a dual indicator, reflecting not only the presence of informed traders but also the influence of market sentiment.

We begin by examining the power of call option imbalance (CIB) to predict cross-sectional stock returns. Following Pan and Poteshman (2006) and Ge, Lin, and Pearson (2016), we adopt a weekly horizon. At the end of each week, we sort stocks into quintiles based on CIB and construct equal-weighted portfolios. These are held for one week, and we calculate the average returns for each portfolio. Panel A of Table 3 presents the performance of these CIB-sorted portfolios, including a long-short strategy that longs the top quintile and shorts the bottom quintile.

[Insert Table 3]

Our cross-sectional findings provide support for the informed trading mechanism. We demonstrate that CIB is a powerful predictor in the cross-section, with a portfolio with high CIB forecasting higher returns. This result aligns with the core mechanism in prior cross-sectional studies. For instance, Ge, Lin, and Pearson (2016) find that the predictive power of the option-to-stock (O/S) ratio stems from informed call option trading. Our finding that CIB itself is a distinct and significant cross-sectional predictor, to the best of our knowledge, is not documented in the literature. Therefore, our empirical tests provide a new and direct contribution to the cross-sectional options literature.

Why do we observe opposite patterns in the cross-sectional (CS) and time-series (TS) predictability of equity option trading? The divergent CS and TS predictive power of CIB can be reconciled by considering the distinct informational components isolated by each empirical design. The CS approach, which relies on a long-short portfolio sorted on CIB ("Port 5−1" in Table 3), effectively neutralizes the influence of market-wide sentiment. This is because sentiment affects all stocks, so the long-short return difference primarily captures the informed trading component inherent in the cross-sectional dispersion of CIB.

In contrast, the aggregation of CIB to the market level (ACIB) has the opposite effect: firm-specific informed trading signals, being often offsetting, are diversified away. The sentiment component, however, is coherent and persists in the aggregate, causing ACIB to exhibit a negative relationship with future market excess returns. Consequently, we derive two testable implications: first, ACIB negatively predicts stock market excess returns and the CIB-sorted portfolio returns given the prevalence of sentiment; second, ACIB has no predictive power for the returns of CIB-sorted long-short portfolios, which are dominated by informed trading.

Our empirical tests confirm the dual nature of CIB. We run predictive regressions of the CIB-sorted portfolio returns on ACIB. As shown in Table 3, Panel B, ACIB negatively predicts the returns of all individual portfolios (Port 1 to Port 5) with similar strength, consistent with a market-wide sentiment effect. However, ACIB has no predictive power for the long-short portfolio return ("Port 5−1"). This critical finding supports our hypothesis: the long-short spread isolates the cross-sectional informed trading component, which is diversified away in the ACIB aggregate. In contrast, the sentiment component persists in ACIB and uniformly impacts broad portfolio returns negatively.

Although firm-specific information typically nets out in the aggregate, an imbalance could exist when more firms have bad news or good news. In such a case, we expect the sentiment effect of ACIB to be weakened. To capture the imbalance between good and bad news, we construct a new measure, *informed-trading intensity* (ITI), defined as the absolute difference between the absolute returns of the top and bottom CIB-sorted portfolios:

$$Informed - Trading\ Intensity\ (ITI) \stackrel{\text{def}}{=} ||\frac{1}{M_t}\sum_{i \in Port\ 5}^{M_t} R_{i,t}| - |\frac{1}{M_t}\sum_{j \in Port\ 1}^{M_t} R_{j,t}||. \qquad (5)$$

A high ITI indicates an imbalance where either good or bad news dominates the market. In this regime, the aggregation into ACIB does not fully offset the informed trading signal, causing ACIB to reflect a mixture of both sentiment and informed trading. Conversely, a low ITI signifies that good and bad news are balanced and thus cancel each other out during aggregation. This process neutralizes the informed trading component, allowing the persistent sentiment component to become the dominant factor in ACIB. Therefore, we expect the negative predictive power of ACIB for market excess returns to be more pronounced during low-ITI periods. To test this, we partition our sample into two regimes based on whether the ITI is below or above its time-series median and test the predictability of ACIB in each regime.

The results in Table 3, Panel C, confirm our conjecture. We find that the negative predictive power of ACIB is concentrated almost exclusively in the low-ITI regime, with little predictability in the high-ITI regime. This pattern strongly suggests that ACIB's forecasting ability is driven by sentiment, which emerges clearly only when the informed trading component is neutralized.

In summary, our findings resolve the appearing contradiction between the time-series and the cross-sectional predictive power of CIB. The cross-sectional analysis, through the high-minus-low portfolio, isolates the informed trading component inherent in the relative ranking of options activity. In contrast, the time-series analysis, through ACIB, captures a market-wide sentiment component that becomes dominant upon aggregation. Thus, our results do not contradict the established literature on informed trading in options but rather refine it by showing that options markets simultaneously contain distinct, separable signals for stock-specific information and broad market sentiment.

4 ACIB as a Proxy for Investor Sentiment

4.1 Decomposition of Equity Option Trading Activity

In this subsection, we provide further evidence that ACIB can be a proxy for investor sentiment, especially for small-volume traders (including retail), by measuring equity option trading activity conditional on the trading size, investor types, open/closing positions, and buying/selling activity.

Decomposition based on trading size

We use the order size labels from CBOE to group equity options by trading size, which divides all option trades into three categories: small trade (trade volume less than 100 contracts each), medium trade (trade volume between 100 and 199), and large trade (trade volume greater than 199). When constructing ACIB, we separate the sample by the trading size specified by CBOE and take a market-value weighted average among stocks with all corresponding equity options in each group.

[Insert Table 4]

Table 4 Panel A demonstrates that the predictive power of ACIB mainly comes from equity call options of small trading size.[13] The forecasting capacity reduces significantly from small size to medium size, and totally disappears for large size. Our finding is consistent with the sentiment explanation, as small-volume traders (including retail) are more likely to be affected by market sentiment (Bryzgalova, Pavlova, and Sikorskaya (2023)).

Decomposition based on investor types

Another classification to group options is based on different types of traders. The CBOE database has detailed documents regarding the types of traders who submit the corresponding trading orders. In particular, CBOE classifies option traders mainly into three types: market makers, customers, and professional customers. Market makers include those option accounts of brokers or dealers that are either options clearing corporation (OCC) members or any affiliations for clearing purposes.[14] Customers are trading accounts of public investors, and their trading activities are used to construct ACIB in our paper. Professional customers are trading accounts classified as professional investors by brokerage firms. Taking advantage

[13] While all the regressions in Table 4 are at weekly frequency, the results are consistent when looking at daily and monthly predictive regressions.

[14] There are three types of accounts affiliated with market makers in the CBOE database: firm, broker-dealer, and market maker. When constructing ACIB for market makers, we combine the trading records for all three types of accounts.

of this classification, we construct ACIB based on public customers, professional customers, and market makers, and use them to forecast stock market excess returns separately. If the forecasting capacity of ACIB is driven by the sentiment effect, we expect a stronger predictive power from public customers but not from professional customers or market makers.

Table 4 Panel B displays the predictive power of ACIB based on the order flows executed by different types of traders. The results are consistent with our conjecture that the predictive power of ACIB is mainly driven by public customers' trading activity. If we construct ACIB using professional customers' order flows, we do not see any predictive power. Similar evidence is found for order flows from market makers. The lack of return predictability by market makers' ACIB can be attributed to the fact that market makers act as the counterparties for both professional customers and public customers, and since only public customers reflect the sentiment effect, the market makers' ACIB will be contaminated by professional customers' trading activity. From another perspective, these results demonstrate that our documented return predictability is specific to investor sentiment and is not mechanically offset by market-making activity.

Decomposition based on open and closing positions

While we only use the option trading data of new opening positions to construct ACIB, the closing position of option orders may also provide useful information to forecast aggregate stock returns. As an alternative, we use closing trading option data from CBOE to construct ACIB. Furthermore, we combine the open and closing trading option data together to compute ACIB, and investigate whether it can improve the predictive performance.

Table 4 Panel C shows that the closing-position trading activity has some predictive power, although the results are not significant and the coefficients are much smaller than those of opening positions. In other words, the closing-position option tradings provide a marginal contribution to the predictive power of ACIB. The lack of return predictability by closing-position ACIB could be attributed to the fact that most of the motivations for the closing-position trading are related to risk management or updating beliefs, instead of new information driven by sentiment (Pan and Poteshman (2006)).

Decomposition based on option buying and selling activity

Motivated by Roll, Schwartz, and Subrahmanyam (2010), Johnson and So (2012), and Ge, Lin, and Pearson (2016), we construct an alternative variable, the option to stock trading volume (O/S) ratio, to measure equity option trading activity. Unlike CIB, which is scaled by the sum of call-buy and call-sell volume, the O/S ratio is scaled by the stock's trading volume. This allows us to utilize a signed version of the ratio once call-buy and call-sell volumes are separated. We decompose the numerator of the O/S ratio into distinct option trading activity, including call option opening buy position (COB) and call option opening sell position (COS). The decomposed O/S ratios at the individual stock are specified in the following equations:

$$\frac{COB_{i,t}}{S_{i,t}} = \frac{\sum_{s \in S} Open\ Buy_{i,s,t}^{Call}}{Stock\ Volume_{i,t}}, \tag{6}$$

$$\frac{COS_{i,t}}{S_{i,t}} = \frac{\sum_{s \in S} Open\ Sell_{i,s,t}^{Call}}{Stock\ Volume_{i,t}}. \tag{7}$$

We then aggregate to the market level by taking a market-value weighted average in the cross-section. The corresponding O/S ratios for different option trading activities are denoted as ACOB/S and ACOS/S, and (ACOB−ACOS)/S. The regression results are displayed in Table 4 Panel D.

The result of the O/S ratio is consistent with that of ACIB that call option O/S ratios are able to forecast market risk premium, although none of them can beat the performance of ACIB.[15] A new finding based on the O/S ratio is that buying call options is more informative about future market excess returns than selling call options. Among all different predictive regressions separated by option moneyness, the magnitude of t-stat for buying call options (i.e., ACOB/S) is larger and more stable than selling call options (i.e., ACOS/S). The finding is consistent with some recent studies, such as Bryzgalova, Pavlova, and Sikorskaya (2023) and Bogousslavsky and Muravyev (2025), who find that buying options by retail investors is more likely to incur losses, while option sales are more profitable than option purchases, indicating that option purchases are more likely related to sentiment trading.

In summary, by computing ACIB based on various groups and formations, we provide further supporting evidence that the predictive power of ACIB mainly comes from investor sentiment, especially from small-volume traders (including retail).

4.2 The Predictive Power of ACIB in Different Regimes

Many previous studies show that the sentiment effect is more significant when the market participants are more optimistic in general. Motivated by this, we conduct empirical tests by separating the sample period into two regimes based on high and low retail sentiment, namely below and above the median of the time-series sentiment level. We use two indices to proxy for retail investors' sentiment. The first one is the AAII sentiment based on survey

[15] Unlike aggregate IB, aggregate O/S ratio is subject to extreme-value issues. Even though we exclude observations beyond 99% and 1% of all the observations in the cross-section, the aggregate O/S ratio is still very sensitive to extreme values, as individual O/S ratios are not bounded.

data conducted by the American Association of Individual Investors.[16] The second one is the retail sentiment index constructed by Henderson, Pearson, and Wang (2023). Henderson, Pearson, and Wang (2023) use retail structured equity product (SEP) issuances to construct a new sentiment measure and also an aggregate sentiment index for the stock market. If ACIB reflects sentiment from small-volume traders (including retail), we expect to observe stronger return predictability in the high regime of the SEP and AAII sentiment level (i.e., retail investors are more optimistic) and weaker or no return predictability in the low regime. Table 5 Panels A and B confirm this hypothesis that stock market excess returns appear more predictable by ACIB only when the level of SEP or AAII sentiment is above the median.

[Insert Table 5]

Second, most equity option traders have an incentive to bet against firms' earnings announcements. For example, Mahani and Poteshman (2008) document that discount clients act irrationally by entering option positions that load up on growth stocks a few days before earnings announcements. Roll, Schwartz, and Subrahmanyam (2010) also show that there is increased option trading around earnings announcements. A recent study by de Silva, Smith, and So (2025) finds that retail investors purchase options in a concentrated fashion before earnings announcements and incur losses around that time. Therefore, the sentiment trading of equity options is more pronounced around firms' earnings seasons.

Motivated by this, we construct an indicator to identify the time period when more companies announce their quarterly earnings. In particular, we collect the earnings announce-

[16] AAII sentiment is a daily survey data constructed by the American Association of Individual Investors, which summarizes opinions from individual investors by asking them their thoughts on where the market is heading in the next six months.

ment data from Compustat and identify each firm's quarterly earnings announcement date. In a certain week, we calculate the proportion of firms with earnings announcements out of the total public firms in the United States. We then separate the sample weeks from 2005 to 2020 into two regimes: above and below the median of the level of the time-series proportion of earnings announcement.[17] The high regime indicates that equity options trading is more likely driven by sentiment. Therefore, within the regime of more firms' earnings announcements, we should observe the stronger predictive power of ACIB. Table 5 Panel C confirms our hypothesis that retail investors incur losses around earnings announcements and reflects sentiment trading, consistent with de Silva, Smith, and So (2025).

5 Discussion

5.1 Out-of-sample Performance

Martin and Nagel (2022) demonstrate that in-sample tests are more likely to overestimate return predictability when investors face a high-dimensional prediction problem, while out-of-sample tests retain their economic meaning. Accordingly, we conduct out-of-sample regressions. The statistical test of equal predictive accuracy in nested models is based on Clark and West (2007). The regression details are given by:

$$\begin{cases} r_{t,t+1} = \alpha + \beta \times x_t + \epsilon_{t,t+1}, & t = 1, \ldots, T_0 - 1, \\ \hat{r}_{t,t+1} = \hat{\alpha} + \hat{\beta} \times x_t, & t = T_0, \ldots, T, \end{cases} \tag{8}$$

$$Benchmark : r^B_{t,t+1} = \frac{1}{t-1} \sum_{s=1}^{t-1} r_{s,s+1}, \; t = T_0, \ldots, T, \tag{9}$$

[17]We use the median of the time series as the cut-off point in order to make the data observations equally separated into each regime.

where $r_{t,t+1}$ is the market excess return from time t to $t+1$ (weekly or monthly), x_t is the value of the predictor at time t, and $\hat{r}_{t,t+1}$ is the forecasted return based on x_t from the recursive regression. The out-of-sample R^2 statistic is defined as one minus the ratio of the mean squared forecast error of the larger model to that of the benchmark model:

$$R^2_{OS} = 1 - \frac{MSFE_1}{MSFE_0}, \tag{10}$$

where $MSFE_1 = \frac{1}{T-T_0}\sum_{t=T_0}^{T}(r_{t,t+1} - \hat{r}_{t,t+1})^2$ and $MSFE_0 = \frac{1}{T-T_0}\sum_{t=T_0}^{T}(r_{t,t+1} - r^B_{t,t+1})^2$.

Time-series predictability of stock market excess returns has important implications for market timing by guiding investors to optimally allocate wealth between stock investments and a risk-free asset. Following Kandel and Stambaugh (1996) and Rapach, Strauss, and Zhou (2010), we consider a mean-variance-utility investor who allocates wealth between the market portfolio and the T-bill. Given an investment horizon of one week or one month, the optimal weight on the market portfolio is:

$$w_{t,t+1} = \frac{1}{\gamma}\frac{\hat{r}_{t,t+1}}{\hat{\sigma}^2_{t,t+1}}, \tag{11}$$

where $\hat{r}_{t,t+1}$ is the conditional expected market excess return (i.e., forecast based on a predictor) given by x_t. The $\hat{\sigma}^2_{t,t+1}$ is estimated using the variance of the past one-year historical returns for weekly frequency and five-year historical returns for monthly frequency, and the relative risk aversion γ is set to be 3. The portfolio is rebalanced every week or month. The corresponding Sharpe ratio of the investor's optimal portfolio is given by:

$$SR = \frac{R_p}{\sigma_p}, \tag{12}$$

where R_p and σ_p are the mean and the standard deviation of the portfolio return, respectively. The average utility gain or the certainty equivalent return (CER) is computed as:

$$CER = R_p - 0.5\gamma\sigma_p^2, \tag{13}$$

To gauge the economic benefit of a predictor to the mean-variance investor, we compare the CER above associated with the optimal portfolio based on the forecasts provided by the predictor to $\overline{CER}$, the certainty equivalent return of a benchmark portfolio formed based on the average return and standard deviation estimated from historical returns. The difference is defined as the CER gain:

$$CER\ Gain = CER - \overline{CER}. \tag{14}$$

To further investigate whether ACIB captures any existing predictors in the literature, we follow Huang et al. (2015) and Huang, Li, and Wang (2021) and construct a combined predictor with a selected set of existing predictors. In particular, we construct a combined predictor with each of the three groups of the existing predictors specified in Section 3.1 (i.e., option-based predictor, sentiment measures, and stock-based predictor) by running partial least squares (PLS) regression and extract a single combined predictor based on one of the three categories (e.g., PLS (Option-based Predictors)). We then include ACIB together with one of the combined PLS predictors to compute OOS R^2. When training the model for each combined predictor, we use all available observations starting from 1960 up to the testing period (starting from 2010).

[Insert Table 6]

Table 6 demonstrates that ACIB has strong and significant out-of-sample predictive power for future stock market excess returns. For the out-of-sample R^2, compared to the historical average estimation as the benchmark, ACIB achieves 0.756% and 6.114% for one-week and one-month forecast horizons.[18] The annualized Sharpe ratios of using ACIB as the trading signal to construct market-timing portfolios are also considerable, with 0.847 (1.360) for one week (month), which are higher than that of the buy-and-hold benchmark with 0.541 (0.725) for one week (month). From a utility-gain perspective, ACIB helps investors achieve annualized CER gains with 2.978% for one week and 10.416% for one month.

Table 6 also shows that in all cases, the OOS R^2, when combined with ACIB, can be improved. For example, the monthly forecasting OOS R^2 combined with ACIB and option-based (sentiment measures) PLS predictor increases from 5.143% (−1.804%) to 7.147% (2.192%). When running PLS with all existing predictors (i.e., PLS (All Existing Predictors)), one can achieve an OOS R^2 of 7.864%, although it can be further improved to 8.957% when combined with ACIB.

The same evidence and conclusion can be found when examining the economic benefits, namely CER gain and Sharpe ratio. For example, the Sharpe ratio (CER gain) is as high as 1.214 (7.132%) for PLS predictors using all existing predictors, although it can be increased further to 1.360 (10.313%) when combining with ACIB to construct market-timing portfolios. The increases in both the OOS R^2 and the Sharpe ratio/CER gain indicate that ACIB contains substantial new information about future stock market excess returns beyond existing predictors in the literature.

[18] At the usual monthly frequency, our out-of-sample R^2 nearly doubles those of typical predictors, as documented in the latest survey by Rapach and Zhou (2022).

5.2 Stock Market Excess Return Predictability by Index Call Options

Having established the role of equity call options, we now extend our analysis to index call options. The predictive power of index option trading is well-documented in the literature, though with a specific focus. For instance, Chen, Joslin, and Ni (2019) find that imbalance in deep out-of-the-money index put options (PNBO) negatively forecasts market excess returns. Similarly, Chordia et al. (2021) show that predictive power for the S&P 500 index lies exclusively with index put order imbalance (IB), with no significant effect observed for index call IB. Notably, Chordia et al. (2021) focus on the S&P 500 index call option and do not consider the impact of order size.

We extend these studies with a comprehensive analysis, i.e., providing a more in-depth investigation of index call options and evaluating the role of order size. Specifically, we choose four representative index options in the CBOE database with enough trading observations. They are Russell 2000 index option (RUT), Dow Jones Industrial Average index option (DJX), Nasdaq 100 index option (NDX), and S&P 500 index option (SPX). We further group option trading into order size marked by CBOE, namely small, medium, and large. Within each group of order size, we compute index CIBs separately. We then run predictive regressions of stock market excess returns (MKTRF) on various index CIBs. The results are provided in Table 7.

[Insert Table 7]

Table 7 Panel A shows that most index CIBs do not predict future stock market excess returns, consistent with the findings in Chordia et al. (2021). Small-order CIBs, in line with the sentiment channel, are negatively associated with future stock market excess returns. It is possible that some small-volume traders (including retail) trade index call options for speculative reasons.

We attribute the weak predictability of index call CIB to fundamental differences in the investor clientele. As documented by Lemmon and Ni (2014), options on individual stocks are actively traded by retail investors, while institutional investors dominate trading in index options. The literature also consistently associates unsophisticated retail investors with noise and sentiment-driven trading, while casting institutional investors in the role of rational arbitrageurs (Kumar and Lee (2006) and Lemmon and Portniaguina (2006)).

This pattern is confirmed in our data: the Aggregate Call Imbalance (ACIB) is strongly correlated with retail sentiment measures, showing correlations of 0.37 with the American Association of Individual Investors (AAII) index and 0.33 with the SEP sentiment index (Henderson, Pearson, and Wang (2023)). In contrast, the Index Call Imbalance (ICIB) shows markedly weaker correlations of 0.15 and 0.02 with the same measures, respectively.

More importantly perhaps, the predictive power of ACIB remains robust when we conduct horse-race regressions that include both ACIB and various index CIBs, as reported in Table 7 Panel B. This confirms that the forecasting ability of ACIB is distinct and cannot be replicated by index option trading activity.

6 Conclusion

This paper demonstrates that the same underlying option trading volume, call order imbalances, can yield seemingly contradictory yet complementary signals when analyzed through cross-sectional versus time-series lenses, thus reconciling their distinct information content. While the cross-sectional approach, which isolates stock-specific informed trading, reveals a positive relationship between call order imbalance and future stock returns, our time-series analysis uncovers a dominant sentiment component at the aggregate level that produces a negative predictive relationship with market excess returns. This divergence explains how equity options simultaneously reflect both informed trading and sentiment-driven speculation.

We introduce the Aggregate Call Order Imbalance (ACIB), the cross-sectional average of equity call option order imbalances, as a novel metric that captures market-wide sentiment. ACIB significantly and negatively forecasts market excess returns, functioning as a contrarian indicator, particularly in market segments and periods dominated by small-volume traders (including retail). Its predictive power surpasses that of index options, highlighting the distinct investor clienteles and informational roles of these markets.

These results align with the emerging literature characterizing option trading from small-volume traders (including retail) as speculative and sentiment-driven (de Silva, Smith, and So, 2025; Bryzgalova, Pavlova, and Sikorskaya, 2023; Henderson, Pearson, and Wang, 2023). We directly connect this behavior to the market risk premium by showing that ACIB is closely correlated with investor sentiment and that its predictive power is most pronounced in market segments and periods dominated by small-volume traders.

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Table 1
Summary Statistics of All Predictors

This table reports the descriptive statistics. Panel A provides the summary statistics of all predictors used in our paper at various frequencies specified in parentheses, including mean, minimum, maximum, standard deviation (STD), and the first-order autocorrelation (ρ_1). "W" stands for weekly and "M" stands for monthly frequency. Panel B provides the pairwise Pearson correlations of ACIB with all predictors used in our paper, including aggregate put order imbalance (APIB), index call IB and index put IB (ICIB and IPIB, Chordia et al. (2021)), variance risk premium (VRP, Bollerslev, Tauchen, and Zhou (2009)), aggregate implied volatility spread (IVS, Han and Li (2021)), the AAII bullish sentiment from American Association of Individual Investors (AAII), SEP sentiment (SEP, Henderson, Pearson, and Wang (2023)), BW sentiment (BW, Baker and Wurgler (2006)), GM sentiment (GM, Gao and Martin (2021)), manager sentiment (Manager, Jiang et al. (2019)), consumer survey sentiment from the University of Michigan (Michigan), PLS sentiment (PLS, Huang et al. (2015)), average skewness (JZZ Skew, Jondeau, Zhang, and Zhu (2019)), aggregate risk neutral skewness (BKM Skew, Bakshi, Kapadia, and Madan (2003)), aggregate disagreement index (HLW Disp, Huang, Li, and Wang (2021)), deep out-of-the-money index put options IB (PNBO, Chen, Joslin, and Ni (2019)), and the first principle component of those classic predictors from Goyal and Welch (2008) (GW PCA). The sample period spans from 2005 to 2020.

Panel A. Summary Statistics for All Predictors

Variable	Mean	Min	Max	STD	ρ_1	Variable	Mean	Min	Max	STD	ρ_1
ACIB (W)	−0.14	−0.49	0.20	0.13	0.72	AAII (M)	0.37	0.21	0.53	0.06	0.61
ACIB(M)	−0.11	−0.35	0.13	0.10	0.79	SEP (M)	0.03	0.00	0.08	0.02	0.60
APIB (W)	−0.17	−0.47	0.19	0.11	0.81	BW (M)	−0.03	−2.49	3.21	0.99	0.98
APIB (M)	−0.12	−0.31	0.13	0.10	0.86	GM (M)	0.04	0.01	0.11	0.03	0.99
ICIB (W)	0.05	−0.67	0.71	0.21	0.35	Manager (M)	0.00	−4.15	1.97	1.00	0.84
ICIB (M)	0.06	−0.28	0.39	0.15	0.57	Michigan (M)	86.56	51.70	112.00	12.30	1.00
IPIB (W)	0.65	−0.43	1.00	0.24	0.25	PLS (M)	0.00	−1.89	4.08	1.00	0.97
IPIB (M)	0.64	0.14	1.00	0.17	0.58	JZZ Skew (M)	0.05	−0.60	0.63	0.19	−0.01
VRP (W)	0.04	−0.71	0.39	0.08	0.13	BKM Skew (W)	−0.63	−1.13	−0.15	0.16	0.86
VRP (M)	0.16	−0.39	1.16	0.16	0.31	BKM Skew (M)	−0.62	−0.98	−0.29	0.15	0.74
IVS (W)	0.00	−0.11	0.03	0.01	0.14	HLW Disp (M)	0.00	−2.41	2.40	0.84	0.98
IVS (M)	0.00	−0.08	0.03	0.01	0.48	PNBO (M)	−0.13	−2.41	2.14	0.52	0.00
AAII (W)	0.37	0.16	0.63	0.08	0.67	GW PCA (M)	0.00	−1.79	6.70	1.00	0.63

Panel B. Pairwise Pearson Correlation with ACIB (Monthly)

Var.	Corr.	Var.	Corr.	Var.	Corr.	Var.	Corr.	Var.	Corr.
APIB	0.43	IVS	0.19	GM	0.55	JZZ Skew	0.03	GW PCA	−0.19
ICIB	0.60	AAII	0.37	Manager	0.19	BKM Skew	0.58		
IPIB	−0.11	SEP	0.33	Michigan	0.24	HLW Disp	0.18		
VRP	−0.10	BW	0.50	PLS	−0.24	PNBO	−0.16		

Table 2

In-sample Predictability of ACIB and APIB

This table reports the results of multiple predictive regressions labeled by the forecast horizons (weekly and monthly). The definition of all the predictors can be found in Section 3.1. Note that some variables are only available at a monthly frequency. The dependent variables are the one-period-ahead (weekly or monthly) excess log returns of the value-weighted market portfolio (MKTRF) in percentage. All predictors are normalized to have a zero mean and unit standard deviation. The t-stat in parentheses is adjusted for heteroskedasticity and autocorrelation using the Newey and West (1987) method. The sample period is from 2005 to 2020. The numbers of observations for each regression are 841 for weekly frequency and 191 for monthly frequency.

	Weekly		Monthly	
Predictor	Slope	t-stat	Slope	t-stat
ACIB	−0.329	(−2.37)	−1.358	(−2.81)
APIB	0.185	(1.10)	1.031	(1.96)
ICIB	−0.068	(−0.78)	0.688	(1.74)
IPIB	0.211	(2.47)	−0.037	(−0.12)
VRP	0.378	(1.98)	1.909	(4.70)
IVS	0.297	(1.63)	−0.228	(−0.57)
BKM Skew	0.001	(0.01)	0.193	(0.42)
AAII Sentiment	0.054	(0.53)	0.275	(0.96)
SEP Sentiment			0.196	(0.64)
BW Sentiment			−1.024	(−1.98)
GM Sentiment			−0.550	(−1.14)
Manager Sentiment			−0.197	(−0.63)
Michigan Sentiment			0.213	(0.41)
PLS Sentiment			−0.956	(−1.70)
JZZ Skew			−0.519	(−2.17)
HLW Disp			−0.480	(−1.22)
PNBO			−0.804	(−3.41)
GW PCA			−1.552	(−2.50)
Adj.R^2(%)		4.77		27.07

Table 3
Cross-sectional and Time-series Comparison

In Panel A, at the end of each week, we sort all stocks with feasible CIB into quintiles based on the value of CIB and then compute the equal-weighted returns for each portfolio next week. In Panel B, we first sort stocks based on CIB into quintiles by the end of each week. Within each portfolio, we compute the equal-weighted portfolio returns for the next week (W=1). The dependent variables are the one-week-ahead portfolio returns for each sorted bin (Port 1 to Port 5) or the long-short spread (Port 5−1) in percentage. All predictors are normalized to have a zero mean and unit standard deviation. The t-stat in parentheses is adjusted for heteroskedasticity and autocorrelation using the Newey and West (1987) method. The independent variable is ACIB. In Panel C, the sample days from 2005 to 2020 are separated into two regimes: above and below the median of the level of the informed-trading intensity (ITI), defined as the absolute value of the absolute return of Port 5 minus the absolute return of Port 1 sorted by CIB for W=1 in Panel A. A higher ITI indicates a higher probability that stock market returns contain firm-level information. We then run weekly predictive regressions of stock market excess returns (MKTRF) in percentage on ACIB within each regime. The t-stat in parentheses is adjusted for heteroskedasticity and autocorrelation using the Newey and West (1987) method. For Panel B, the number of observations for each regression is 841. For Panel C, the number of observations for each regression is 420.

Panel A. Cross-sectional Equal-weighted Portfolio Sorting by CIB						
Horizon	Port 1	Port 2	Port 3	Port 4	Port 5	Port 5−1
W=1	0.190	0.220	0.234	0.293	0.366	0.176
						(6.34)

Panel B. Time-series Prediction of Equal-weighted Portfolio Returns Sorted by CIB						
W=1	Port 1	Port 2	Port 3	Port 4	Port 5	Port 5−1
ACIB	−0.404	−0.398	−0.379	−0.442	−0.423	−0.019
	(−3.28)	(−3.13)	(−2.84)	(−3.20)	(−3.13)	(−0.56)
Adj.R^2(%)	1.27	1.35	1.22	1.48	1.26	0.21

Panel C. ACIB Prediction Separated by Equal-Weighted Informed-Trading Intensity (ITI)					
Regime of	Slope	t-stat	Regime of	Slope	t-stat
Low ITI	−0.375	(−3.15)	High ITI	−0.133	(−1.07)
Adj.R^2(%)		3.12	Adj.R^2(%)		−0.08

Table 4
Decomposition of Equity Option Trading Activity

In Panel A, we separate the sample of order imbalance (IB) into "small", "medium", and "large" orders, as tagged by the CBOE database. Within each type, we aggregate all option IBs using a market value-weighted scheme. Similarly, in Panel B, we construct ACIB by aggregating individual IBs by different investor types tagged by CBOE, including "customer", "professional customer", and "market maker" (including "market maker", "firm" and "broker-dealer"). In Panel C, instead of using the CBOE opening trading data, we use the CBOE closing trading data to construct ACIB and APIB. "Open+Close" positions are defined as the combinations of open and closing trading data together. In Panel D, following Ge, Lin, and Pearson (2016), we decompose the option volume into different parts, divide it by weekly stock trading volume, and aggregate individual O/S ratios to the market level by market value-weighted average within each group. The two different components are aggregate call opening buy volume to stock volume (ACOB/S) and aggregate call opening sell volume to stock volume (ACOS/S). The different types of ACIB or O/S ratios are used to forecast market excess returns in percentage one week ahead. All predictors are normalized to have a zero mean and unit standard deviation. The *t*-stat in parentheses is adjusted for heteroskedasticity and autocorrelation using the Newey and West (1987) method. The sample period is from 2005 to 2020, except for professional customers and market makers, whose sample period is from 2009 to 2020. The number of observations for each regression is 841, except for the cases of professional customers and market makers, which have 631 observations.

Panel A:	Small	Medium	Large
Order Size	−0.233	−0.148	0.038
	(−2.61)	(−1.54)	(0.44)
Adj.R^2(%)	0.88	0.40	0.09
Panel B:	Public Customers	Professional Customers	Market Makers
Investor Types	−0.240	0.086	0.046
	(−2.69)	(0.82)	(0.45)
Adj.R^2(%)	0.92	0.11	−0.06
Panel C:	Open Position	Closing Position	Open+Close Position
Open/Closing Position	−0.240	0.130	−0.124
	(−2.69)	(1.13)	(−1.33)
Adj.R^2(%)	0.92	0.30	0.27
Panel D:	ACOB/S	ACOS/S	(ACOB−ACOS)/S
Buying/Selling Activity	−0.138	−0.007	−0.161
	(−1.54)	(−0.08)	(−1.82)
Adj.R^2(%)	0.36	0.07	0.45

Table 5

Predictive Power of ACIB in Different Regimes

In Panel A, the sample days from 2005 to 2020 are separated into two regimes at weekly frequency: above and below the median of the level of the AAII sentiment from the survey data by the American Association of Individual Investors. We run weekly predictive regressions of stock market excess returns on ACIB within each regime. We conduct a similar test in Panel B, except that the separation is based on the SEP sentiment index by Henderson, Pearson, and Wang (2023). In Panel C, in a certain week, we calculate the proportion of firms with earnings announcements out of the total public firms in the United States. We then compute the proportion of firms with earnings announcements out of the total public firms over weeks. A higher proportion indicates higher sentiment periods over time. The dependent variables are the one-week-ahead market excess returns (MKTRF) in percentage. All predictors are normalized to have a zero mean and unit standard deviation. The t-stat in parentheses is adjusted for heteroskedasticity and autocorrelation using the Newey and West (1987) method. The sample period is from 2005 to 2020. The number of observations for each regression is 420.

Panel A. ACIB Prediction Separated by AAII Sentiment					
Low AAII	Slope	t-stat	High AAII	Slope	t-stat
Sentiment	−0.175	(−1.43)	Sentiment	−0.294	(−2.32)
Adj.R^2(%)		0.19	Adj.R^2(%)		1.44
Panel B. ACIB Prediction Separated by SEP Sentiment					
Low SEP	Slope	t-stat	High SEP	Slope	t-stat
Sentiment	−0.210	(−1.86)	Sentiment	−0.256	(−2.00)
Adj.R^2(%)		0.27	Adj.R^2(%)		1.18
Panel C. ACIB Prediction Separated by Earnings Announcements					
Few Earnings	Slope	t-stat	Many Earnings	Slope	t-stat
Announcements	−0.170	(−1.54)	Announcements	−0.337	(−2.33)
Adj.R^2(%)		0.07	Adj.R^2(%)		1.98

Table 6

Out-of-sample Predictability by ACIB

The performance evaluation period to compute the statistics in the table is from 2010 to 2020. When training the model for each combined predictor based on Section 5.1, we use all available observations starting from 1960 up to the testing period. The forecast target is the market excess returns (MKTRF) one week or one month ahead. "PLS (Option-based Predictors)" is constructed following Huang et al. (2015) and Huang, Li, and Wang (2021). "All Existing Predictors" include all the option-based predictors except for ACIB specified in Section 3.1. "ACIB+PLS (All Existing Predictors)" stands for using ACIB and PLS (All Existing Predictors) together in a multiple regression to forecast MKTRF. The other group by "Option-based predictors/Sentiment Measures/Stock-based Predictors" is constructed by a similar approach but with different groups when constructing by PLS. We report the out-of-sample (OOS) R^2 statistic in percentage and the Clark and West (2007) t-stat of OOS R^2 (in parentheses) in Panel A. In Panel B, the annualized certainty equivalent return (CER) and the annualized Sharpe ratio (in parentheses) are reported. The details are specified in Section 5.1.

	Panel A: Out-of-sample R^2 (%)		Panel B: CER Gain/Sharpe Ratio	
Variable	Weekly	Monthly	Weekly	Monthly
ACIB	0.756	6.114	2.978	10.416
	(1.926)	(2.835)	(0.847)	(1.360)
PLS (Option-based Predictors)	1.198	5.143	1.412	3.435
	(1.740)	(1.815)	(0.685)	(0.830)
ACIB+PLS (Option-based Predictors)	1.482	7.147	3.688	3.462
	(2.231)	(2.244)	(0.903)	(0.931)
PLS (Sentiment Measures)		−1.804		1.769
		(1.027)		(0.870)
ACIB+PLS (Sentiment Measures)		2.192		8.524
		(2.258)		(1.159)
PLS (Stock-based Predictors)		−1.834		−3.979
		(−1.222)		(0.490)
ACIB+PLS (Stock-based Predictors)		5.721		5.501
		(2.958)		(1.043)
PLS (All Existing Predictors)		7.864		7.132
		(2.480)		(1.214)
ACIB+PLS (All Existing Predictors)		8.957		10.313
		(2.693)		(1.360)
Benchmark Sharpe Ratio			(0.541)	(0.725)

Table 7

Stock Market Return Predictability by Index Options

We examine the predictive power of index call option order imbalance (CIB). We select four index options actively traded at CBOE: Russell 2000 index option (RUT), Dow Jones Industrial Average index option (DJX), Nasdaq 100 index option (NDX), and S&P 500 index option (SPX). When constructing index CIBs, we separate the sample by the trading size tagged by CBOE as "small", "medium", and "large" orders. In Panel A, we run predictive regressions of stock market excess returns (MKTRF) in percentage one week ahead on CIB for each index and trading size, respectively. In Panel B, we run multiple predictive regressions of MKTRF in percentage one week ahead on all selected CIBs and ACIB for each trading size. Each row in Panel B stands for one multiple predictive regression. All predictors are normalized to have a zero mean and unit standard deviation. The t-stat in parentheses is adjusted for heteroskedasticity and autocorrelation using the Newey and West (1987) method. The sample period is from 2005 to 2020. The number of observations for each regression is 841.

Panel A. Market Return Prediction by Index Options

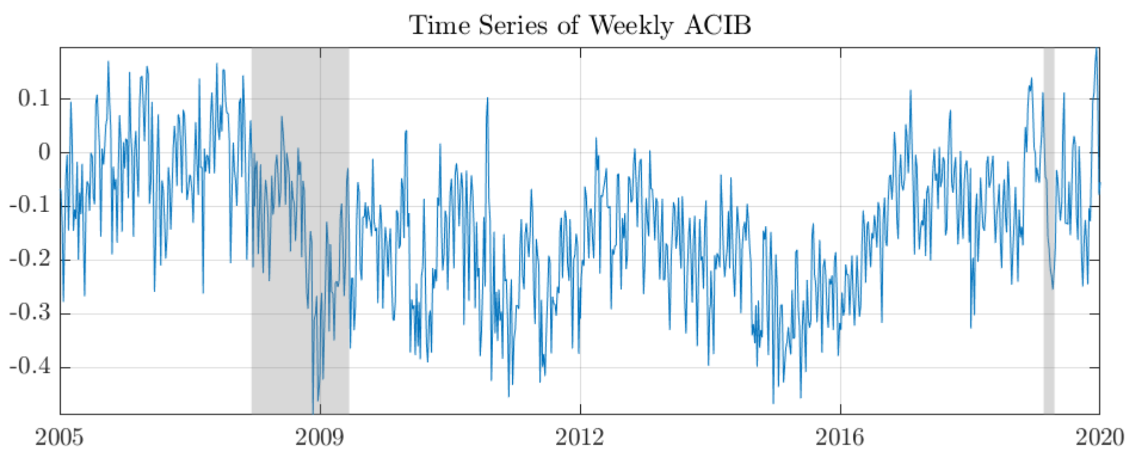
Predictor	Small	Medium	Large	Predictor	Small	Medium	Large
RUT CIB	−0.067	−0.053	0.130	DJX CIB	−0.135	0.021	−0.066
	(−0.74)	(−0.73)	(1.37)		(−1.61)	(0.22)	(−0.66)
Adj.R^2(%)	0.01	−0.05	0.19	Adj.R^2(%)	0.21	−0.02	−0.07
NDX CIB	−0.016	−0.072	−0.070	SPX CIB	−0.072	0.076	0.018
	(−0.18)	(−0.67)	(−0.59)		(−0.86)	(0.82)	(0.19)
Adj.R^2(%)	0.55	−0.01	−0.20	Adj.R^2(%)	0.02	0.03	−0.06

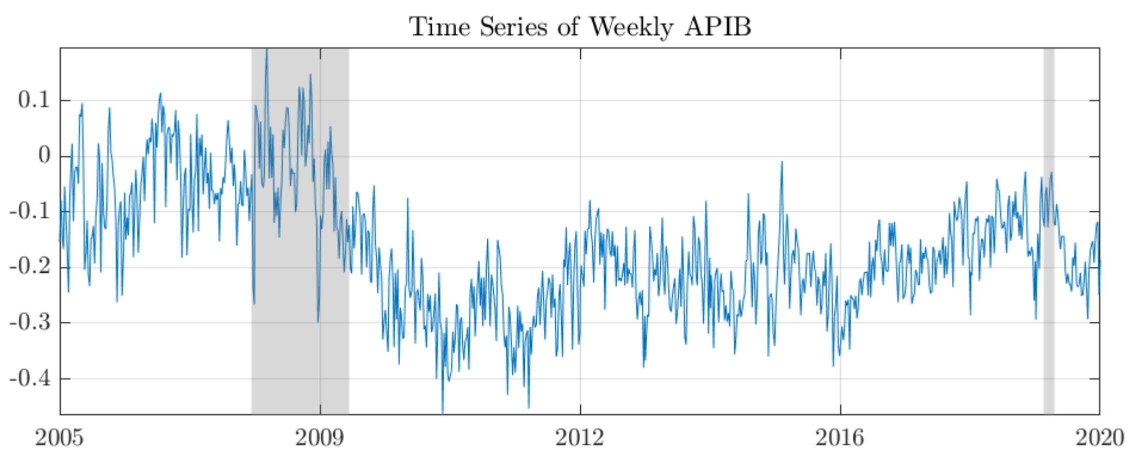
Panel B. Multiple Regression Controlling for ACIB

2005 to 2020	RUT	DJX	NDX	SPX	ACIB	Adj.R^2(%)
Small	−0.041	0.007	0.044	0.102	−0.302	
	(−0.41)	(0.07)	(0.49)	(1.00)	(−2.46)	1.20
Medium	−0.093	−0.027	−0.064	0.183	−0.341	
	(−1.11)	(−0.24)	(−0.58)	(1.50)	(−2.77)	1.06
Large	0.024	−0.002	0.039	0.140	−0.326	
	(0.25)	(−0.01)	(0.29)	(0.98)	(−2.11)	0.49

Figure 1
The Time Series of ACIB and APIB

Figure 1 depicts the time series of ACIB and APIB from 2005 to 2020 at a weekly frequency. The option data is collected from the Chicago Board Options Exchange (CBOE). The grey areas indicate the National Bureau of Economic Research (NBER) recession periods. ACIB and APIB are constructed by aggregating all available order imbalances of individual equity call and put options in the cross-section at each time point separately.





Internet Appendix for

"Betting Against the Crowd: Option Trading and Market Risk Premium"

This document supplements the paper "Betting Against the Crowd: Option Trading and Market Risk Premium". It provides additional results and robustness analyses, which are not displayed in the published text.

IA.1 In-sample Predictive Regression

We first follow Section 3.1 and provide the univariate predictive regressions for daily and monthly frequency for ACIB and APIB. In particular,

$$\sum_{k=1}^{K} \frac{r_{t+k}}{K} \equiv r_{t,t+K} = a + b \times X_t + \varepsilon_{t,t+K}, \tag{1}$$

where r_{t+k} is the value-weighted market excess return in the logarithm (MKTRF) at time $t+k$ obtained from Kenneth French's website; X_t is the predictor variable of interest; K stands for the forecast horizon, specified by days (D), weeks (W), and months (M). We scale all independent variables to have a zero mean and one standard deviation.

[Insert Table A3]

The t-stat is computed based on Newey and West (1987) standard errors. In particular, the standard error for a specific parameter estimate $\hat{\theta}_j$ (i.e., $\hat{b}^C$ in Equation (4) in the main draft) is the square root of the j-th diagonal element of this covariance matrix. The asymptotic variance-covariance matrix for the generalized method of moments (GMM) estimator $\hat{\theta}$ is:

$$Var(\hat{\theta}) = \frac{1}{T}(D'WD)^{-1}D'WSWD(D'WD)^{-1}, \tag{2}$$

where D is the Jacobian matrix of the moment conditions with respect to θ; W is the weighting matrix used in the GMM objective function. The optimal weight W is chosen from $W_{opt} = \hat{S}^{-1}$, where $\hat{S}$ is the heteroskedasticity and autocorrelation consistent (HAC) estimator based on the Newey and West (1987):

$$\hat{S} = \hat{\Gamma}_0 + \sum_{j=1}^{L} w_j(\hat{\Gamma}_j + \hat{\Gamma}_j'), \tag{3}$$

where $\hat{\Gamma}_j$ is the sample autocovariance matrix at lag j, L is the maximum lag (bandwidth parameter) chosen by the user ($L = K-1$ in our case), and w_j is the Bartlett kernel weight calculated as $w_j = 1 - \frac{j}{L+1}$. Then the standard error (SE) for parameter $\hat{\theta}_j$ is:

$$SE(\hat{\theta}_j) = \sqrt{\frac{1}{T}[(D'WD)^{-1}D'W\hat{S}WD(D'WD)^{-1}]_{jj}}. \tag{4}$$

The t-stat is computed by t-stat$= \frac{\hat{\theta}_j}{SE(\hat{\theta}_j)/\sqrt{T}}$.

We also conduct in-sample predictive multiple regressions to investigate whether ACIB captures any existing predictors at weekly and monthly frequencies. Specifically, we run multiple predictions with ACIB and a selected set of existing predictors to investigate whether ACIB could be explained by any existing predictors in the literature. We run the multi-period predictive regressions below:

$$\sum_{k=1}^{K} \frac{r_{t+k}}{K} \equiv r_{t,t+K} = a + b^C \times ACIB_t + b^P \times APIB_t + \sum_{j=1}^{J} b_j \times X_{j,t} + \varepsilon_{t,t+K}, \tag{5}$$

where $X_{j,t}$ specifies the control variable j listed in Section 3.1. In particular, we classify existing predictors into three categories: 1) *Option-based predictors*, including variance risk premium (VRP, Bollerslev, Tauchen, and Zhou (2009)), aggregate implied volatility spread (IVS, Han and Li (2021)), index call IB and index put IB (ICIB and IPIB, Chordia et al. (2021)), deep out-of-the-money index put options IB (PNBO, Chen, Joslin, and Ni (2019)), and aggregate risk neutral skewness (BKW Skew, Bakshi, Kapadia, and Madan (2003)); 2) *Sentiment measures*, such as BW sentiment (Baker and Wurgler (2006)), GM sentiment (Gao and Martin (2021)), consumer survey sentiment from the University of Michigan, SEP sentiment (Henderson, Pearson, and Wang (2023)), manager sentiment (Jiang et al. (2019)), PLS sentiment (Huang et al. (2015)), and the AAII bullish sentiment from the American Association of Individual Investors; 3) *Stock-based predictors*, including the classic predictors from Goyal and Welch (2008), the aggregate disagreement index (HLW Disp, Huang, Li, and Wang (2021)), and average skewness (JJZ Skew, Jondeau, Zhang, and Zhu (2019)).[1] Note that some control variables are only available at the monthly level, so the regressions are run at different frequencies accordingly.

[Insert Table A4]

Table A4 demonstrates that ACIB is a strong and new predictor which is different from other existing predictors. ACIB outperforms all the other existing predictors, not only because it has the highest t-stat and coefficient magnitude among all the predictors in most cases, but also because ACIB's forecasting capacity holds strongly in both short horizons (e.g., weeks) and long horizons (e.g., months). More importantly, the predictive power of ACIB is robust after controlling for other existing predictors.

[1] Following Rapach, Ringgenberg, and Zhou (2016), we extract and include the principal component of the 22 predictors collected from Amit Goyal's website as a single predictor (GW PCA).

IA.2 Out-of-sample Predictive Performance

As a comparison, we list the out-of-sample (OOS) R^2, CER gain, and Sharpe ratio as conducted in our Section 5.1 for each individual predictor controlled in Table A4. The existing predictors' OOS performances are provided in Table A5 below. When training the model for each combined predictor, we use all available observations starting from 1960 up to the testing period (2010).

[Insert Table A5]

Table A5 shows that, for our testing period (from 2010 to 2020), the OOS R^2 of ACIB (6.11%) outperforms any other existing predictors and often more than doubles those common individual predictors documented by Rapach and Zhou (2022).

IA.3 Robustness Checks of Weighting Schemes

As a robustness check, we use alternative weighting schemes for both ACIB construction and market excess return calculation. Instead of using the value-weighted average, we construct ACIB using an equally weighted average:

$$ACIB\text{-}EW_t = \frac{1}{N_t}\sum_{i=1}^{N_t} CIB_{i,t}. \tag{6}$$

We define a similar target for equal-weighted market excess returns (MKTRF-EW), which is obtained from CRSP and subtracts the risk-free rate from Kenneth French's website. The results are provided in Table A6 and show that all of our results hold for the alternative weighting scheme.

[Insert Table A6]

IA.4 Decomposition of Equity Option Tradings

Following Section 4.1, we conduct decomposition of equity option trading activity at daily frequency and monthly frequency, conditional on the order size, time to maturity, and moneyness.

[Insert Table A7]

Table A7 Panel A demonstrates that the predictive power of ACIB mainly comes from the small trading size of equity call options. The forecasting capacity reduces significantly from small size to medium size and totally disappears for large size. In addition to this, Panel B also shows that among options with different moneyness, ACIB constructed using ATM options has the best performance across different moneyness, further consistent with our sentiment explanation, as Bryzgalova, Pavlova, and Sikorskaya (2023) find that retail traders prefer trading at-the-money options. The next well-performed type of option is ITM ACIB, while the worst performed ACIB is constructed using OTM options. Note that from Panel C, the factor of time to maturity does not affect the predictive power of ACIB, although options with middle and long horizon time to maturity have relatively stronger predictive power.

Furthermore, we construct IB for professional customers and market makers based on the CBOE specification and use them to forecast stock market excess returns separately. If the forecasting capacity of ACIB is mainly driven by the sentiment effect, we expect to observe insignificant predictive power from professional customers or market makers. Second, since our data only covers option trading activity on CBOE, our results may be sensitive to exchange and data-specific issues. To reconcile this concern, we re-compute ACIB and APIB using the alternative database from the Nasdaq International Securities Exchange (ISE), which is widely used in many other papers in the literature. The results are provided in Table A8 below.

[**Insert Table A8**]

The results in Table A8 are consistent with our conclusion that the predictive power of ACIB is mainly driven by small-volume traders (including retail). If we construct ACIB (APIB) using professional customers' or market makers' order flows, we do not see any predictive power of ACIB (APIB). Similarly, Table A8 Panel C demonstrates that our finding is not driven by exchange specification, as we obtain similar stock market excess return predictability using the ISE database. The correlation between the alternative ACIB constructed from ISE and ACIB based on CBOE is as high as 0.78, suggesting a market-wide sentiment effect across option exchanges. Given that both ISE and CBOE cover a significant proportion of total option trading activity, the results are largely consistent with each other.

Another popular variable of option trading volume is the O/S ratio used by Ge, Lin, and Pearson (2016). We conduct further tests to justify equity call option trading as a proxy for sentiment using the alternative variable O/S ratio to measure option trading activities. One advantage of using the O/S ratio is that it can separate the effect between buy and sell trading activities, so that we can further examine the source of the predictive power of distinct option trading activities. We calculate the ratio of option trading volume to stock trading volume and aggregate it to the market level by taking the cross-sectional market-value weighted average.

Following Ge, Lin, and Pearson (2016), we decompose the numerator of the O/S ratio into distinct option trading activities, including call option opening buy position (COB), call option opening sell position (COS), put option opening buy position (POB), and put option opening sell position (POS). All the denominators remain as the total stock trading volume at a certain point of time. We first take the ratio of the decomposed option trading to stock trading (O/S ratio) at the individual stock level, and then aggregate to the market level by taking a market-value weighted average. The corresponding O/S ratios for different option trading activities are denoted as ACOB/S, ACOS/S, APOB/S, and APOS/S. The regression results are displayed in Table A9.

[Insert Table A9]

The conclusion is consistent that only those variables related to call option trading are able to forecast market risk premium, although none of them can beat the performance of ACIB. Put option trading still does not provide any useful information about future stock market excess returns. A new finding based on the O/S ratio is that buying call options is more informative to future stock returns than selling call options. Among all different predictive regressions separated by option moneyness, the magnitude of t-stat for buying call options (i.e., ACOB/S) is larger and more stable than selling call options (i.e., ACOS/S). Buying call options can be more easily driven by sentiment (e.g., optimistic mood), while selling call options is linked to other trading purposes such as writing call options to collect premiums (e.g., covered call strategy) and hedging an existing long position. Therefore, the O/S ratio tests further support our argument of sentiment trading among equity call options.

IA.5 The Predictive Power of ACIB in Different Regimes and CIB Portfolios

Following Section 4.2, we conduct empirical tests by separating the sample period into two regimes based on high and low retail sentiment, namely below and above the median of the time-series sentiment level. We also separate the sample period based on the proportion of firms with earnings announcements out of the total public firms in the United States. We then conduct predictive regressions in each regime of stock market excess returns on ACIB. Table A10 shows that all of our conclusions in Section 4.2 are held for daily and monthly frequency.

[Insert Table A10]

IA.6 Stock Market Excess Return Predictability by Index Call Options

We extend our analysis to index call options. The predictive power of index option trading is well-documented in the literature, though with a specific focus. Specifically, we choose four representative index options in the CBOE database with enough trading observations. They are Russell 2000 index option (RUT), Dow Jones Industrial average index option (DJX), Nasdaq 100 index option (NDX), and S&P 500 index option (SPX). We further group option trading into order size marked by CBOE, namely small, medium, and large. Within each group of order size, we compute index CIBs separately. We then run predictive regressions of stock market excess returns (MKTRF) on various index CIBs. The results are provided in Table A11.

[Insert Table A11]

Table A11 shows that most index CIBs do not predict future stock market excess returns. Small-order CIBs, in line with the sentiment channel, are negatively associated with future stock market excess returns. It is possible that some small-volume traders (including retail) trade index call options for speculative reasons, although none of their performance can beat ACIB.

IA.7 International Market Return Predictability

We also examine whether ACIB can forecast international stock market returns. Baker, Wurgler, and Yuan (2012) document that there exists a global sentiment index that can spread across markets through private capital flows and functions as a contrarian predictor of country-level returns. Given that ACIB represents an option-based sentiment measure and is closely linked to stock market sentiment, it could also help identify such a global sentiment index and forecast other countries' stock market excess returns. We then test our hypothesis by using ACIB and APIB to forecast various countries' stock market returns through the same framework in Section 3.1.

The data of country-level stock market indices is collected from Global Financial Data (GFD). For each country, we select one of the most representative stock market indices in the country, denominated in local currency. We then calculate their daily, weekly, and monthly raw returns as dependent variables. Our country sample covers almost all the developed markets and some crucial emerging markets, including Australia (ASX All-Ordinaries), Canada (TSX 300 Composite), Finland (OMX All-Share Index), France (CAC All-Tradeable Index), Germany (CDAX Index), Hong Kong SAR (Hang Seng Index), Italy (Banca Commerciale Italiana Index), Japan (Nikkei 500 Index), Netherlands (All-Share Price Index), New Zealand (NZX All-Share Capital Index), Spain (Madrid SE General Index), Sweden (OMX All-Share Index), Switzerland (Switzerland Price Index), and the United Kingdom (FTSE All-Share Index). The predictive regression is the same as specified in Section 3.1. When running regressions, we control for the contemporaneous local stock market returns and the U.S. stock market excess returns suggested by Rapach, Strauss, and Zhou (2013).

[**Insert Tables A12 and A13**]

Tables A12 and A13 show consistent evidence that ACIB is not only related to future U.S. stock market excess returns but can also forecast international stock market returns, at least among fourteen major economies. The significance cannot be explained by the local stock market momentum or the role of the U.S. stock market excess returns as documented in Rapach, Strauss, and Zhou (2013). All the coefficients of ACIB are negative, indicating a strong sentiment effect identified by call option trading activities. Moreover, consistent with the U.S. market, APIB does not have forecasting capacity for any of them. Our paper thus provides novel evidence that the equity call option trading activities in the U.S. market contain information for international stock markets in time series. The evidence supports a global sentiment effect and further suggests that ACIB can be used as an index to measure global sentiment.

IA.8 Equity Put Option Trading and Stock Market Volatility

In this subsection, we further explore different trading motivations between equity call and put options. More specifically, we study whether ACIB and APIB can forecast either future stock market volatility or future aggregate firm-level volatility in time series. The stock market volatility is computed as the standard deviation of the past 22 daily stock market excess returns (MKTRF). As for the aggregate firm-level volatility, we first compute a daily standard deviation of stock returns using a 22-day rolling window for each firm, and then take the cross-sectional market-value weighted average to obtain an aggregate firm-level volatility measure as in Goyal and Santa-Clara (2003) and Han and Li (2025). We then run a similar predictive regression as in Section 3.1:

$$\sum_{k=1}^{K} \frac{\sigma_{t+k}}{K} \equiv \sigma_{t,t+K} = a + b \times X_t + \epsilon_{t,t+K}, \tag{7}$$

where σ_{t+k} is either the stock market volatility or the value-weighted firm-level volatility at time $t + k$; X_t is the predictor variable of interest (either ACIB or APIB); K stands for the forecast horizon. We then run the predictive regressions with K equal to one week. When running regressions, all independent variables are scaled to have a zero mean and one standard deviation.

Volatility is well known to be forecastable, as it is quite persistent over time. In order to demonstrate the incremental volatility information contained in equity options trading, when running the predictive regression, we control for various existing volatility predictors documented in the literature. In particular, we control for the contemporaneous market excess return in the regression for leverage effect (Black (1976)), VIX, long-memory volatility persistence (Corsi (2009)), and index option IB. For the long-memory volatility persistence, we follow Corsi (2009) and construct the Heterogeneous Autoregressions (HAR) model with 1, 5, 10, and 20-day moving-average volatility. The HAR model has been demonstrated to have superior performance in capturing conditional volatility dynamics.[2] The regression results are presented in Table A14.

[Insert Table A14]

Table A14 demonstrates that although APIB does not forecast stock market excess returns, it has significant incremental explanatory power on both future stock market volatility and future aggregate firm-level volatility at weekly frequency. A higher APIB is always followed by higher future stock market volatility, indicating equity put option trading is more likely related to hedging demand and volatility trading. The significance is considerable and robust after controlling for existing volatility predictors. On the contrary, ACIB does

[2]For example, Andersen and Bollerslev (1998) and Corsi (2009) demonstrate that the HAR model provides higher R^2 than the GARCH model.

not show any forecasting capacity on stock volatility this time. Our empirical result thus indicates a significant difference in trading motivations between equity call and equity put options.

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Table A1 Summary Statistics of Predictors at Daily Frequency

This table provides the summary statistics of all predictors in our paper that are avaiable at daily frequency, including index call IB and index put IB (ICIB and IPIB, Chordia et al. (2021)), variance risk premium (VRP, Bollerslev, Tauchen, and Zhou (2009)), aggregate implied volatility spread (IVS, Han and Li (2021)), the AAII bullish sentiment from American Association of Individual Investors, and aggregate risk neutral skewness (BKM Skew, Bakshi, Kapadia, and Madan (2003)).

Variable	Mean	Min	Max	STD	ρ_1
ACIB	−0.16	−0.59	0.29	0.14	0.78
APIB	−0.20	−0.56	0.24	0.12	0.80
ICIB	0.07	−0.91	0.95	0.30	0.28
IPIB	0.74	−0.60	1.00	0.31	0.17
VRP	0.03	−0.50	0.23	0.05	0.92
IVS	0.00	−0.11	0.11	0.01	0.21
AAII	0.37	0.16	0.63	0.08	0.93
BKM Skew	−0.62	−1.15	−0.14	0.15	0.90

Table A2 Percentage of the Option Trading by Trader Types

This table reports the percentage distribution of total option trading volume by trader classification and option type for individual stock and index options. Trader types follow the CBOE classification: "customer", "professional customer", "firm", and "market maker". For "customer" and "professional customer", we further split the sample by the trading size specified in CBOE as "small", "medium", and "large" orders. The option trading is classified into call and put options, specified by the column. We aggregate all option trading volume within each group and then scale it by the total trading volume of each group to obtain the percentage distribution. For index options, we choose four representative index options in the CBOE database. They are Russell 2000 index option (RUT), Dow Jones Industrial Average index option (DJX), Nasdaq 100 index option (NDX), and S&P 500 index option (SPX). The sample period spans from January 2009 to December 2020.

Option Trading (%)	Index		Equity	
	Call Option	Put Option	Call Option	Put Option
Customer (Small)	11.07	9.90	23.70	19.80
Customer (Medium)	3.17	2.93	3.59	3.30
Customer (Large)	12.12	14.43	8.04	10.14
Customer Subtotal	26.36	27.25	35.34	33.24
Professional (Small)	0.83	0.50	0.72	0.73
Professional (Medium)	0.25	0.18	0.09	0.10
Professional (Large)	0.47	0.51	0.24	0.27
Professional Subtotal	1.55	1.18	1.05	1.11
Firm	0.83	0.50	6.73	8.49
Market Maker	71.25	71.06	56.88	57.16
Total	100.00	100.00	100.00	100.00

Table A3 In-sample Predictive Regression using ACIB and APIB

This table reports the results of univariate and bivariate predictive time-series regressions. The dependent variables are daily (D), weekly (W), and monthly (M) excess returns in the logarithm of the value-weighted market portfolio (MKTRF) in percentage over the relevant forecast horizons. All predictors are normalized to have a zero mean and one standard deviation. D/W/M represents the forecast horizon in the number of days/weeks/months. The t-stat in parentheses is computed using the Newey and West (1987) method with D/W/M−1 lag correction. The numbers of observations for each regression are 4027/4025/4022 for D=1/3/6, 841/840/839 for W=1/2/3, and 191/190/189 for M=1/2/3.

		D=1			D=3			D=6	
Predictor	I	II	III	I	II	III	I	II	III
ACIB	−0.070		−0.075	−0.045		−0.046	−0.045		−0.045
	(−2.94)		(−2.70)	(−2.81)		(−2.49)	(−3.26)		(−2.93)
APIB		0.002	0.020		−0.009	0.002		−0.010	0.0007
		(0.06)	(0.62)		(−0.45)	(0.10)		(−0.56)	(0.04)
adj. R^2 (%)	1.88	1.59	1.88	0.76	0.35	0.73	1.67	0.82	1.64
Predictor		W=1			W=2			W=3	
ACIB	−0.240		−0.211	−0.216		−0.187	−0.223		−0.201
	(−2.69)		(−1.67)	(−3.21)		(−1.95)	(−3.58)		(−2.37)
APIB		−0.157	−0.061		−0.147	−0.062		−0.138	−0.047
		(−1.43)	(−0.42)		(−1.68)	(−0.54)		(−1.54)	(−0.42)
Predictor		M=1			M=2			M=3	
ACIB	−1.024		−1.013	−0.734		−0.710	−0.658		−0.627
	(−2.91)		(−2.78)	(−2.66)		(−2.38)	(−2.94)		(−2.55)
APIB		−0.255	−0.066		−0.267	−0.138		−0.299	−0.182
		(−0.69)	(−0.18)		(−0.77)	(−0.38)		(−0.83)	(−0.48)
adj. R^2 (%)	4.73	−0.30	4.23	4.14	−0.43	3.79	5.56	0.33	5.49

Table A4 In-sample Multiple Regressions with Existing Predictors

This table reports the results of multiple predictive regressions. Each column in this table corresponds to one multiple predictive regression, labelled by the forecast horizons (D=day, W=week, and M=month). The definition of all the predictors can be found in Section 3.1. The dependent variable is the average daily/weekly/monthly value-weighted market excess return (MKTRF) in percentage over the relevant forecast horizon. All predictors are normalized to have a zero mean and one standard deviation. The t-stat in parentheses is computed using the Newey and West (1987) method with D/W/M−1 lag correction. The sample period is from 2005 to 2020. The numbers of observations for each regression are 4027/4025 for D=1/3, 841/840 for W=1/2, and 191/190 for M=1/2.

Predictor	D=1	D=3	W=1	W=2	M=1	M=2
ACIB	−0.107	−0.067	−0.329	−0.292	−1.358	−0.884
	(−3.11)	(−3.20)	(−2.37)	(−2.80)	(−2.81)	(−2.53)
APIB	0.059	0.021	0.158	0.047	1.031	0.903
	(1.55)	(0.89)	(1.10)	(0.40)	(1.96)	(2.19)
ICIB	−0.015	−0.010	−0.068	−0.092	0.688	0.095
	(−0.71)	(−0.78)	(−0.78)	(−1.55)	(1.74)	(0.29)
IPIB	0.005	0.029	0.211	0.100	−0.037	−0.066
	(0.24)	(2.47)	(2.47)	(1.79)	(−0.12)	(−0.24)
VRP	0.029	0.011	0.378	−0.023	1.909	0.838
	(0.69)	(0.39)	(1.98)	(−0.26)	(4.70)	(2.04)
IVS	0.153	0.077	0.297	0.309	−0.228	0.275
	(2.90)	(2.60)	(1.63)	(3.04)	(−0.57)	(0.85)
BKM Skew	−0.025	−0.0004	0.001	0.080	0.193	−0.214
	(−0.93)	(−0.00)	(0.01)	(0.70)	(0.42)	(−0.53)
AAII Sentiment	0.020	0.005	0.054	0.052	0.275	0.312
	(0.88)	(0.34)	(0.53)	(0.71)	(0.96)	(1.32)
SEP Sentiment					0.196	0.403
					(0.64)	(1.68)
BW Sentiment					−1.024	−0.566
					(−1.98)	(−1.26)
GM Sentiment					−0.550	−0.314
					(−1.14)	(−0.71)
Manager Sentiment					(−0.20)	(−0.39)
					−0.63	−1.25
Michigan Sentiment					0.213	0.643
					(0.41)	(1.51)
PLS Sentiment					−0.956	−0.501
					(−1.70)	(−1.02)
JJZ Skew					−0.519	−0.244
					(−2.17)	(−1.13)
HLW Disp					−0.480	−0.735
					(−1.22)	(−2.17)
PNBO					−0.804	−0.462
					(−3.41)	(−2.52)
GW PCA					−1.552	−0.246
					(−2.50)	(−0.67)
$adj.\ R^2$ (%)	3.08	2.10	4.77	4.55	27.07	20.88

Table A5 Out-of-sample R^2 and Economic Benefit

The performance evaluation period to compute the statistics is from 2010 to 2020. When training the model, we use all available observations starting from 1960 up to the testing period. The predictors are specified in Section 3.1. The forecast target is the market excess returns (MKTRF) one week (weekly) and one month (monthly) ahead. The out-of-sample (OOS) R^2, the annualized certainty equivalent return (CER), and the annualized Sharpe ratio (in parentheses) are specified in Section 5.1. The t-stat in parentheses of OOS R^2 is computed based on Clark and West (2007). The benchmark Sharpe ratio using recursive historical average MKTRF as a predictor for weekly (monthly) is 0.541 (0.725).

	Out-of-Sample R^2 Statistic (%)		CER Gain and Sharpe Ratio	
Predictor	Weekly	Monthly	Weekly	Monthly
ACIB	0.756	6.114	2.978	10.416
	(1.926)	(2.835)	(0.847)	(1.360)
APIB	0.020	0.343	2.083	2.948
	(1.060)	(1.080)	(0.789)	(0.843)
ICIB	−0.704	1.904	−2.066	1.950
	(0.074)	(1.582)	(0.271)	(0.816)
IPIB	0.200	−1.302	0.673	−1.503
	(1.371)	(−1.164)	(0.606)	(0.608)
VRP	0.394	−1.027	−1.707	−6.200
	(0.903)	(0.414)	(0.378)	(0.459)
IVS	1.183	−2.456	0.086	3.273
	(1.119)	(0.447)	(0.546)	(0.856)
BKM Skew	−0.769	−1.004	−0.995	−3.326
	(−1.438)	(−0.214)	(0.126)	(0.532)
AAII Sentiment	−0.100	0.063	−0.518	−0.445
	(−0.979)	(0.301)	(0.464)	(0.671)
SEP Sentiment		−0.203		−0.396
		(0.066)		(0.559)
BW Sentiment		2.610		4.967
		(1.978)		(0.832)
GM Sentiment		4.648		9.086
		(2.468)		(0.959)
Manager Sentiment		−3.386		−7.181
		(−0.981)		(0.052)
Michigan Sentiment		0.793		1.239
		(1.146)		(0.683)
PLS Sentiment		−0.097		0.107
		(0.543)		(0.513)
JZZ Skew		0.782		1.936
		(1.093)		(0.791)
HLW Disp		0.043		1.483
		(1.807)		(0.784)
PNBO		0.738		0.780
		(1.619)		(0.586)
GW PCA		4.669		6.056
		(2.148)		(0.849)

Table A6 Robustness Checks for Alternative Weighting Scheme

This table reports the results of univariate predictive time-series regressions. The dependent variables are the daily (D), weekly (W), and monthly (M) value-weighted market excess returns (MKTRF-VW) in percentage in Panel A and equal-weighted market excess returns (MKTRF-EW) in percentage in Panel B, over the relevant forecast horizons. The independent variables are market-value weighted aggregate call order imbalance (ACIB-VW) and equal-weighted aggregate call order imbalance (ACIB-EW). All predictors are normalized to have a zero mean and one standard deviation. D/W/M represents the forecast horizon in the number of days/weeks/months. The t-stat in parentheses is computed using the Newey and West (1987) method with D/W/M−1 lag correction. The sample period is from 2005 to 2020. The numbers of observations for each regression are 4027/4025 for D=1/3, 841/840 for W=1/2, and 191/190 for M=1/2.

Predictor	D=1	D=3	W=1	W=2	M=1	M=2
Panel A. Forecast Value-weighted Market Excess Returns (MKTRF-VW)						
ACIB-VW	−0.075	−0.054	−0.240	−0.216	−0.945	−0.822
	(−3.36)	(−3.58)	(−2.69)	(−3.21)	(−2.89)	(−3.28)
adj. R^2 (%)	1.92	0.93	0.92	1.24	4.11	5.36
ACIB-EW	−0.071	−0.042	−0.182	−0.160	−0.676	−0.522
	(−3.00)	(−2.60)	(−1.95)	(−2.11)	(−1.74)	(−1.85)
adj. R^2 (%)	1.88	0.69	0.56	0.57	1.86	1.50
Panel B. Forecast Equal-weighted Market Excess Returns (MKTRF-EW)						
ACIB-VW	−0.066	−0.058	−0.297	−0.249	−1.264	−1.146
	(−3.18)	(−3.70)	(−3.09)	(−3.43)	(−3.35)	(−4.11)
adj. R^2 (%)	0.25	0.91	0.99	2.38	7.39	7.94
ACIB-EW	−0.071	−0.053	−0.246	−0.192	−0.998	−0.863
	(−3.15)	(−3.13)	(−2.45)	(−2.35)	(−2.23)	(−2.64)
adj. R^2 (%)	0.29	0.79	0.60	1.70	5.17	4.29

Table A7 Decomposition of Equity Option Trading Activities

In Panel A, when constructing ACIB and APIB, we separate the sample by the order size specified in CBOE as "small", "medium", and "large" orders. In Panel B, we repeat a similar process, but separate the sample based on time to maturity. The short horizon group is defined as options traded less than 15 days to maturity, the middle horizon group is defined as options traded between 15 and 60 days to maturity, and the long horizon group is defined as options traded greater than 60 days to maturity. In Panel C, we separate the sample by its moneyness (strike price over spot price). Out-of-the-money (OTM) options are classified as moneyness less (greater) than 0.9 for put (call) options, in-the-money (ITM) options are classified as moneyness greater (less) than 1.1 for put (call) options, and at-the-money (ATM) options for the rest of the classifications. The different types of ACIB or APIB are then used to run predictive regressions at daily frequency (D) and monthly frequency (M). The dependent variables are daily (D) and monthly (M) excess returns in the logarithm of the value-weighted market portfolio (MKTRF) in percentage over the relevant forecast horizons. All predictors are normalized to have a zero mean and one standard deviation. The t-stat in parentheses is computed using the Newey and West (1987) method with D/M−1 lag correction. The sample period is from 2005 to 2020. The numbers of observations for each regression are 4027/4025 for D=1/3 and 191 for M=1.

Panel A. Different Trading Order Size									
	Small			Medium			Large		
Predictor	D=1	D=3	M=1	D=1	D=3	M=1	D=1	D=3	M=1
ACIB	−0.086	−0.053	−1.581	−0.033	−0.021	−1.125	−0.009	−0.009	0.333
	(−3.01)	(−2.84)	(−3.65)	(−1.47)	(−1.51)	(−2.61)	(−0.39)	(−0.64)	(1.51)
APIB	0.020	0.0005	0.036	−0.001	−0.018	−0.250	−0.015	−0.0002	−0.041
	(0.64)	(0.03)	(0.34)	(−0.06)	(−1.51)	(−1.05)	(−0.73)	(−0.01)	(−0.17)
adj. R^2 (%)	1.95	0.88	4.81	1.64	0.50	2.23	1.59	0.32	0.92
Panel B. Different Time to Maturity									
	Short			Middle			Long		
Predictor	D=1	D=3	M=1	D=1	D=3	M=1	D=1	D=3	M=1
ACIB	−0.041	−0.037	−0.810	−0.068	−0.052	−1.127	−0.063	−0.047	−0.952
	(−1.89)	(−2.48)	(−2.13)	(−2.89)	(−3.22)	(−3.55)	(−2.70)	(−3.07)	(−3.17)
APIB	0.004	0.011	0.113	0.0009	0.017	0.414	0.008	0.011	0.416
	(0.25)	(1.05)	(0.67)	(0.04)	(1.49)	(1.01)	(0.51)	(1.22)	(1.42)
adj. R^2 (%)	1.74	0.60	1.91	1.84	0.85	2.82	1.79	0.76	2.56
Panel C. Different Moneyness									
	OTM			ATM			ITM		
Predictor	D=1	D=3	M=1	D=1	D=3	M=1	D=1	D=3	M=1
ACIB	−0.030	−0.021	−0.361	−0.076	−0.047	−1.567	−0.053	−0.044	−1.044
	(−1.04)	(−1.09)	(−1.86)	(−2.76)	(−2.65)	(−3.29)	(−2.00)	(−2.67)	(−3.10)
APIB	−0.027	−0.017	−0.525	0.010	−0.001	0.088	−0.003	−0.006	−0.833
	(−1.37)	(−1.24)	(−1.41)	(0.33)	(−0.06)	(0.09)	(−0.10)	(−0.31)	(−0.41)
adj. R^2 (%)	1.64	0.43	1.10	1.88	0.78	3.76	1.74	0.78	2.61

Table A8 ACIB and APIB based on Alternative Types of Option Traders and Database

In Panel A, we use the market makers' buy and sell trading volume to construct ACIB and APIB. Market makers are defined by combining trading volume from "firm", "broker-dealer", and "market maker" tagged by CBOE. We then group the data by moneyness. In Panel B, we repeat a similar process but choose the type of "professional customer" tagged by CBOE. The sample period in Panel B is only available since 2009. In Panel C, instead of using the CBOE data, we use option data from the Nasdaq International Securities Exchange (ISE) to construct ACIB and APIB. The results are displayed by grouping options into different moneyness. Out-of-the-money (OTM) options are classified as moneyness less (greater) than 0.9 for put (call) options, in-the-money (ITM) options are classified as moneyness greater (less) than 1.1 for put (call) options, and at-the-money (ATM) options for the rest of the classifications. The different types of ACIB and APIB are then used to run predictive regressions at daily frequency (D) and monthly frequency (M). All dependent variables are market excess returns (MKTRF) in percentage. The t-stat is computed using the Newey and West (1987) method with D/M−1 lag correction. The sample period is from 2005 to 2020 (2009 to 2020) for Panel C (Panels A and B). The numbers of observations in Panel C (Panels A and B) for each regression are 4027/4025 (3020/3018) for D=1/3 and 191 (143) for M=1.

Panel A. Market Maker									
	OTM			ATM			ITM		
Predictor	D=1	D=3	M=1	D=1	D=3	M=1	D=1	D=3	M=1
ACIB	0.029	−0.010	−0.135	0.083	0.019	0.544	0.053	0.010	0.144
	(1.23)	(−0.69)	(−0.85)	(2.60)	(1.04)	(1.43)	(1.72)	(0.56)	(0.40)
APIB	−0.015	−0.014	0.215	−0.035	−0.0004	0.451	0.023	0.029	0.412
	(−0.61)	(−0.89)	(0.31)	(−1.25)	(−0.03)	(0.98)	(1.10)	(2.00)	(1.67)
adj. R^2 (%)	1.82	0.19	0.59	2.15	0.21	1.81	1.97	0.37	0.75
Panel B. Professional Customer									
	OTM			ATM			ITM		
Predictor	D=1	D=3	M=1	D=1	D=3	M=1	D=1	D=3	M=1
ACIB	0.023	0.019	0.821	0.017	0.012	0.902	0.018	0.005	0.340
	(0.72)	(1.01)	(0.92)	(0.71)	(0.81)	(1.55)	(0.89)	(0.40)	(0.56)
APIB	0.029	0.003	−0.083	−0.026	−0.021	−0.098	−0.019	0.021	−0.417
	(0.98)	(0.17)	(−0.28)	(−1.03)	(−1.29)	(−0.29)	(−0.87)	(1.56)	(−1.67)
adj. R^2 (%)	1.51	0.47	0.67	1.64	0.25	1.59	1.96	0.30	0.97
Panel C. Alternative Database using ISE									
	OTM			ATM			ITM		
Predictor	D=1	D=3	M=1	D=1	D=3	M=1	D=1	D=3	M=1
ACIB	−0.018	−0.024	−0.569	−0.038	−0.038	−1.789	−0.051	−0.029	−1.291
	(−0.80)	(−1.54)	(−1.90)	(−1.45)	(−2.13)	(−3.46)	(−2.52)	(−2.20)	(−3.10)
APIB	−0.018	−0.012	−0.303	−0.004	0.0004	−0.117	0.017	−0.001	−0.079
	(−0.76)	(−0.68)	(−0.83)	(−0.14)	(0.02)	(−0.27)	(0.96)	(−0.08)	(−0.31)
adj. R^2 (%)	1.64	0.48	1.18	1.70	0.61	3.43	1.75	0.49	3.10

Table A9 O/S Ratio Time-series Decomposition and Stock Market Return Predictability

Following Ge, Lin, and Pearson (2016), we decompose the option volume into different parts, divide it by the daily stock trading volume, and aggregate individual O/S ratios to the market level by market-weighted average within each group. The four different components are aggregate call opening buy volume to stock volume (ACOB/S), aggregate call opening sell volume to stock volume (ACOS/S), aggregate put opening buy volume to stock volume (APOB/S), and aggregate put opening sell volume to stock volume (APOS/S). We then run bivariate and multiple regressions for the O/S ratios within each group at daily frequencies. The dependent variable is the excess daily (D) or monthly (M) returns in logarithms of the value-weighted market portfolio (MKTRF) in percentage over the relevant forecast horizons. The results are displayed by grouping options into different moneyness. Out-of-the-money (OTM) options are classified as moneyness less (greater) than 0.9 for put (call) options, in-the-money (ITM) options are classified as moneyness greater (less) than 1.1 for put (call) options, and at-the-money (ATM) options for the rest of the classifications. The different types of ACIB and APIB are then used to run predictive regressions at a daily frequency (D) and monthly frequency (M). All predictors are normalized to have a zero mean and one standard deviation. The *t*-stat is computed using the Newey and West (1987) method with D/M−1 lag correction. The sample period is from 2005 to 2020. The numbers of observations for each regression are 4027/4025 for D=1/3 and 191 for M=1.

Predictor	D=1			D=3			M=1		
Panel A. Out-of-the-Money Options (OTM)									
ACOB/S	−0.080		−0.075	−0.046		−0.043	−1.175		−0.615
	(−2.40)		(−1.71)	(−1.56)		(−1.21)	(−1.95)		(−1.72)
ACOS/S	0.063		0.066	0.031		0.031	0.959		0.911
	(2.00)		(2.00)	(1.24)		(1.19)	(2.07)		(1.93)
APOB/S		−0.018	−0.007		−0.017	−0.005		−0.264	0.144
		(−1.04)	(−0.16)		(−1.13)	(−0.16)		(−0.86)	(0.48)
APOS/S		−0.002	−0.003		0.006	0.005		0.134	0.122
		(−0.08)	(−0.17)		(0.35)	(0.34)		(0.40)	(0.77)
adj. R^2 (%)	1.64	1.59	1.59	0.41	0.36	0.36	0.99	0.81	0.96
Panel B. At-the-Money Options (ATM)									
ACOB/S	−0.057		−0.067	−0.057		−0.070	−1.182		−1.268
	(−1.84)		(−2.12)	(−2.48)		(−2.95)	(−2.68)		(−2.81)
ACOS/S	0.028		0.010	0.031		0.011	0.666		0.413
	(0.98)		(0.27)	(1.47)		(0.45)	(1.70)		(0.90)
APOB/S		−0.045	−0.027		−0.034	−0.016		−0.884	−0.587
		(−1.55)	(−0.90)		(−1.62)	(−0.73)		(−2.19)	(−1.43)
APOS/S		0.020	0.054		0.015	0.049		0.393	0.860
		(0.69)	(1.57)		(0.70)	(1.98)		(0.91)	(1.76)
adj. R^2 (%)	1.67	1.64	1.68	0.66	0.46	0.76	1.42	1.20	2.66
Panel C. In-the-Money Options (ITM)									
ACOB/S	−0.054		−0.043	−0.056		−0.051	−1.199		−1.052
	(−1.59)		(−1.07)	(−2.22)		(−1.75)	(−2.44)		(−2.83)
ACOS/S	0.037		0.043	0.040		0.044	0.835		0.880
	(0.88)		(0.87)	(1.27)		(1.23)	(1.41)		(1.28)
APOB/S		−0.032	−0.022		−0.026	−0.010		−0.624	−0.272
		(−1.52)	(−0.77)		(−1.61)	(−0.41)		(−1.86)	(−0.58)
APOS/S		0.013	0.0008		0.011	−0.003		0.337	0.062
		(0.49)	(0.03)		(0.53)	(−0.13)		(0.87)	(0.14)
adj. R^2 (%)	1.64	1.61	1.61	0.60	0.40	0.56	1.34	0.98	1.31

Table A10 Predictive Power of ACIB in Different Regimes

In Panel A, the sample days from 2005 to 2020 are separated into two regimes: above and below the median of the level of the AAII sentiment from the survey data by the American Association of Individual Investors. We run daily (D) and monthly (M) predictive regressions of stock market excess returns (MKTRF) in percentage on ACIB within each regime. We conduct a similar test in Panel B, except that the separation is based on the SEP sentiment index by Henderson, Pearson, and Wang (2023). In Panel C, we use the proportion of firms with earnings announcements out of total public firms over time. A higher proportion indicates higher sentiment periods over time. All predictors are normalized to have a zero mean and one standard deviation. The t-stat in parentheses is computed using the Newey and West (1987) method with D/M−1 lag correction. The sample period is from 2005 to 2020. The numbers of observations for each regression are 2013/2012 for D=1/3 and 95/94 for M=1/2.

		D=1	D=3	M=1	M=2
Panel A. ACIB Prediction Separated by AAII Sentiment					
High AAII Sentiment	ACIB	−0.095	−0.056	−1.322	−0.998
		(−2.74)	(−2.60)	(−4.13)	(−4.53)
	adj. R^2 (%)	3.09	1.58	9.59	9.49
Low AAII Sentiment	ACIB	−0.043	−0.042	−0.346	−0.451
		(−1.40)	(−1.99)	(−0.63)	(−1.07)
	adj. R^2 (%)	0.45	0.38	−0.53	0.73
Panel B. ACIB Prediction Separated by SEP Sentiment					
		D=1	D=3	M=1	M=2
High SEP Sentiment	ACIB	−0.142	−0.068	−1.672	−1.188
		(−4.02)	(−2.94)	(−3.41)	(−3.43)
	adj. R^2 (%)	4.09	1.18	8.42	9.76
Low SEP Sentiment	ACIB	−0.043	−0.041	−0.796	−0.723
		(−1.02)	(−1.54)	(−1.47)	(−1.53)
	adj. R^2 (%)	2.19	0.58	2.14	2.63
Panel C. ACIB Prediction Separated by Earnings Announcements					
		D=1	D=3	M=1	M=2
High Earnings Announce	ACIB	−0.150	−0.083	−1.147	−0.765
		(−3.43)	(−3.25)	(−2.53)	(−2.25)
	adj. R^2 (%)	4.64	1.76	5.16	3.21
Low Earnings Announce	ACIB	−0.003	−0.022	−0.688	−0.742
		(−0.07)	(−0.82)	(−1.15)	(−1.57)
	adj. R^2 (%)	0.29	0.35	2.19	3.16

Table A11 Predictive Regression by Index Options

This table examines the predictive power of index call option order imbalance (CIB). We select four index options actively traded at CBOE: Russell 2000 index option (RUT), Dow Jones Industrial Average index option (DJX), Nasdaq 100 index option (NDX), and S&P 500 index option (SPX). We run predictive regressions of stock market excess returns (MKTRF) in percentage days (D) or months (M) ahead on CIB for each index, respectively. All predictors are normalized to have a zero mean and one standard deviation. The t-stat in parentheses is computed using the Newey and West (1987) method with D/M−1 lag correction. The sample period is from 2005 to 2020. The numbers of observations for each regression are 4027/4025 for D=1/3 and 191/190 for M=1/2.

Predictor	D=1	D=3	M=1	M=2
RUT CIB	0.004	−0.005	0.204	0.032
	(0.15)	(−0.36)	(0.58)	(0.11)
adj. R^2 (%)	1.74	0.40	0.16	−1.03
DJX CIB	−0.035	−0.020	−0.795	−0.772
	(−1.87)	(−1.75)	(−2.48)	(−3.41)
adj. R^2 (%)	1.84	0.47	3.20	4.57
NDX CIB	−0.008	−0.007	−0.340	−0.464
	(−0.28)	(−0.44)	(−1.18)	(−1.64)
adj. R^2 (%)	0.67	0.41	1.25	1.77
SPX CIB	0.022	−0.014	−0.617	−0.583
	(0.90)	(−0.92)	(−1.83)	(−2.74)
adj. R^2 (%)	1.82	0.42	1.92	2.21

Table A12 International Stock Market Return Predictability

This table reports the results of multiple predictive regressions. Each column in this table corresponds to one multiple predictive regression for one country's stock market returns, labeled by the forecast horizons (D=day, W=week, and M=month) in Panels A, B, and C. The dependent variable is the average daily/weekly/monthly stock market returns in percentage in each country specified at the top of the columns of each panel, over the relevant forecast horizon, and all predictors are normalized to have a zero mean and one standard deviation. Within all regressions, we include other control variables, which are not listed in the table, including the local country's stock market returns and the US stock market returns. The t-stat in parentheses is computed using the Newey and West (1987) method with D/W/M−1 lag correction. The sample period is from 2005 to 2020. The numbers of observations for each regression are 4025 for D=3, 841 for W=1, and 191 for M=1.

	Australia	Canada	Finland	France	Germany	Hong Kong	Italy
Panel A. Time-series Return Predictability (D=3)							
ACIB	−0.039	−0.040	−0.060	−0.065	−0.064	−0.085	−0.049
	(−2.34)	(−2.16)	(−2.70)	(−2.93)	(−2.83)	(−3.28)	(−2.07)
APIB	−0.013	−0.002	−0.015	−0.004	−0.011	0.046	−0.024
	(−0.72)	(−0.08)	(−0.64)	(−0.18)	(−0.44)	(1.68)	(−1.06)
adj. R^2 (%)	1.05	1.01	2.19	3.07	2.18	7.74	5.93
Panel B. Time-series Return Predictability (W=1)							
ACIB	−0.196	−0.176	−0.309	−0.357	−0.315	−0.361	−0.287
	(−1.55)	(−1.23)	(−1.99)	(−2.30)	(−1.96)	(−2.53)	(−1.72)
APIB	−0.042	−0.075	−0.071	−0.037	−0.065	0.134	−0.100
	(−0.34)	(−0.53)	(−0.46)	(−0.23)	(−0.39)	(0.91)	(−0.64)
adj. R^2 (%)	2.27	0.29	0.86	1.39	0.96	2.20	1.75
Panel C. Time-series Return Predictability (M=1)							
ACIB	−0.807	−0.758	−1.060	−1.236	−1.358	−1.092	−0.802
	(−2.10)	(−2.22)	(−2.14)	(−2.82)	(−2.79)	(−2.34)	(−1.59)
APIB	0.397	0.230	0.454	0.432	0.662	0.696	0.357
	(1.17)	(0.59)	(0.95)	(1.13)	(1.54)	(1.22)	(0.74)
adj. R^2 (%)	3.95	2.89	4.07	4.61	5.49	1.19	0.72

Table A13 International Stock Market Return Predictability (Continue)

This table reports the results of multiple predictive regressions. Each column in this table corresponds to one multiple predictive regression for one country's stock market returns, labeled by the forecast horizons (D=day, W=week, and M=month) in Panels A, B, and C. The dependent variable is the average daily/weekly/monthly stock market returns in percentage in each country specified at the top of the columns of each panel, over the relevant forecast horizon, and all predictors are normalized to have zero mean and one standard deviation. Within all regressions, we include other control variables, which are not listed in the table, including the local country's stock market returns and the US stock market returns. The t-stat in parentheses is computed using the Newey and West (1987) method with D/W/M−1 lag correction. The sample period is from 2005 to 2020. The numbers of observations for each regression are 4025 for D=3, 841 for W=1, and 191 for M=1.

	Japan	Netherland	New Zealand	Spain	Sweden	Switzerland	UK
Panel A. Time-series Return Predictability (D=3)							
ACIB	−0.065	−0.065	−0.020	−0.039	−0.073	−0.041	−0.053
	(−2.78)	(−3.10)	(−1.73)	(−1.51)	(−3.25)	(−2.30)	(−2.78)
APIB	−0.029	−0.012	−0.030	0.006	−0.0004	0.002	0.0008
	(−1.15)	(−0.54)	(−2.40)	(0.22)	(−0.00)	(0.10)	(0.04)
adj. R^2 (%)	9.75	3.24	6.10	1.14	2.83	2.93	3.41
Panel B. Time-series Return Predictability (W=1)							
ACIB	−0.301	−0.342	−0.207	−0.342	−0.434	−0.292	−0.360
	(−2.13)	(−2.22)	(−2.10)	(−2.14)	(−2.87)	(−2.21)	(−2.61)
APIB	−0.133	−0.087	−0.136	0.079	−0.007	−0.034	−0.008
	(−0.98)	(−0.52)	(−1.61)	(0.49)	(−0.04)	(−0.24)	(−0.06)
adj. R^2 (%)	1.85	1.34	4.61	1.08	2.58	3.83	1.84
Panel C. Time-series Return Predictability (M=1)							
ACIB	−1.019	−1.286	−0.736	−1.083	−1.216	−0.399	−1.141
	(−2.67)	(−3.88)	(−2.54)	(−2.16)	(−3.09)	(−1.21)	(−3.57)
APIB	0.123	0.427	0.123	0.712	0.430	0.072	0.433
	(0.26)	(1.11)	(0.51)	(1.57)	(1.05)	(0.23)	(1.33)
adj. R^2 (%)	5.56	6.54	5.87	1.48	4.01	1.26	5.56

Table A14 Predictive Regression of Stock Market Volatility

This table reports the results of multiple predictive regressions at weekly frequency. The definition of all the predictors can be found in Section 3.1. The dependent variables are average weekly stock market volatility and value-weighted average of firm-level volatility in percentage, over the relevant forecast horizon, and all predictors are normalized to have a zero mean and one standard deviation. The "Other Controls" include: market excess returns (MKTRF), VIX, and the Heterogeneous Autoregressions (HAR) model with 1, 5, 10, and 20-day moving-average volatility suggested by Corsi (2009). The t-stat in parentheses is adjusted for heteroskedasticity and autocorrelation using the Newey and West (1987) method. The sample period is from 2005 to 2020. The number of observations for each regression is 841.

	Forecast Stock Market Volatility		Forecast Value-weighted Volatility	
Predictor	Slope	t-stat	Slope	t-stat
ACIB	−0.621	(−1.49)	−0.141	(−1.39)
APIB	1.455	(3.50)	0.530	(4.44)
ICIB	0.480	(1.71)	0.130	(1.61)
IPIB	−0.065	(−0.24)	−0.022	(−0.34)
Other Controls		Yes		Yes
Adj.R^2 (%)		64.10		98.00