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

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ABSTRACT

We find that the cross-sectional average of equity call options order imbalance (ACIB) negatively forecasts future market risk premium. The predictability by ACIB is robust to different horizons, from days to months. Though constructed from the options market, ACIB represents a general investor sentiment which is closely related to the Baker-Wurgler sentiment index. We do not find a significant effect of the average put options order imbalance. Further evidence indicates that ACIB tends to reflect sentiment from retail investors. We document consistent results using stock market returns from fourteen alternative financial markets.

Keywords: Equity option trading, investor sentiment, time-series market predictability, option-implied information, retail investors

JEL Classification: G11, G12, G13, G14, G17

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1 Introduction

The equity options market has traditionally been viewed as popular for institutional and sophisticated investors. However, a recent seminal work by Bryzgalova, Pavlova, and Sikorskaya (2023) finds that retail investors contribute to 62% of the total trading volume in equity options. Financial media often reports investors lose hundreds of millions of dollars by playing equity options for speculation.[1] The fact that retail investors, on average, lose money indicates that their trading is likely motivated by sentiment, which are beliefs about future stock prices that are not justified by rational evaluation of available information. In line with the sentiment motivation of retail investor trading, Henderson, Pearson, and Wang (2023) construct a sentiment measure of retail investors using the issuance of retail structured equity products. In this paper, we propose a novel sentiment measure constructed from equity call options and test its implication on the stock market risk premium in the U.S. market.

When retail investors are over-optimistic about a stock, the buying pressure for the stock's call options increases without fundamental drives. To measure such buying pressure, we make use of the trading data from the Chicago Board Options Exchange (CBOE), which allows us to identify the signs of the trading as well as the trader types. At the individual stock level, call option order imbalance (CIB) is defined as the net open buy volume (i.e., open buy minus open sell) divided by the total open trading volume. To obtain an overall sentiment measure, we take the cross-sectional average of individual stock's CIB and label the average call option order imbalance as aggregate equity call option order imbalance (ACIB). In our paper, ACIB is constructed at the daily, weekly, and monthly levels. Similarly, we construct aggregate equity put option order imbalance (APIB).

Our empirical evidence shows that ACIB strongly and negatively predicts future stock

[1] See for example recent news by Forbes "The Put/Call Ratio Says 'Get In The Market Now!'" (2021), and news by Bloomberg "Mom and Pop Investors Took a Billion-Dollar Bath Trading Options During the Pandemic" (2022).

market excess returns, from days to months. For example, a one-standard-deviation increase in ACIB leads to a decrease in stock market excess returns of 0.075% next day, 0.240% next week, 0.945% next month, and 2.316% next quarter on average. Aggregate equity put option order imbalance (APIB), however, demonstrates no market return predictability at any horizon. As documented by Bryzgalova, Pavlova, and Sikorskaya (2023), retail investors tend to prefer call options over put options. Therefore, the non-results of put option order imbalance in our paper align with the idea of retail investor sentiment.

To validate that ACIB captures sentiment from a new perspective, we conduct our predictive regressions by controlling for a comprehensive set of existing sentiment measures as well as option-based predictors for market risk premium. Specifically, we include the following sentiment measures, such as BW sentiment (Baker and Wurgler (2007)), the surveyed consumer sentiment index from Michigan University, PLS sentiment (Huang, Jiang, Tu, and Zhou (2015)), manager sentiment (Jiang, Lee, Martin, and Zhou (2019)), GM sentiment (Gao and Martin (2021)), as well as SEP sentiment (Henderson, Pearson, and Wang (2023)), which captures retail sentiment using the issuance of retail structured equity products. The monthly ACIB measure has high correlations with BW sentiment (0.50) and with SEP sentiment (0.33), indicating that ACIB likely captures investor sentiment, especially from retail traders. After controlling for these existing investor sentiment measures, we find that the negative forecasting capacity of ACIB remains significant. The coefficients of all the sentiment variables are consistent with the conjecture that future stock market price declines when sentiment is high. Yet, the effects of alternative sentiment measures are relatively weaker than ACIB.

Beyond its robustness to existing sentiment measures, the predictive power of ACIB also remains strong when accounting for market return predictors derived from the options market. Specifically, we control for order imbalance of call and put index options (i.e., ICIB and IPIB, respectively, as in Chordia, Kurov, Muravyev, and Subrahmanyam (2021)), variance risk premium (VRP, as in Bollerslev, Tauchen, and Zhou (2009)), aggregate implied volatility spread (IVS, as in Han and Li (2021)), and aggregate purchase of deep-out-of-the-money SPX index put options (PNBO, as in Chen, Joslin, and Ni (2019)). Moreover, Huang, Li, and Wang (2021) construct a disagreement measure and document its predictive power in the stock market. As disagreement based on option open interest is an ingredient of the aggregate disagreement measure, we control for the predictor in Huang, Li, and Wang (2021) as well. The robustness of ACIB to other option-based variables highlights that ACIB contains underexplored yet unique information useful for the market risk premium.

ACIB also effectively predicts stock market excess returns in two out-of-sample tests. First, we split our sample into two subperiods, i.e., before 2010 and after 2010 (2010 included). We estimate the effect of ACIB using the earlier sample and forecast market risk premium in the later period. We obtain economically large out-of-sample R^2 statistic. For example, at the monthly level, the out-of-sample R^2 reaches 6.114% when ACIB is used to predict the next month stock market excess returns. A mean-variance-utility investor who allocates wealth between the market portfolio and T-bill would obtain an annualized Sharpe ratio of 1.360 if she follows a monthly portfolio rebalancing strategy based on the predictive signal of ACIB. Second, we examine the validity of ACIB in forecasting international stock market returns. According to Baker, Wurgler, and Yuan (2012), a global sentiment index spreads across markets through private capital flows. If ACIB represents sentiment in the U.S., it would negatively forecast stock market returns in different financial markets as well. We collect the most representative stock market indices of fourteen financial markets from Global Financial Data (GFD). We calculate the raw returns of these indices at different horizons and again test the predictive power of CBOE-based ACIB in these financial markets. Consistent with a global sentiment framework, we find that ACIB negatively predicts future stock market returns in all the alternative fourteen financial markets. Similar to the findings in the U.S. stock market, CBOE-based APIB does not predict stock market returns in any of these alternative financial markets.

So far, our results suggest that ACIB predicts stock market returns through a sentiment channel, especially through the sentiment of retail investors. Next, we present additional supporting evidence. First, we decompose option orders into three groups, according to trading size, moneyness, and time to maturity. Then we construct ACIB by taking the average of call options order imbalance among options only within each group. Trading of smaller sizes is generally initiated by retail investors. We find consistent results that the ACIB of small trading size has stronger market return predictability compared with the ACIB of median or large trading size. Moreover, we find that ACIB from ATM call options has stronger market return predictability than ACIB from OTM or ITM options. It is consistent with the evidence in Bryzgalova, Pavlova, and Sikorskaya (2023) that retail investors prefer trading at-the-money options.

Second, we examine the trading by market makers and professional customers, who are less likely to trade because of sentiment. Consequently, we expect that the aggregate call option order imbalance (ACIB) constructed from the trading by these investors to have no predictive power on future stock market returns. This is indeed the case as we observe from the data, consistent with our sentiment explanation of ACIB forecasting market risk premium.

Third, we examine the predictability of ACIB conditional on the level of sentiment. As suggested by Stambaugh, Yu, and Yuan (2012), the sentiment effect by ACIB (i.e., the predictive power of ACIB) should be more salient when market participants are more optimistic in general. Henderson, Pearson, and Wang (2023) offer a very insightful way to measure retail investors' sentiment, i.e., from the retail structured equity products (SEP) issuance. We thus split our sample into two regimes based on the level of SEP. We find that the predictability by ACIB is much stronger and significant only when SEP is high. The SEP results further confirm that our sentiment index extracted from equity call options mostly reflects retail investors' sentiment.

Lastly, we reconcile the aggregate sentiment effect with the cross-sectional informed trading effect. A large body of literature documents that the cross-sectional variations in call and put option trading have meaningful implications for future cross-sectional stock returns (e.g., Pan and Poteshman (2006), Johnson and So (2012), Hu (2014), and Ge, Lin, and Pearson (2016)). We confirm the cross-sectional return implications in our sample using stock-level CIB and PIB. Specifically, when sorting stocks into quintiles according to CIB (PIB), we find stocks with high CIB (PIB) outperform (underperform) stocks with low CIB (PIB) in the cross section. To disentangle the opposite patterns observed between cross-sectional and time-series results for equity option trading, we further investigate the time-series return predictability of ACIB (APIB) on the portfolio return of each CIB (PIB) quintile. We find strong and consistent evidence that ACIB negatively forecasts the portfolio return of each CIB quintile at all levels, indicating a general sentiment effect across individual call options. Again, APIB fails to predict the portfolio returns of PIB quintiles at any level. The seemingly contradictory results from cross-sectional and time-series analyses could be reconciled by considering a common sentiment component among equity call options trading.

Our paper contributes to the literature by proposing a novel sentiment measure from equity options. Measuring investor sentiment is undeniably challenging.[2] Baker and Wurgler (2007) pioneered by constructing a stock market sentiment index. Recent literature sets to distinguish sentiment by different types of investors. Focusing on retail structured equity product (SEP) issuance, Henderson, Pearson, and Wang (2023) construct the first retail sentiment measure for reference stocks. Using 200 million pages of US local newspapers, van Binsbergen, Bryzgalova, Mukhopadhyay, and Sharma (2024) construct a 170-year-long measure of economic sentiment at the country and state levels. Different from previous studies, we are motivated by Bryzgalova, Pavlova, and Sikorskaya (2023) that retail investors contribute a significant portion to the trading of equity options, and construct a sentiment measure from the order imbalance of equity call options. Our measure can be easily constructed using exchange-traded equity options volume and is available at a higher frequency, i.e., daily and weekly levels.

[2] 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."

Moreover, our study deepens the understanding of interactions between options and stock markets. Motivations for trading options could be very different, including speculating, hedging, gambling, and informed trading (e.g., Lakonishok, Lee, Pearson, and Poteshman (2007), Johnson and So (2012), Hu (2014), Byun and Kim (2016), Ge, Lin, and Pearson (2016), and Bryzgalova, Pavlova, and Sikorskaya (2023)). Previous literature largely documents informed trading effects by examining the implications of cross-sectional variations in equity options trading and prices on the cross-section of future stock returns.[3] Turning to the effect of options on the aggregate stock market, the literature diverges more. For example, Chordia et al. (2021) find that option-based risk protection strategies used by retail investors explain the positive predictability of weekly index put order flow on the International Securities Exchange (ISE) on weekly S&P 500 index returns. Han and Li (2021) document that the aggregate implied volatility spread (IVS) significantly and positively predicts future stock market returns via a common informed trading channel. We offer the first piece of evidence that the equity options market contains useful information for investor sentiment and predicts aggregate stock market returns. Furthermore, the sentiment channel holds when we extend the predictability to other financial markets.

The rest of the paper is organized as follows. Section 2 describes the construction of our predictors, data, and other key variables. Section 3 presents both in-sample and out-of-sample evidence on the aggregate market predictability by ACIB and APIB. Section 4 clarifies the economic channel of market predictability by ACIB. Section 5 investigates various discussions. Section 6 concludes the paper.

[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).

2 Variable Construction

We measure equity option trading activities through *order imbalance* (IB) proposed by, for example, Hu (2014), Chen, Joslin, and Ni (2019), and Chordia et al. (2021) for several reasons. First, the signal IB is widely used in both practice and academia to measure trading activities in either option or stock markets.[4] Second, the calculation of IB only involves option trading activities, making it ideal to separate option trading from the underlying stock trading. Third, IB can be constructed using call or put volume separately, allowing us to identify the different trading effects from call and put options. Fourth, since the value of IB is bounded between -1 and $+1$, it does not need to deal with extreme outliers as for alternative volume ratios.[5] 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 activities across all exchanges in the United States.[6] The CBOE open-close data documents detailed volume information for option trading activities on CBOE. The trading volume is aggregated and bucketed by origins, such as public customers, professional customers, broker-dealers, 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 logarithm (MKTRF) obtained from Kenneth French's website.

[4] Order imbalance is widely used in the stock literature as well, such as Chan and Fong (2000), Chordia, Roll, and Subrahmanyam (2002), and Chordia and Subrahmanyam (2004).

[5] The extreme value issue for option trading is mentioned in Johnson and So (2012) and Ge, Lin, and Pearson (2016).

[6] We also construct our main predictors using another commonly used database, Nasdaq International Securities Exchange (ISE), and find similar and robust results of the stock return predictability. The results are shown as robustness checks in Section 4.

To construct 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 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 public customers in Equations (1) and (2), in order to better reflect retail investors' trading activities. 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 feasible traded options tagged as customers with all trading sizes (i.e., small, medium, and large) to construct IB. In Section 4, we conduct a detailed decomposition of IB based on different trading sizes, moneyness, and time to maturity, 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] The empirical results are robust if we use absolute delta-weighted or moneyness-weighted summation across all option contracts.

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. In general, one can think ACIB (APIB) as the aggregate end-user demand for equity call (put) options in the market. We then examine the predictive power of ACIB and APIB at daily, weekly, and monthly frequency.

[**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 between call and put options do not always move opposite to each other as commonly thought. In particular, investors trade more equity call options than equity put options in the recent period of Covid, consistent with Bryzgalova, Pavlova, and Sikorskaya (2023) 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, consistent with Bryzgalova, Pavlova, and Sikorskaya (2023) that, in general, equity call options are traded more popularly than equity put options by public customers, making call option trading a reasonable proxy for sentiment. The time-series averages for both ACIB and APIB are negative, implying that option traders are net sellers for both equity call and put options, similar to the findings by Lakonishok et al. (2007). Furthermore, ACIB is highly and positively related to 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, manager sentiment by Jiang et al. (2019) with a correlation of 0.19, and the consumer sentiment index from University of Michigan with a correlation of 0.24.

3 Aggregate Equity Option Order Imbalance and Stock Market Risk Premium

3.1 In-sample Predictive Regression

To test our hypothesis that ACIB captures investor sentiment, we expect that ACIB negatively forecasts future stock market excess returns. The most commonly used multi-period predictive regression follows Fama and French (1988, 1989):[8]

$$\sum_{k=1}^{K} \frac{r_{t+k}}{K} \equiv r_{t,t+K} = a + b \times X_t + \epsilon_{t,t+K}, \tag{4}$$

where r_{t+k} is MKTRF at time $t+k$ defined in Section 2; X_t is the predictor variable of interest (i.e., ACIB and APIB); K stands for the forecast horizon. In our paper, K is specified by days (D), weeks (W), or months (M). We then run the predictive regressions with K equal to 1, 2, 3, and 6 days/weeks/months. When $K > 1$, we correct the serial correlation and conditional heteroscedasticity using the Newey-West correction with $K-1$ lags (Newey and West (1987)). When running regressions, to make the coefficients comparable, we standardize all independent variables to have zero mean and one standard deviation.

[Insert Table 2]

Table 2 provides evidence that ACIB is a strong and contrarian predictor at daily, weekly, and monthly frequency. For example, a one-standard-deviation increase in daily ACIB forecasts an average decrease in stock market returns of 0.075% next day, 0.240% next week,

[8] In an untabulated table, we also run an alternative predictive regression suggested by Hodrick (1992) and confirm that our results are robust to non-overlapped observations.

0.945% next month, and 2.316% next quarter, with the corresponding t statistics of -3.36, -2.69, -2.89, and -3.63.[9] When running daily and weekly predictive regressions, we include (but not show in the tables) past one-period stock market returns to control for stock return autocorrelation. Regarding the empirical results, since the signs of ACIB are all negative, the results indicate ACIB captures the market sentiment effect instead of informed trading, which is supposed to be a positive relationship between buying call options and future stock market returns.

Note that APIB does not help forecast stock returns at any horizon. There could be a couple of reasons why APIB does not work. First, given an unlimited payoff, the sentiment effect is supposed to be stronger for lottery-liked call options than protection-liked put options, especially for unsophisticated option traders and speculators (Bryzgalova, Pavlova, and Sikorskaya (2023)). Second, unlike optimistic investors, pessimistic traders can simply do nothing and leave the market away when they lose confidence to the stock market, thus their perceptions may not be reflected in put option trading activities. Third, trading put options is mostly related to risk management, instead of sentiment trading (Chen, Joslin, and Ni (2019) and Chordia et al. (2021)).

To investigate whether ACIB captures any existing predictors in the literature, especially those predictors related to sentiment, we run multiple regressions with ACIB and a selected set of existing predictors. We first include the principal component of the 22 predictors based on Goyal and Welch (2008) from Amit Goyal's website.[10] Second, we collect all the alternative popular sentiment predictors documented in the literature, such as BW sentiment by Baker and Wurgler (2007), SEP sentiment by Henderson, Pearson, and Wang (2023), consumer survey sentiment from the University of Michigan, GM sentiment by Gao and

[9] The numbers of market return changes in Table 2 are adjusted based on different forecast horizons (0.075% =1.659%/22, 0.240% =0.958%/4, and 2.316%=0.772% $\times$ 3), as all dependent variables in Table 2 are expressed at monthly frequency.

[10] We follow Rapach, Ringgenberg, and Zhou (2016) to construct the principle components from Amit Goyal's website. For concision, we only include the first principle component, though the results are robust to including all the three principle components as in Rapach, Ringgenberg, and Zhou (2016).

Martin (2021), manager sentiment by Jiang et al. (2019), and PLS sentiment by Huang et al. (2015). We further include all other option-based predictors, such as variance risk premium (VRP) by Bollerslev, Tauchen, and Zhou (2009), index call IB (ICIB) and index put IB (IPIB) based on Chordia et al. (2021), PNBO proposed by Chen, Joslin, and Ni (2019), aggregate implied volatility spread by Han and Li (2021).[11] We then run multiple regressions, including ACIB, APIB, and other control predictors:

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

where $X_{j,t}$ specifies the control variable j listed above. Similarly, we run the predictive regressions at daily, weekly, and monthly frequency. Since some predictors are only available at a certain frequency, when running regressions, we only include those predictors that fit the corresponding feasible frequency.

[Insert Table 3]

The regression results are consistent with many previous studies on time-series predictions. For example, consistent with Bollerslev, Tauchen, and Zhou (2009), VRP is a strong predictor at monthly and quarterly frequency. PNBO proposed by Chen, Joslin, and Ni (2019) significantly and negatively forecasts future stock market returns. The index put option order imbalance (IPIB) proposed by Chordia et al. (2021) positively forecasts stock market returns at weekly frequency, while the index call option order imbalance (ICIB) does not forecast stock market returns at any horizons. More importantly, Table 3 demonstrates that ACIB is a strong and new predictor that is different from other existing predictors. The forecasting capacity of ACIB holds strongly in short horizons such as daily and weekly, and also in the long run. ACIB is largely different from those option-based predictors with the magnitude of correlations less than 0.15. The regression results also demonstrate that

[11] We are grateful for Neil Pearson to provide us the aggregate SEP sentiment data. All the other predictors are either constructed by ourselves or collected from the corresponding authors' websites.

the predictive power of ACIB is not driven by any existing stock return predictors in the literature. Consistent with our previous findings, APIB is not a useful signal for future stock market returns at any horizons.

3.2 Out-of-sample Predictive Regression

In addition to in-sample evidence, we also 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:

$$\begin{cases} r_{t,t+k} = \alpha + \beta \times x_t + \epsilon_{t,t+K}, & t = 1, \ldots, T_0 - K, \\ \hat{r}_{t,t+k} = \hat{\alpha} + \hat{\beta} \times x_t, & t = T_0, \ldots, T, \end{cases} \tag{6}$$

$$Benchmark : r^B_{t,t+k} = \frac{1}{t-K} \sum_{s=1}^{t-K} r_{s,s+K}, \ t = T_0, \ldots, T, \tag{7}$$

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

$$R^2_{OS} = 1 - \frac{MSFE_1}{MSFE_0}, \tag{8}$$

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

Time-series predictability of stock market 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 T-bill. Given an investment horizon of K periods, her optimal weight on the market portfolio is:

$$w_{t,t+K} = \frac{1}{\gamma}\frac{\hat{r}_{t,t+k}}{\hat{\sigma}^2_{t,t+k}}, \tag{9}$$

where $\hat{r}_{t,t+k}$ is conditional expected market excess return (i.e., forecast based on a predictor) given by ACIB or APIB. The $\hat{\sigma}^2_{t,t+k}$ is estimated using the variance of the past one-year historical returns for daily and 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 day, week, or month. The corresponding Sharpe ratio of the investor's optimal portfolio is given by:

$$SR = \frac{R_p}{\sigma_p}, \tag{10}$$

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

$$CER = R_p - 0.5\gamma\sigma_p^2. \tag{11}$$

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:

$$CER\ Gain = CER - \overline{CER}. \tag{12}$$

[Insert Table 4]

Both Panel A and Panel B in Table 4 demonstrate that ACIB has strong and significant out-of-sample predictive power to future stock market returns. For the out-of-sample R^2 compared with the historical average estimation as the benchmark, ACIB achieves 2.23%, 0.76%, and 6.11% for one-day, one-week, and one-month forecast horizons. The Sharpe ratios of using ACIB as the trading signal to construct market-timing portfolios are also considerable, with 0.212 for one day, 0.394 for one week, and 1.360 for one month, which are all higher than those of the buy-and-hold benchmark with 0.147 for one day, 0.252 for one week, and 0.725 for one month. From a utility-gain perspective, ACIB is able to help investors achieve CER gains with 0.372% for one day, 1.385% for one week, and 10.416% for one month.[12] All in all, we show that investors can significantly benefit from using our variable ACIB to adjust positions of risky assets over time.

3.3 International Stock Market Return Predictability by ACIB

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 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 by 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, Canada, Finland, France, Germany, Hong Kong SAR, Italy, Japan, the Netherlands, New Zealand, Spain, Sweden, Switzerland, and the United Kingdom. The predictive regression is the same as specified

[12] Note that the out-of-sample R^2 for longer time horizons such as M=2 and 3 may be subject to small-sample biases, as there are only 132 out-of-sample observations from 2010 to 2020.

in Section 3.1. When running regressions, we control for the contemporaneous local stock market returns and the U.S. stock market returns suggested by Rapach, Strauss, and Zhou (2013).

[Insert Table 5]

Table 5 shows consistent evidence that ACIB is not only related to future U.S. stock market 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 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 as documented by Baker, Wurgler, and Yuan (2012) and further suggests that ACIB can be used as an index to measure global sentiment.

4 ACIB as a Proxy for Investor Sentiment

4.1 Decomposition of Equity Option Trading Activities

So far we have provided sufficient empirical evidence to show that ACIB is a strong sentiment signal to future stock market returns. In this subsection, we provide further evidence that ACIB can be a proxy for investor sentiment, especially for retail investors, by separating equity option trading activities based on their trading size, option moneyness, and option time to maturity. 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.

With respect to option moneyness, which is defined as an option's strike price over its underlying stock's spot price, we separate options into out-of-the-money (OTM), at-the-money (ATM), and in-the-money (ITM). OTM options are classified as moneyness less (greater) than 0.9 (1.1) for put (call) options, ITM options are options with moneyness greater (less) than 1.1 (0.9) for put (call) options, and ATM options are options for the rest cases. As to option time to maturity, we separate option trading into three groups: short, middle, and long horizons. The short horizon group is defined as options traded less than 15 days to maturity, the middle horizon group includes options traded between 15 and 60 days to maturity, and the long horizon group covers options traded greater than 60 days to maturity. Note that each time when constructing sub-group ACIB or APIB, we classify options by only one feature (i.e., trading size, moneyness, or time to maturity), in order to concentrate on one-dimension analysis for its effect on stock market predictability.

[**Insert Table 6**]

Table 6 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. Given that trading size is widely used to identify retail and professional investors (Hvidkjaer (2008) and Barber, Odean, and Zhu (2008)), the main predictive power of ACIB coming from small trading size is consistent with the sentiment explanation that retail investors are more likely affected by market sentiment.[13]

In addition to this, Table 6 Panel B also shows that among options with different mon-

[13] As stated by Ge, Lin, and Pearson (2016), professional investors are likely to slice the trading but less subject to sentiment effect. Thus trading size is only an indicative way to identify trading by retail investors. We will conduct further tests to identify retail trading.

eyness, 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 options is ITM ACIB, while the worst performed ACIB is constructed using OTM options. Using O/S ratio, Ge, Lin, and Pearson (2016) find that informed trading of equity options mainly concentrates among OTM call options. Thus our finding is more consistent with sentiment trading instead of informed trading. It is worth noting that APIB does not help to forecast stock market returns among any option groups, implying that equity put option trading is less likely driven by sentiment motivation. Note that from Table 6 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. In summary, by computing ACIB and APIB based on various groups, we provide further supporting evidence that the predictive power of ACIB mainly comes from investor sentiment, especially from retail investors.

4.2 Different Types and Exchanges of Equity Option Traders

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 for brokers or dealers which are either options clearing corporation (OCC) members or any affiliations for clearing purposes.[14] Customers are trading accounts for public investors, which are the main trading activities we used to construct ACIB in our paper. Professional customers are trading accounts classified as professional investors by brokerage firms. Taking advantage of this classification, we construct IB based on customers,

[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.

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

While we only use 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 and APIB. The empirical results are available in Table 7 Panel C. In addition to this, since our data only covers option trading activities 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 Nasdaq International Securities Exchange (ISE), which is widely used in many other papers in the literature such as Ge, Lin, and Pearson (2016), Chordia et al. (2021), and Ni et al. (2021). The results are provided in Table 7 Panel D.

[Insert Table 7]

Table 7 displays the predictive power of ACIB and APIB based on the order flows executed by different types of traders and alternative data sources. The results are consistent with our conclusion that the predictive power of ACIB is mainly driven by retail investors' trading activities. If we construct ACIB (APIB) using professional customers' order flows, we do not see any predictive power of ACIB (APIB). The similar evidence is found for order flows from market makers. Note that ATM ACIB from market makers has positive signs to forecast stock market returns, which is mechanically driven by taking counter-party positions of public customers, therefore still reflecting sentiment effect instead of informed trading.

Table 7 Panel C shows that the closing position trading activities have some predictive power, although the results are not as strong as opening positions.[15] As discussed in Pan and

[15] Note that the positive signs of ACIB from the closing positions of option orders do not contradict our

Poteshman (2006) and Ge, Lin, and Pearson (2016), the closing position trading activities mainly involve the closing of previously established long positions; thus they could be less informative to the current market status, either fundamentals or sentiment.

Similarly, Table 7 Panel D demonstrates that our finding is not driven by exchange specification, as we obtain similar stock market 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 both ISE and CBOE cover a significant proportion of total option trading activities, the results are largely consistent with each other. In summary, as falsification tests, we demonstrate in this subsection that the predictive power of ACIB is more likely driven by sentiment trading and is persistent across different option exchanges.

4.3 Option to Stock Volume (O/S) Ratio

In Section 2, we discussed the motivations and reasons why we choose IB as the main predictor. Another popular variable of option trading volume is O/S ratio used by Roll, Schwartz, and Subrahmanyam (2010), Johnson and So (2012), and Ge, Lin, and Pearson (2016). In this subsection, 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 O/S ratio is that it can separate the effect between buy and sell trading activities, so that we can examine further 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),

main findings, because closing buy activities defined by CBOE are equivalent to selling owned call options to close the existing positions (https://www.nasdaq.com/articles/buy-to-open-vs.-buy-to-close:-investment-guide).

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 8.

[Insert Table 8]

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.[16] Put option trading still does not provide any useful information of future stock market returns. A new finding based on O/S ratio is that net buying call options are more informative to future stock returns than net selling call options. Among all different predictive regressions separated by option moneyness, the magnitude of t statistics for net buying call options (i.e., ACOB/S) is larger and more stable than net 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.

4.4 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

[16]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.

separating the sample period into two regimes based on high and low sentiment, namely below and above average (i.e., the median of time-series sentiment level). 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. To identify the high and low sentiment status (particularly related to option investors' sentiment), we use the SEP sentiment index to identify the different regimes. If ACIB reflects sentiment, we should observe stronger return predictability in the high regime of the SEP sentiment level (i.e., retail investors are more optimistic) and no return predictability in the low regime. Table 9 Panel A confirms this finding that stock market returns appear predictable by ACIB only when the level of SEP sentiment is above the median.

[Insert Table 9]

Second, most equity option traders have an incentive to bet against firms' earnings announcements. Therefore, the sentiment trading of equity options should be more salient 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 announcement data from Compustat and identify each firm's quarterly earnings announcement date. On a certain day, we calculate the proportion of firms with earnings announcements out of the total public firms in the United States. The time-series proportions of firms with earnings announcements displayed in Figure 2 are then used as a proxy for the intensity of sentiment trading by option traders on that day. Lastly, we separate the sample days 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. Our regression results in Table 9 Panel B confirm this hypothesis.

[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.

[Insert Figure 2]

Since we aim at forecasting aggregate stock returns of the whole stock market, options trading coverage on the underlying stocks can also play an important role in determining the predictive power of ACIB. When options trading coverage is lower, namely fewer stocks with available options trading, ACIB will not be able to stand for the whole market status, therefore not functioning well as a sentiment indicator. Motivated by this, we construct a time-series variable as a proxy for option trading coverage, which is defined as the total number of stocks with available call option trading activities divided by the total number of stocks traded on exchanges in the United States. The time-series option trading coverage is displayed in Figure 2. One can see that equity option trading accounts for a relatively small portion of all available traded stocks. The average coverage ratio of option trading to stock trading is about 30%. However, the ratio significantly increases to more than 80% on average if we only look at the stocks belonging to the S&P 500 index members. Since the stock market returns in the U.S. are mainly driven by large-cap stocks, it is reasonable that ACIB can forecast the whole stock market returns, even if the total number of stocks with options trading only accounts for a small portion among all available traded stocks.

Similarly, we separate the time-series sample from 2005 to 2020 into two regimes: above and below the median of the level of option trading coverage. We then run daily, weekly, and monthly predictive regressions of stock market returns on ACIB and APIB within each regime. Table 9 Panel C shows a persistent pattern that the predictive power of ACIB is only significant when the options trading coverage is higher than the median level, while it totally loses significance when the options trading coverage is lower than the median. The effect of option trading coverage on predictive power of ACIB also demonstrates that it is less likely driven by some common systematic risks among equity option trading activities. Our results in Table 9 thus demonstrate that the predictive power of ACIB is more related to sentiment effect instead of risk premium or informed trading, which is not supposed to have such a predictive pattern.

5 Discussion

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

One may argue that our finding contradicts some previous studies such as Pan and Poteshman (2006), Johnson and So (2012), Hu (2014), and Ge, Lin, and Pearson (2016) that options trading volume conveys informed trading in the equity options market. In this subsection, we demonstrate that our results do not contradict but complement the previous findings that option trading activities not only convey informed trading but also reflect sentiment.

We first investigate the cross-sectional pattern of CIB (PIB) forecasting stock returns. Following Pan and Poteshman (2006) and Ge, Lin, and Pearson (2016), we focus on weekly return prediction. By the end of each week (i.e., Friday), we sort all stocks into quintiles based on either CIB or PIB. Within each quintile, we form a portfolio with equal-weighted stock positions, and hold for one, two, or three weeks. We compute the average stock returns over the corresponding non-overlapped holding period for each portfolio. Table 10 Panel A displays the investment performance for stock portfolio returns sorted by either CIB or PIB as well as the difference in returns between the top and bottom quintiles, namely the long-short portfolios. For $W > 1$ in Table 10 Panel A, the weekly portfolio returns are computed using the return of the corresponding weeks without overlaps. We also provide portfolio returns for the contemporaneous week (i.e., $W = 0$) when the portfolios are formed based on CIB or PIB.

[Insert Table 10]

Consistent with the informed trading mechanism documented in cross-sectional option studies, we find that IB is a strong cross-sectional predictor among individual stocks. A higher CIB (PIB), on average, forecasts a relatively higher (lower) future stock return, indicating informed trading among equity options. The long-short portfolio returns remain significant for up to two weeks. Pan and Poteshman (2006) document that the put-to-call volume ratio can negatively forecast stock returns the next day and week. Similarly, Ge, Lin, and Pearson (2016) decompose the O/S ratio and find that the predictive power of O/S ratio in cross-section mainly comes from buying and selling call options by informed traders. To the best of our knowledge, however, there are no papers documenting either call IB or put IB can forecast stock returns in cross section separately. Our empirical tests thus make a new contribution to the cross-sectional studies of the option literature as well.

So why do we observe the opposite pattern between cross-sectional (CS) and time-series (TS) results for equity option trading? Note that in Table 10 Panel A, although high CIBs generate higher stock returns in the next period cross-sectionally, the pattern is not the same if we look at it from a time-series perspective. Comparing the portfolio performance from $W = 0$ to $W = 1$, except for the portfolio with the highest CIB (i.e., Port 5), the rest portfolios show significant drop-offs of stock returns. In particular, the average returns of portfolio 1 to 4 drop from 0.362%, 0.616%, 0.600%, 0.471% at $W = 0$, to 0.190%, 0.220%, 0.234%, 0.293% at $W = 1$. In other words, while we observe high CIB portfolios outperform low CIB portfolios in the cross section, most CIB portfolio returns consistently show a return reversal pattern in the next period, indicating overbought or oversold activities of equity option trading at $W = 0$.

[**Insert Figure 3**]

Figure 3 illustrates the pattern described above. Following this logic, we might be able to explain the opposite pattern between the cross-sectional (CS) and time-series (TS) predictive power of CIB. The main reason comes from the different empirical designs between CS and TS analyses. The target for the CS test focuses on a long-short portfolio sorted by CIB, which computes the difference in future stock returns between the top portfolio and the bottom portfolio:

$$Long - Short\ Return = \frac{1}{M}\sum_{i\in Port\ 5}^{M} R_{i,t} - \frac{1}{M}\sum_{j\in Port\ 1}^{M} R_{j,t}. \tag{13}$$

The high minus low portfolio (i.e., positive news minus negative news, namely "Port 5-1" in Table 10) will largely keep the informed trading information in the cross section, although the sentiment effect will be offset, as it has the same sign for different levels of CIB. As a result, the stock return predictability by CIB will be more related to informed trading. On the other hand, when CIBs are aggregated to the market level, known as ACIB, the positive and negative news of individual firms largely cancel each other out. As a result, stock market returns are primarily influenced by systematic information such as sentiment. Specifically, since the sentiment effect has a consistent direction across different levels of CIB portfolios, sentiment information persists at the market level and, consequently, in ACIB. This leads to a negative relationship between ACIB and future stock market returns over time. In summary, our hypothesis predicts two main outcomes: first, ACIB not only negatively forecasts stock market returns but also negatively forecasts other portfolio-level stock returns that are influenced by market sentiment. Second, ACIB is not expected to predict the returns of CIB-sorted long-short portfolios, which are dominated by informed trading.

To test our hypothesis, we run predictive regressions of the portfolio returns sorted by CIB (PIB) on ACIB (APIB) at daily, weekly, and monthly frequency, and see whether there is a persistent sentiment pattern by ACIB across different portfolios. The results are provided in Table 10 Panel B. In the last row of Table 10 Panel B, we also run regressions of the long-short portfolio returns (i.e., "Port 5-1") sorted by CIB (PIB) on ACIB (APIB). The regression results are consistent with our predictions that although higher CIBs lead to higher stock returns in the cross section, all the CIB portfolios show a strong return reversal pattern in time series, as their returns can be negatively predicted by ACIB, indicating a general sentiment effect across individual call options. On the contrary, ACIB has no predictive power on the long-short portfolio spread (i.e., "Port 5-1" in Table 10 Panel B), which can be treated as a proxy for portfolio returns dominated by informed trading.

It is worth noting that although PIB has predictive power in the cross section, APIB does not forecast either stock market returns or portfolio-level stock returns in time series. The finding is consistent with our explanation based on Figure 3 and Table 10 Panel A that the sentiment effect of PIB does not have the same sign across different levels of PIB. From $W = 0$ to $W = 1$, PIB portfolios within the top and the fourth bins present return reversal, while PIB portfolios from the bottom to the third bins display return momentum. Therefore, when PIBs are aggregated across portfolios, there is no consistent sentiment effect reserved like ACIB.

In summary, we argue the reason why TS and CS analyses generate different outcomes of CIB forecasting stock returns is because the CS analysis (i.e. the high-minus-low portfolio spread) reflects informed trading across equity options while the TS analysis (i.e., ACIB) echoes investor sentiment. Our time-series results do not reject the conclusion of informed trading that has been widely documented in the option literature, but highlight the different information sets among equity options trading activities.

5.2 Stock Market Return Predictability by Index Options

So far, we focus on equity option trading activities. In this subsection, we conduct a similar analysis for index option trading activities. Compared with equity options trading, index options trading is well-studied in the literature. For example, Chen, Joslin, and Ni (2019) use deep out-of-the-money index put options to construct an order imbalance variable PNBO and find it negatively forecasts stock market returns. Similarly, Chordia et al. (2021) conduct a detailed analysis on stock market return predictability using index options. They examine both index put and index call option IB to forecast stock market returns and find that only index put IB has predictive power for S&P 500 index returns at the weekly frequency. However, to the best of our knowledge, there are no papers documenting index call option trading activities forecasting stock market returns.

In this subsection, we conduct a comprehensive study across all available index options in our database. Besides those index options used by Chen, Joslin, and Ni (2019) and Chordia et al. (2021), we choose seven 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), CBOE Mini-NDX index option (MNX), S&P 500 index option (SPX), S&P 100 index option (OEX), and CBOE VIX option (VIX). For each index option, we construct the corresponding index IB for call and put options, namely ICIB and IPIB. To examine the predictive power of index options in detail, following our previous settings, we further group index options by three categories of option moneyness: ITM (moneyness greater than 1.1 for put and less than 0.9 for call), OTM (moneyness less than 0.9 for put and greater than 1.1 for call), and ATM (otherwise). Within each group of moneyness, we compute the IB for index call and put options separately. We then run predictive regressions of stock market excess returns (MKTRF) on various index call and put IBs. The results are provided in Table 11.

[Insert Table 11]

The general conclusion is that the predictive power of index IB is sensitive to option moneyness and also index types. For example, consistent with Chordia et al. (2021), we find that the IPIBs of RUT and DJX from index put options have significant predictive power to MKTRF at the weekly frequency, although the forecasting capacity concentrates on ATM options. Similar to Chordia et al. (2021), the ICIBs of RUT and DJX from index call options do not help forecast stock returns at any horizon. However, the results are different for OEX options. The ICIBs of OEX from both OTM and ATM index call options have significant and negative predictive power, whereas the IPIBs of OEX from index put options show no forecasting capacity at any horizon. More importantly, among all index call options, no matter significant or insignificant, ICIB shows a consistently negative correlation with future stock market returns, suggesting sentiment trading.

In an untabulated table, we run multiple predictive regressions by including both index IB and aggregate equity option IB as predictors for each index option. We find that the predictive power of ACIB survives in all cases, implying that our findings cannot be explained by index option trading activities. More importantly, we link our finding of ACIB to market sentiment effect, which is not documented by index option trading in the literature. Given index options are mostly traded by institutional investors for risk management while equity options are used by retail investors for speculation (Bollen and Whaley (2004) and Bryzgalova, Pavlova, and Sikorskaya (2023)), our results are consistent with other option studies in the literature and further document the crucial impact of equity call options on the market risk premium in aggregate.

5.3 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 to 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 (2023). We then run a similar predictive regression as in Section 3.1:

$$\sum_{k=1}^{K} \frac{\sigma_{t+k}}{K} \equiv \sigma_{t,t+K} = a + b \times X_t + \epsilon_{t,t+K}, \tag{14}$$

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, specified by days (D), weeks (W), and months (M). We then run the predictive regressions with K equal to 1, 2, and 3 days/weeks/months. When $K > 1$, we correct the serial correlation and conditional heteroscedasticity using the Newey-West correction with $K-1$ lags (Newey and West (1987)). When running regressions, all independent variables are scaled to have 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 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.[18] The regression results are presented in Table 12.

[Insert Table 12]

One can clearly see that although APIB does not forecast stock market returns, it has significant incremental explanatory power on both future stock market volatility and future aggregate firm-level volatility up to two weeks. 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 not show any forecasting capacity on stock volatility this time. Our empirical result thus indicates a

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

significant difference in trading motivations between equity call and equity put options.

6 Conclusion

Previous studies find equity option trading activities are related to informed trading of their underlying stocks. Applying a time-series analysis, we show that equity options trading in the aggregate is also related to investors' sentiment, especially by retail options traders. We find that aggregate equity call option order imbalance (ACIB), defined as the cross-sectional average order imbalance of equity call options, predicts significantly and negatively future stock market returns. Its predictive power cannot be explained by existing return predictors and is significant both in-sample and out-of-sample. Our findings are consistent with many recent studies on retail option trading activities (e.g., Bryzgalova, Pavlova, and Sikorskaya (2023) and Henderson, Pearson, and Wang (2023)) and further show their impact on market risk premium.

We find ACIB is closely related to investor sentiment. Further evidence demonstrates that the predictive power of ACIB is mainly driven by the sentiment effect that option traders overbuy options, therefore functioning as contrarian signals to future stock market returns. We observe similar evidence using index call options, although it is much weaker. Furthermore, ACIB can also forecast international stock market returns, suggesting it can be used as a global sentiment index. Our findings complement existing cross-sectional studies that equity option trading is not only related to informed trading, but also reflects investors' sentiment trading from a time-series perspective. Our study also highlights different trading motivations between equity call and put options, and shows the important role of retail option trading on investor sentiment and on the market risk premium.

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Table 1

Summary Statistics of Equity Option Trading Activities

Table 1 reports the descriptive statistics. Panel A provides the summary statistics of ACIB and APIB at various frequencies specified in parentheses. Panel B provides the Pearson correlations of ACIB and APIB with the selected variables. "STD" is short for standard deviation of each time-series variable. In Panel B, BW sentiment, SEP sentiment, PLS sentiment, GM sentiment, Manager sentiment, and Michigan sentiments are based on Baker and Wurgler (2007), Henderson, Pearson, and Wang (2023), Huang et al. (2015), Gao and Martin (2021), Jiang et al. (2019), and University of Michigan consumer survey data, respectively.

Panel A. Summary Statistics

						Autocorrelation at Lag (Number of Days/Weeks/Months)			
Variable	# of Firm	Mean	Median	STD	Skewness	1	2	3	4
ACIB (Daily)	1395	−0.16	−0.15	0.14	−0.08	0.78	0.68	0.63	0.60
ACIB (Weekly)	2053	−0.14	−0.14	0.13	−0.07	0.72	0.56	0.54	0.63
ACIB(Monthly)	2525	−0.11	−0.10	0.10	−0.09	0.79	0.65	0.58	0.51
APIB (Daily)	1054	−0.20	−0.21	0.12	0.33	0.80	0.72	0.69	0.69
APIB (Weekly)	1718	−0.17	−0.18	0.11	0.37	0.81	0.73	0.69	0.73
APIB (Monthly)	1718	−0.12	−0.14	0.10	0.47	0.86	0.81	0.78	0.74

Panel B. Pearson Correlation Matrix (Monthly)

Variable	APIB	MKTRF	VIX	BW Sentiment	SEP Sentiment	Michigan Sentiment	PLS Sentiment	GM Sentiment	Manager Sentiment
ACIB	0.43	−0.04	−0.28	0.50	0.33	0.24	−0.24	0.55	0.19
APIB		−0.22	0.14	0.41	0.15	−0.03	−0.32	0.62	0.27
MKTRF			−0.42	−0.06	0.06	0.01	0.00	−0.17	−0.13
VIX				−0.28	0.00	−0.59	0.48	0.05	0.07
BW Sentiment					0.24	0.35	−0.40	0.51	0.29
SEP Sentiment						−0.40	0.08	0.24	0.17
Michigan Sentiment							−0.47	0.04	−0.05
PLS Sentiment								−0.34	−0.36
GM Sentiment									0.43

Table 2

In-sample Predictability of ACIB and APIB

Table 2 reports the results of univariate and bivariate predictive time-series regressions. The dependent variables are the daily (D), weekly (W), and monthly (M) excess returns in the logarithm of the value-weighted market portfolio (MKTRF) over the relevant forecast horizons. All dependent variables are expressed at monthly frequency. All predictors are normalized to have zero mean and one standard deviation. $D/W/M$ represents the forecast horizon in the number of days/weeks/months. "b" is the slope coefficient on the predictor and is expressed as a percentage of the raw value (multiplied by 100). When $D/W/M > 1$, to adjust for the overlapping dependent variable, the t-stat is computed using the GMM standard errors with $D/W/M - 1$ Newey-West lag correction.

Forecast Horizon		I	II	III	I	II	III	I	II	III
Predictor	Coefficient		D=1			D=3			D=6	
ACIB	b	−1.659		−1.831	−1.176		−1.217	−1.092		−1.091
	t-stat	(−3.36)		(−2.78)	(−3.58)		(−2.87)	(−3.86)		(−3.09)
APIB	b		−0.331	0.401		−0.391	0.096		−0.439	−0.003
	t-stat		(−0.60)	(0.56)		(−0.99)	(0.20)		(−1.18)	(−0.01)
	R^2 (%)	1.92	1.60	1.91	0.93	0.40	0.91	1.88	0.96	1.85
Predictor	Coefficient		W=1			W=2			W=3	
ACIB	b	−0.958		−0.844	−0.863		−0.747	−0.892		−0.804
	t-stat	(−2.69)		(−1.67)	(−3.21)		(−1.95)	(−3.58)		(−2.37)
APIB	b		−0.627	−0.244		−0.587	−0.248		−0.553	−0.188
	t-stat		(−1.43)	(−0.42)		(−1.68)	(−0.54)		(−1.54)	(−0.42)
	R^2 (%)	0.92	0.45	0.85	1.24	0.47	1.22	2.15	0.78	2.12
Predictor	Coefficient		M=1			M=2			M=3	
ACIB	b	−0.945		−0.949	−0.822		−0.779	−0.772		−0.701
	t-stat	(−2.89)		(−2.42)	(−3.28)		(−2.35)	(−3.63)		(−2.47)
APIB	b		−0.413	0.010		−0.447	−0.099		−0.481	−0.168
	t-stat		(−1.27)	(0.03)		(−1.44)	(−0.26)		(−1.56)	(−0.45)
	R^2 (%)	4.11	0.37	3.59	5.36	0.75	4.92	7.92	2.33	7.75

Table 3

Comparison with Existing Predictors

Table 3 reports the results of multiple predictive regressions. Each column in this table corresponds to one multiple predictive regression, labeled 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 returns (MKTRF) over the relevant forecast horizon. All dependent variables are expressed at monthly frequency, and all predictors are normalized to have zero mean and one standard deviation. "b" is the slope coefficient on the predictor and expressed as percentage of the raw value (multiplied by 100). When $D/W/M > 1$, the t-stat is computed using the GMM standard errors with $D/W/M-1$ Newey-West lag correction. The sample period is from 2005 to 2020.

Predictor	Coefficient	D=1	D=3	W=1	W=2	M=1	M=2
ACIB	b	−2.298	−1.423	−1.230	−1.000	−1.140	−0.810
	t-stat	(−3.29)	(−3.28)	(−2.35)	(−2.60)	(−2.78)	(−2.56)
APIB	b	0.979	0.443	0.680	0.223	0.997	0.755
	t-stat	(1.34)	(0.94)	(1.21)	(0.56)	(2.00)	(1.78)
ICIB	b	−0.340	−0.219	−0.259	−0.321	0.673	0.068
	t-stat	(−0.74)	(−0.79)	(−0.74)	(−1.35)	(1.60)	(0.21)
IPIB	b	0.155	0.632	0.807	0.302	−0.010	−0.031
	t-stat	(0.37)	(2.46)	(2.39)	(1.33)	(−0.03)	(−0.12)
GW PCA	b					−1.627	−0.307
	t-stat					(−2.72)	(−0.87)
SEP Sentiment	b					0.220	0.382
	t-stat					(0.69)	(1.57)
BW Sentiment	b					−1.028	−0.565
	t-stat					(−2.00)	(−1.23)
GM Sentiment	b					−0.522	−0.327
	t-stat					(−1.25)	(−0.80)
Manager Sentiment	b					−0.222	−0.346
	t-stat					(−0.69)	(−1.14)
Michigan Sentiment	b					0.278	0.589
	t-stat					(0.59)	(1.43)
PLS Sentiment	b					−0.962	−0.531
	t-stat					(−1.72)	(−1.08)
VRP	b	0.492	0.239	1.533	−0.061	2.039	0.868
	t-stat	(0.54)	(0.39)	(2.04)	(−0.17)	(5.07)	(2.05)
IVS	b	3.257	1.668	1.168	1.290	−0.205	0.228
	t-stat	(2.87)	(2.62)	(1.69)	(3.28)	(−0.55)	(0.74)
PNBO	b					−0.725	−0.403
	t-stat					(−3.22)	(−2.18)
HLW Disagreement	b					−0.506	−0.803
	t-stat					(−1.28)	(−2.31)
	R^2 (%)	3.09	2.15	4.97	4.57	27.06	21.32

Table 4

Out-of-sample Predictability

For out-of-sample tests in Table 4, we split the data sample into two parts: 2005 to 2009 as the in-sample estimation period and 2010 to 2020 as the out-of-sample performance evaluation period. The forecast target is the market excess returns (MKTRF) at daily (D), weekly (W), and monthly frequency (M). The out-of-sample R^2 statistic and the certainty equivalent return (CER) are specified in Section 3. The z-stat is computed based on Clark and West (2007). We reject the null hypothesis if the z-stat is greater than 1.282 (for a one-sided test at 10% confidence), 1.645 (for a one-sided test at 5% confidence), or 2.334 (for a one-sided test at 1% confidence). Benchmark is the buy-and-hold strategy for the market portfolio.

Panel A. Out-of-sample R^2				
2010 to 2020	Coefficient	D=1	D=3	D=6
ACIB	R^2 (%)	2.225	0.672	1.964
	z-stat	(2.55)	(2.63)	(3.70)
2010 to 2020	Coefficient	W=1	W=2	W=3
ACIB	R^2 (%)	0.756	1.757	2.308
	z-stat	(1.93)	(2.65)	(2.84)
2010 to 2020	Coefficient	M=1	M=2	M=3
ACIB	R^2 (%)	6.114	9.833	13.725
	z-stat	(2.84)	(3.11)	(2.85)
Panel B. Sharpe Ratio and CER Gain				
2010 to 2020	Coefficient	D=1	D=3	D=6
ACIB	CER Gain (%)	0.372	0.086	0.168
	Sharpe Ratio	0.212	0.163	0.184
Benchmark	Sharpe Ratio	0.147	0.155	0.156
2010 to 2020	Coefficient	W=1	W=2	W=3
ACIB	CER Gain (%)	1.385	0.217	0.147
	Sharpe Ratio	0.394	0.276	0.255
Benchmark	Sharpe Ratio	0.252	0.258	0.232
2010 to 2020	Coefficient	M=1	M=2	M=3
ACIB	CER Gain (%)	10.416	11.114	6.329
	Sharpe Ratio	1.360	1.431	1.371
Benchmark	Sharpe Ratio	0.725	0.687	0.801

Table 5

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 Panel A, B, and C. The definition of all the predictors can be found in Section 3.1. The dependent variable is the average daily/weekly/monthly stock market returns 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. All dependent variables are expressed at monthly frequency. 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. "b" is the slope coefficient on the predictor and expressed as a percentage of the raw value (multiplied by 100). When $D/W/M > 1$, the t-stat is computed using the GMM standard errors with $D/W/M-1$ Newey-West lag correction. The sample period is from 2005 to 2020.

		Australia	Canada	Finland	France	Germany	Hong Kong	Italy	Japan	Netherlands	New Zealand	Spain	Sweden	Switzerland	UK
Predictor	Coefficient	ASX All-Ordinaries	TSX 300 Composite	OMX All-Share Price Index	CAC All-Tradable Index	CDAX Composite Index	Hang Seng Composite Index	Banca Commerciale Italiana Index	Nikkei 500 Index	All-Share Price Index	NZX All-Share Capital Index	Madrid SE General Index	OMX All-Share Price Index	Switzerland Price Index	FTSE All-Share Index
Panel A. Time-series Return Predictability (D=3)															
ACIB	b	−0.860	−0.887	−1.321	−1.422	−1.411	−1.869	−1.072	−1.422	−1.432	−0.455	−0.860	−1.600	−0.901	−1.161
	t−stat	(−2.34)	(−2.16)	(−2.70)	(−2.93)	(−2.83)	(−3.28)	(−2.07)	(−2.78)	(−3.10)	(−1.73)	(−1.51)	(−3.25)	(−2.30)	(−2.78)
APIB	b	−0.292	−0.039	−0.331	−0.089	−0.230	1.010	−0.531	−0.644	−0.272	−0.650	0.125	−0.001	0.045	0.018
	t−stat	(−0.72)	(−0.08)	(−0.64)	(−0.18)	(−0.44)	(1.68)	(−1.06)	(−1.15)	(−0.54)	(−2.40)	(0.22)	(−0.00)	(0.10)	(0.04)
	R^2 (%)	11.05	1.01	2.19	3.07	2.18	7.74	5.93	9.75	3.24	6.10	1.14	2.83	2.93	3.41
Panel B. Time-series Return Predictability (W=1)															
ACIB	b	−0.782	−0.702	−1.234	−1.429	−1.261	−1.442	−1.147	−1.204	−1.369	−0.828	−1.373	−1.734	−1.169	−1.441
	t−stat	(−1.55)	(−1.23)	(−1.99)	(−2.30)	(−1.96)	(−2.53)	(−1.72)	(−2.13)	(−2.22)	(−2.10)	(−2.14)	(−2.87)	(−2.21)	(−2.61)
APIB	b	−0.167	−0.299	−0.284	−0.147	−0.260	0.537	−0.399	−0.531	−0.346	−0.543	0.315	−0.026	−0.134	−0.031
	t−stat	(−0.34)	(−0.53)	(−0.46)	(−0.23)	(−0.39)	(0.91)	(−0.64)	(−0.98)	(−0.52)	(−1.61)	(0.49)	(−0.04)	(−0.24)	(−0.06)
	R^2 (%)	2.27	0.29	0.86	1.39	0.96	2.20	1.75	1.85	1.34	4.61	1.08	2.58	3.83	1.84
Panel C. Time-series Return Predictability (M=1)															
ACIB	b	−0.807	−0.758	−1.060	−1.236	−1.358	−1.092	−0.802	−1.019	−1.286	−0.736	−1.083	−1.216	−0.399	−1.141
	t−stat	(−2.10)	(−2.22)	(−2.14)	(−2.82)	(−2.79)	(−2.34)	(−1.59)	(−2.67)	(−3.88)	(−2.54)	(−2.16)	(−3.09)	(−1.21)	(−3.57)
APIB	b	0.397	0.230	0.454	0.432	0.662	0.696	0.357	0.123	0.427	0.123	0.712	0.430	0.072	0.433
	t−stat	(1.17)	(0.59)	(0.95)	(1.13)	(1.54)	(1.22)	(0.74)	(0.26)	(1.11)	(0.51)	(1.57)	(1.05)	(0.23)	(1.33)
	R^2 (%)	3.95	2.89	4.07	4.61	5.49	1.19	0.72	5.56	6.54	5.87	1.48	4.01	1.26	5.56

Table 6

Decomposition of Equity Option Trading Activities

In Panel A, we separate the sample by the trading size specified in CBOE as small, medium, and large orders. Within each type, we aggregate all available option IBs using a market value-weighted scheme. In Panel B, we group the data by moneyness, defined as the strike 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), and at-the-money (ATM) options for the rest cases. In Panel C, we repeat a similar process but separate the data by time to maturity. The short horizon group includes options less than 15 days to maturity, the middle horizon group covers options between 15 and 60 days to maturity, and the long horizon group contains options greater than 60 days to maturity. The different types of ACIB and APIB are used to forecast market excess returns at the daily frequency (D). The t-stat is computed using the GMM standard errors with $D-1$ Newey-West lag correction. The sample period is from 2005 to 2020.

Panel A. Different Trading Order Size

		Small			Medium			Large		
Predictor	Coefficient	D=1	D=3	D=6	D=1	D=3	D=6	D=1	D=3	D=6
ACIB	b	−1.882	−1.156	−1.084	−0.732	−0.471	−0.625	−0.188	−0.190	−0.333
	t-stat	(−3.01)	(−2.84)	(−3.24)	(−1.47)	(−1.51)	(−2.60)	(−0.39)	(−0.64)	(−1.51)
APIB	b	0.437	0.012	0.016	−0.027	−0.401	−0.250	−0.332	−0.002	−0.090
	t-stat	(0.64)	(0.03)	(0.04)	(−0.06)	(−1.51)	(−1.05)	(−0.73)	(−0.01)	(−0.37)
	R^2 (%)	1.95	0.88	1.81	1.64	0.50	1.23	1.59	0.32	0.87

Panel B. Different Moneyness

		OTM			ATM			ITM		
Predictor	Coefficient	D=1	D=3	D=6	D=1	D=3	D=6	D=1	D=3	D=6
ACIB	b	−0.656	−0.470	−0.561	−1.660	−1.042	−1.067	−1.159	−0.974	−0.844
	t-stat	(−1.04)	(−1.09)	(−1.56)	(−2.76)	(−2.65)	(−3.29)	(−2.00)	(−2.67)	(−2.80)
APIB	b	−0.591	−0.382	−0.425	0.228	−0.028	0.028	−0.059	−0.136	−0.233
	t-stat	(−1.37)	(−1.24)	(−1.41)	(0.33)	(−0.06)	(0.06)	(−0.10)	(−0.31)	(−0.61)
	R^2 (%)	1.64	0.43	1.10	1.88	0.78	1.76	1.74	0.78	1.61

Panel C. Different Time to Maturity

		Short			Middle			Long		
Predictor	Coefficient	D=1	D=3	D=6	D=1	D=3	D=6	D=1	D=3	D=6
ACIB	b	−0.901	−0.813	−0.590	−1.489	−1.149	−1.107	−1.375	−1.032	−0.952
	t-stat	(−1.89)	(−2.48)	(−2.13)	(−2.89)	(−3.22)	(−3.69)	(−2.70)	(−3.07)	(−3.17)
APIB	b	0.085	0.251	0.113	0.021	0.374	0.214	0.181	0.245	0.216
	t-stat	(0.25)	(1.05)	(0.67)	(0.04)	(1.49)	(1.01)	(0.51)	(1.22)	(1.42)
	R^2 (%)	1.74	0.60	0.91	1.84	0.85	1.82	1.79	0.76	1.56

Table 7

ACIB and APIB of Different Option Traders and Alternative Database

In Panel A, we use the market makers' trading volume to construct ACIB and APIB. Market makers are defined as combinations of firms, broker-dealers, and market makers classified by CBOE. In Panel B, we repeat a similar process but use professional customers' trading volume marked by CBOE. In Panel C, instead of using the CBOE opening trading data, we use the CBOE closing trading data to construct ACIB and APIB. In Panel D, 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 puts (calls), in-the-money (ITM) options are options with moneyness greater (less) than 1.1 for puts (calls), and at-the-money (ATM) options for the rest classifications. The different types of ACIB and APIB are used to forecast market excess returns at daily frequency (D). The t-stat is computed using the GMM standard errors with $D-1$ Newey-West lag correction. The sample period is from 2005 to 2020, except for Panel A and Panel B, which are only available since 2009.

Panel A. Market Makers

		OTM			ATM			ITM		
Predictor	Coefficient	D=1	D=3	D=6	D=1	D=3	D=6	D=1	D=3	D=6
ACIB	b	0.643	−0.215	−0.035	1.817	0.421	0.544	1.160	0.233	0.144
	t-stat	(1.23)	(−0.69)	(−0.15)	(2.60)	(1.04)	(1.73)	(1.72)	(0.56)	(0.40)
APIB	b	−0.321	−0.298	−0.205	−0.779	−0.010	−0.251	0.510	0.632	0.412
	t-stat	(−0.61)	(−0.89)	(−0.71)	(−1.25)	(−0.03)	(−0.78)	(1.10)	(2.00)	(1.66)
	R^2 (%)	1.82	0.19	0.59	2.15	0.21	0.81	1.97	0.37	0.75

Panel B. Professional Customers

		OTM			ATM			ITM		
Predictor	Coefficient	D=1	D=3	D=6	D=1	D=3	D=6	D=1	D=3	D=6
ACIB	b	0.505	0.407	0.221	0.368	0.269	0.302	0.403	0.114	0.140
	t-stat	(0.72)	(1.01)	(0.72)	(0.71)	(0.81)	(1.05)	(0.89)	(0.40)	(0.56)
APIB	b	0.635	0.070	−0.083	−0.574	−0.470	−0.098	−0.425	0.459	0.417
	t-stat	(0.98)	(0.17)	(−0.28)	(−1.03)	(−1.29)	(−0.29)	(−0.87)	(1.56)	(1.67)
	R^2 (%)	1.51	0.47	0.67	1.64	0.25	0.59	1.96	0.30	0.97

Panel C. Alternative Database Using CBOE Closing Trading Data

		OTM			ATM			ITM		
Predictor	Coefficient	D=1	D=3	D=6	D=1	D=3	D=6	D=1	D=3	D=6
ACIB	b	−0.358	0.165	0.180	0.319	0.766	0.751	0.372	0.678	0.690
	t-stat	(−0.70)	(0.49)	(0.63)	(0.62)	(2.44)	(2.89)	(0.82)	(2.04)	(2.39)
APIB	b	0.428	0.278	0.303	0.426	−0.200	−0.209	−0.190	−0.149	−0.069
	t-stat	(1.14)	(1.05)	(1.30)	(0.78)	(−0.59)	(−0.70)	(−0.31)	(−0.33)	(−0.17)
	R^2 (%)	1.61	0.35	0.86	1.61	0.54	1.24	1.59	0.52	1.22

Panel D. Alternative Database Using ISE

		OTM			ATM			ITM		
Predictor	Coefficient	D=1	D=3	D=6	D=1	D=3	D=6	D=1	D=3	D=6
ACIB	b	−0.384	−0.529	−0.569	−0.837	−0.828	−0.789	−1.128	−0.636	−0.591
	t-stat	(−0.80)	(−1.54)	(−1.90)	(−1.45)	(−2.13)	(−2.46)	(−2.52)	(−2.20)	(−2.40)
APIB	b	−0.401	−0.261	−0.303	−0.094	0.009	−0.117	0.367	−0.024	−0.079
	t-stat	(−0.76)	(−0.68)	(−0.83)	(−0.14)	(0.02)	(−0.27)	(0.96)	(−0.08)	(−0.31)
	R^2 (%)	1.64	0.48	1.18	1.70	0.61	1.43	1.75	0.49	1.10

Table 8

O/S Ratio 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 ratio to the market level by market value-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 multiple predictive regressions for the O/S ratios within each group at the daily frequency. The dependent variable is the excess daily (D) returns in the logarithm of the value-weighted market portfolio (MKTRF) over the relevant forecast horizons. All dependent variables are expressed at monthly frequency. The results are displayed by grouping options into different moneyness. The t-stat is computed using the GMM standard errors with $D-1$ Newey-West lag correction. The sample period is from 2005 to 2020.

Panel A. Out-of-the-money Options (OTM)

Predictor	Coefficient		D=1			D=3			D=6	
ACOB/S	b	−1.752		−1.653	−1.004		−0.951	−1.175		−1.215
	t-stat	(−2.40)		(−1.71)	(−1.56)		(−1.21)	(−1.95)		(−1.72)
ACOS/S	b	1.385		1.445	0.690		0.677	0.959		0.911
	t-stat	(2.00)		(2.00)	(1.24)		(1.19)	(2.07)		(1.93)
APOB/S	b		−0.389	−0.146		−0.364	−0.101		−0.264	0.044
	t-stat		(−1.04)	(−0.16)		(−1.13)	(−0.16)		(−0.86)	(0.08)
APOS/S	b		−0.034	−0.075		0.121	0.116		0.134	0.122
	t-stat		(−0.08)	(−0.17)		(0.35)	(0.34)		(0.40)	(0.37)
	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)

Predictor	Coefficient		D=1			D=3			D=6	
ACOB/S	b	−1.262		−1.480	−1.244		−1.537	−1.182		−1.268
	t-stat	(−1.84)		(−2.12)	(−2.48)		(−2.95)	(−2.68)		(−2.81)
ACOS/S	b	0.616		0.209	0.675		0.245	0.666		0.413
	t-stat	(0.98)		(0.27)	(1.47)		(0.45)	(1.70)		(0.90)
APOB/S	b		−0.991	−0.598		−0.756	−0.352		−0.884	−0.587
	t-stat		(−1.55)	(−0.90)		(−1.62)	(−0.73)		(−2.19)	(−1.43)
APOS/S	b		0.445	1.181		0.336	1.080		0.393	0.860
	t-stat		(0.69)	(1.57)		(0.70)	(1.98)		(0.91)	(1.76)
	R^2 (%)	1.67	1.64	1.68	0.66	0.46	0.76	1.42	1.20	1.66

Panel C. In-the-money Options (ITM)

Predictor	Coefficient		D=1			D=3			D=6	
ACOB/S	b	−1.195		−0.938	−1.236		−1.128	−1.199		−1.052
	t-stat	(−1.59)		(−1.07)	(−2.22)		(−1.75)	(−2.44)		(−1.83)
ACOS/S	b	0.811		0.941	0.879		0.972	0.835		0.880
	t-stat	(0.88)		(0.87)	(1.27)		(1.23)	(1.41)		(1.28)
APOB/S	b		−0.699	−0.486		−0.568	−0.209		−0.624	−0.272
	t-stat		(−1.52)	(−0.77)		(−1.61)	(−0.41)		(−1.86)	(−0.58)
APOS/S	b		0.277	0.019		0.234	−0.064		0.337	0.062
	t-stat		(0.49)	(0.03)		(0.53)	(−0.13)		(0.87)	(0.14)
	R^2 (%)	1.64	1.61	1.61	0.60	0.40	0.56	1.34	0.98	1.31

Table 9

Predictive Power of ACIB in Different Regimes

In Table 9 Panel A, the sample days from 2005 to 2020 are separated into two regimes: above and below the median of the level of the SEP sentiment index by Henderson, Pearson, and Wang (2023). We run daily, weekly, and monthly predictive regressions of stock market excess returns (MKTRF) on ACIB and APIB within each regime. We conduct a similar test in Panel B, except that the separation is based on the proportion of firms with earnings announcements out of total public firms over time. A higher proportion indicates higher sentiment periods over time. In Panel C, we use the option trading coverage, which is defined as the number of stocks with call option trading divided by the number of available trading stocks, to separate regimes of the sample. "$D/W/M$" stands for the forecast time horizon in a number of days/weeks/months. "b" is the slope coefficient on the predictor and is expressed as a percentage of the raw value (multiplied by 100). The t-stat is computed using the GMM standard errors with $D/W/M-1$ Newey-West lag correction.

Panel A. ACIB Prediction Separated by SEP Sentiment									
2005 to 2020	Predictor	Coefficient	D=1	D=3	W=1	W=2	M=1	M=2
Regime of High SEP Sentiment	ACIB	b	−3.126	−1.491	−1.187	−1.172	−1.672	−1.188
		t-stat	(−4.02)	(−2.94)	(−1.87)	(−2.76)	(−3.41)	(−3.43)
	APIB	b	1.451	0.577	0.329	0.291	0.444	0.145
		t-stat	(2.13)	(1.31)	(0.64)	(0.75)	(1.07)	(0.36)
		R^2 (%)	4.09	1.18	1.06	1.88	8.42	9.76
Regime of Low SEP Sentiment	ACIB	b	−0.939	−0.910	−0.550	−0.529	−0.796	−0.723
		t-stat	(−1.02)	(−1.54)	(−0.82)	(−0.99)	(−1.47)	(−1.53)
	APIB	b	−0.270	−0.187	−0.671	−0.720	−0.182	−0.137
		t-stat	(−0.23)	(−0.23)	(−0.70)	(−0.94)	(−0.32)	(−0.26)
		R^2 (%)	2.19	0.58	0.33	1.24	2.14	2.63
Panel B. ACIB Prediction Separated by Firm Earnings Announcements									
2005 to 2020	Predictor	Coefficient	D=1	D=3	W=1	W=2	M=1	M=2
Regime of Many Earnings Announcements	ACIB	b	−3.297	−1.831	−1.632	−1.428	−1.147	−0.765
		t-stat	(−3.43)	(−3.25)	(−1.99)	(−2.66)	(−2.53)	(−2.25)
	APIB	b	1.495	0.652	0.916	0.711	0.697	0.012
		t-stat	(1.51)	(1.12)	(1.17)	(1.25)	(1.55)	(0.03)
		R^2 (%)	4.64	1.76	2.02	2.38	5.16	3.21
Regime of Few Earnings Announcements	ACIB	b	−0.059	−0.477	0.092	0.071	−0.688	−0.742
		t-stat	(−0.07)	(−0.82)	(0.16)	(0.14)	(−1.15)	(−1.57)
	APIB	b	−1.071	−0.553	−1.566	−1.447	−0.619	−0.232
		t-stat	(−1.07)	(−0.77)	(−1.95)	(−2.13)	(−0.95)	(−0.43)
		R^2 (%)	0.29	0.35	1.96	3.95	2.19	3.16
Panel C. ACIB Prediction Separated by Option Trading Coverage									
2005 to 2020	Predictor	Coefficient	D=1	D=3	W=1	W=2	M=1	M=2
Regime of High Coverage of Option Trading	ACIB	b	−3.565	−1.726	−0.759	−1.073	−0.969	−0.632
		t-stat	(−4.20)	(−3.38)	(−1.18)	(−2.74)	(−2.09)	(−2.04)
	APIB	b	1.929	0.460	0.185	0.186	0.291	0.350
		t-stat	(2.38)	(0.88)	(0.28)	(0.34)	(0.74)	(1.40)
		R^2 (%)	5.98	1.33	−0.07	1.81	3.46	5.19
Regime of Low Coverage of Option Trading	ACIB	b	−0.418	−0.678	−0.812	−0.395	−0.916	−0.891
		t-stat	(−0.43)	(−1.08)	(−1.08)	(−0.66)	(−1.47)	(−1.58)
	APIB	b	−0.603	−0.255	−0.782	−0.747	0.062	−0.112
		t-stat	(−0.55)	(−0.34)	(−0.86)	(−1.11)	(0.10)	(−0.19)
		R^2 (%)	0.26	0.70	1.36	1.04	2.93	3.85

Table 10

Cross-sectional and Time-series Comparison

In Panel A, we compare the time series of portfolio returns sorted by call IB (CIB) and put IB (PIB) over different time periods without overlaps at the weekly frequency. At the end of each week, we sort all stocks with feasible CIB (PIB) into quintiles based on the value of CIB (PIB). In Panel B, we first sort stocks based on CIB into quintiles at each specified frequency W. Within each portfolio, we compute the equal-weighted portfolio returns for the next specified period (e.g., $W = 1/2/3$). The dependent variable is the time-series portfolio returns for each sorted bin (Port 1 to Port 5), expressed at monthly frequency. The independent variable is the time series of ACIB or APIB. "W" stands for the forecast time horizon in number of days/weeks/months. The t-stat is computed using the GMM standard errors with $W-1$ Newey-West lag correction.

Panel A. Cross-sectional Portfolio Sorting based on Order Imbalance

	CIB				PIB			
Portfolio (%)	W=0	W=1	W=2	W=3	W=0	W=1	W=2	W=3
Port 1 (Bottom)	0.362	0.190	0.247	0.225	0.012	0.333	0.323	0.276
Port 2	0.616	0.220	0.239	0.247	−0.035	0.295	0.254	0.252
Port 3	0.600	0.234	0.249	0.248	0.176	0.257	0.230	0.255
Port 4	0.471	0.293	0.250	0.257	0.507	0.206	0.232	0.239
Port 5 (Top)	−0.066	0.365	0.298	0.298	0.633	0.153	0.212	0.216
Port 5-1	−0.428	0.176	0.052	0.074	0.621	−0.180	−0.111	−0.060
t-stat	(−12.86)	(6.30)	(1.91)	(2.88)	(22.28)	(−6.18)	(−3.93)	(−2.14)

Panel B. Time-series Prediction of Portfolio Returns Sorted by Order Imbalance

		ACIB				APIB		
Portfolio	Coefficient	W=1	W=2	W=3		W=1	W=2	W=3
CIB	b	−1.617	−1.348	−1.388	PIB	−0.622	−0.488	−0.353
Port 1	t-stat	(−3.28)	(−3.45)	(−3.97)	Port 1	(−0.97)	(−0.91)	(−0.68)
	R^2 (%)	1.27	2.02	2.73		0.10	0.17	−0.05
CIB	b	−1.591	−1.293	−1.342	PIB	−0.603	−0.500	−0.358
Port 2	t-stat	(−3.13)	(−3.12)	(−3.70)	Port 2	(−0.98)	(−0.99)	(−0.73)
	R^2 (%)	1.35	1.70	2.58		0.06	0.17	−0.03
CIB	b	−1.514	−1.235	−1.248	PIB	−0.599	−0.471	−0.353
Port 3	t-stat	(−2.84)	(−2.85)	(−3.32)	Port 3	(−0.98)	(−0.96)	(−0.74)
	R^2 (%)	1.22	1.38	2.12		0.29	0.03	0.08
CIB	b	−1.765	−1.466	−1.468	PIB	−0.542	−0.434	−0.298
Port 4	t-stat	(−3.19)	(−3.24)	(−3.72)	Port 4	(−0.93)	(−0.90)	(−0.63)
	R^2 (%)	1.47	1.83	2.76		0.26	0.07	−0.01
CIB	b	−1.693	−1.427	−1.407	PIB	−0.477	−0.369	−0.291
Port 5	t-stat	(−3.14)	(−3.20)	(−3.63)	Port 5	(−0.80)	(−0.76)	(−0.61)
	R^2 (%)	1.27	1.90	2.46		0.11	0.09	−0.07
CIB	b	−0.076	−0.078	−0.019	PIB	0.145	0.119	0.063
Port 5-1	t-stat	(−0.57)	(−0.64)	(−0.17)	Port 5-1	(1.14)	(1.13)	(0.65)
	R^2 (%)	0.22	−0.12	0.09		−0.04	0.07	−0.14

Table 11

Stock Market Return Predictability by Index Options

We examine the predictive power of index option order imbalance. We select seven index options actively traded at CBOE, which are specified in Section 5.2. We then run multiple predictive regressions for index IB at the daily frequency. The dependent variable is the excess daily (D) returns in the logarithm of the value-weighted market portfolio (MKTRF) over the relevant forecast horizon. 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 cases. "b" is the slope coefficient on the predictor and expressed as a percentage of the raw value (multiplied by 100). When $D > 1$, to adjust for the overlapping dependent variable, the t-stat is computed using the GMM standard errors with $D-1$ Newey-West lag correction. The sample period is from 2005 to 2020. "$-$" indicates insufficient observations.

			OTM			ATM			ITM		
Ticker	Predictor	Coefficient	D=1	D=3	D=6	D=1	D=3	D=6	D=1	D=3	D=6
RUT	ICIB	b	2.403	0.673	0.052	−0.049	0.090	−0.040	0.120	−0.105	0.066
		t-stat	(1.85)	(0.89)	(0.08)	(−0.10)	(0.35)	(−0.19)	(0.29)	(−0.42)	(0.29)
	IPIB	b	−0.275	−0.182	−0.324	0.269	0.409	0.296	−0.643	−0.128	−0.212
		t-stat	(−0.27)	(−0.29)	(−0.64)	(0.57)	(1.60)	(1.47)	(−1.55)	(−0.54)	(−1.15)
		R^2 (%)	1.608	−0.180	0.203	1.668	0.395	0.810	1.700	0.312	0.754
DJX	ICIB	b	0.541	−0.706	0.635	−0.228	−0.220	−0.164	−0.591	−0.541	−0.513
		t-stat	(0.28)	(−0.68)	(0.82)	(−0.55)	(−0.87)	(−0.87)	(−0.96)	(−1.45)	(−1.75)
	IPIB	b	0.828	−0.244	−0.119	0.890	0.822	0.597	−0.939	−0.664	−0.525
		t-stat	(0.44)	(−0.21)	(−0.12)	(1.99)	(3.13)	(2.95)	(−1.32)	(−1.59)	(−1.69)
		R^2 (%)	−0.261	−0.428	−0.062	1.762	0.637	1.086	1.974	0.500	0.763
NDX	ICIB	b	−6.315	−2.714	−3.082	−0.026	0.070	−0.074	−0.018	0.137	0.052
		t-stat	(−1.59)	(−1.12)	(−2.20)	(−0.05)	(0.21)	(−0.34)	(−0.03)	(0.40)	(0.20)
	IPIB	b	5.811	3.055	2.579	−0.952	−0.280	−0.044	0.235	0.084	−0.189
		t-stat	(1.65)	(1.53)	(2.54)	(−1.64)	(−0.79)	(−0.17)	(0.36)	(0.24)	(−0.71)
		R^2 (%)	0.452	2.095	1.657	0.658	0.479	0.591	0.317	0.400	0.714
MNX	ICIB	b	-	-	-	−0.914	−0.353	−0.189	−2.198	−0.412	−0.748
		t-stat	-	-	-	(−1.16)	(−0.88)	(−0.62)	(−0.90)	(−0.26)	(−0.50)
	IPIB	b	-	-	-	1.367	0.274	0.384	−4.979	−0.892	−0.763
		t-stat	-	-	-	(1.88)	(0.65)	(1.34)	(−2.07)	(−0.61)	(−0.76)
		R^2 (%)	-	-	-	1.140	0.369	0.407	0.617	0.233	−0.263
SPX	ICIB	b	−1.000	−0.447	−0.411	−0.800	−0.102	−0.055	−0.173	−0.092	−0.021
		t-stat	(−1.97)	(−1.56)	(−2.05)	(−1.44)	(−0.35)	(−0.23)	(−0.53)	(−0.46)	(−0.14)
	IPIB	b	0.857	0.336	0.343	−0.308	0.060	−0.089	−0.133	−0.171	−0.218
		t-stat	(1.89)	(1.24)	(1.72)	(−0.69)	(0.22)	(−0.42)	(−0.38)	(−0.81)	(−1.35)
		R^2 (%)	1.671	0.300	0.781	1.755	0.315	0.727	1.684	0.328	0.763
OEX	ICIB	b	−4.756	−3.228	−1.606	−1.053	−0.784	−0.794	−0.070	−0.198	−0.213
		t-stat	(−1.94)	(−2.42)	(−1.60)	(−2.09)	(−2.85)	(−3.77)	(−0.12)	(−0.56)	(−0.70)
	IPIB	b	2.193	1.708	0.545	0.179	0.069	0.141	0.449	−0.139	−0.211
		t-stat	(1.10)	(1.52)	(0.64)	(0.36)	(0.26)	(0.68)	(0.67)	(−0.34)	(−0.65)
		R^2 (%)	1.330	0.936	0.080	1.790	0.582	1.303	2.075	0.136	0.213
VIX	ICIB	b	−0.267	−0.520	−0.250	−0.323	0.203	0.030	0.405	−0.236	−0.526
		t-stat	(−0.62)	(−1.96)	(−1.16)	(−0.75)	(0.78)	(0.15)	(0.74)	(−0.76)	(−1.87)
	IPIB	b	−0.581	0.078	0.149	−0.542	0.078	−0.047	−0.236	−0.590	−0.462
		t-stat	(−1.24)	(0.29)	(0.67)	(−1.15)	(0.28)	(−0.21)	(−0.55)	(−2.24)	(−2.14)
		R^2 (%)	1.703	0.244	0.670	1.817	0.142	0.509	1.841	0.328	0.983

Table 12

Predictive Regression of Stock Market Volatility

This table reports the results of multiple predictive regressions. Each column in this table corresponds to one multiple predictive regression, labeled 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 stock market volatility in Panel A and the value-weighted average of firm-level volatility in Panel B, over the relevant forecast horizon, and all predictors are normalized to have zero mean and one standard deviation. All dependent variables are expressed at monthly frequency. 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). "b" is the slope coefficient on the predictor and expressed as percentage of the raw value (multiplied by 100). When $D/W/M > 1$, the t-stat is computed using the GMM standard errors with $D/W/M-1$ Newey-West lag correction. The sample period is from 2005 to 2020.

Panel A: Forecast Future Stock Market Volatility							
Predictor	Coefficient	D=1	D=3	W=1	W=2	M=1	M=2
ACIB	b	−0.006	−0.024	−0.621	−0.113	1.200	0.946
	t-stat	(−0.29)	(−0.75)	(−1.49)	(−0.33)	(1.51)	(1.37)
APIB	b	0.060	0.123	1.455	1.245	0.595	0.681
	t-stat	(2.92)	(4.10)	(3.50)	(3.30)	(0.92)	(0.86)
ICIB	b	0.004	0.046	0.480	0.336	0.737	1.447
	t-stat	(0.20)	(2.06)	(1.71)	(1.44)	(1.00)	(2.24)
IPIB	b	0.011	0.030	−0.065	−0.255	−1.094	−1.185
	t-stat	(0.80)	(1.56)	(−0.24)	(−1.07)	(−1.69)	(−1.71)
Other Controls		Yes	Yes	Yes	Yes	Yes	Yes
	R^2 (%)	99.38	99.02	64.10	68.83	58.69	48.60

Panel B: Forecast Future Value-weighted Average of Firm-level Volatility							
Predictor	Coefficient	D=1	D=3	W=1	W=2	M=1	M=2
ACIB	b	−0.010	−0.027	−0.141	−0.124	0.863	0.887
	t-stat	(−0.52)	(−0.80)	(−1.39)	(−0.88)	(1.18)	(1.38)
APIB	b	0.098	0.204	0.530	0.774	1.244	1.036
	t-stat	(5.49)	(6.56)	(4.44)	(4.75)	(1.57)	(1.23)
ICIB	b	0.013	0.056	0.130	0.170	0.678	1.216
	t-stat	(1.02)	(2.85)	(1.61)	(1.81)	(1.15)	(2.05)
IPIB	b	−0.012	−0.003	−0.022	−0.057	−0.988	−1.093
	t-stat	(−1.11)	(−0.18)	(−0.34)	(−0.65)	(−2.01)	(−1.85)
Other Controls		Yes	Yes	Yes	Yes	Yes	Yes
	R^2 (%)	99.67	99.37	98.00	96.74	70.36	60.62

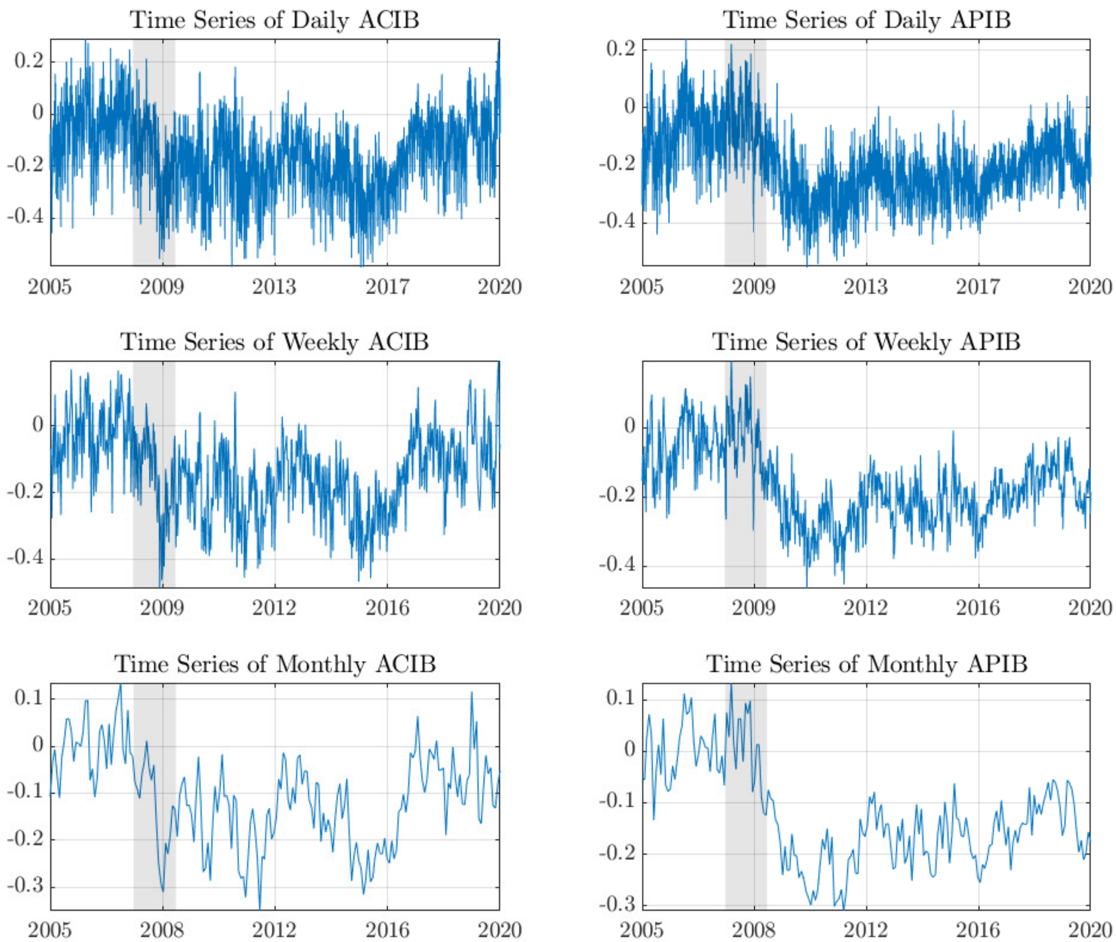

Figure 1. The Time Series of ACIB and APIB. Figure 1 depicts the time series of ACIB and APIB from 2005 to 2020 at daily, weekly, and monthly frequency. The option data is collected from the Chicago Board Options Exchange (CBOE). The grey areas indicate the National Bureau of Economic Research (NBER)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

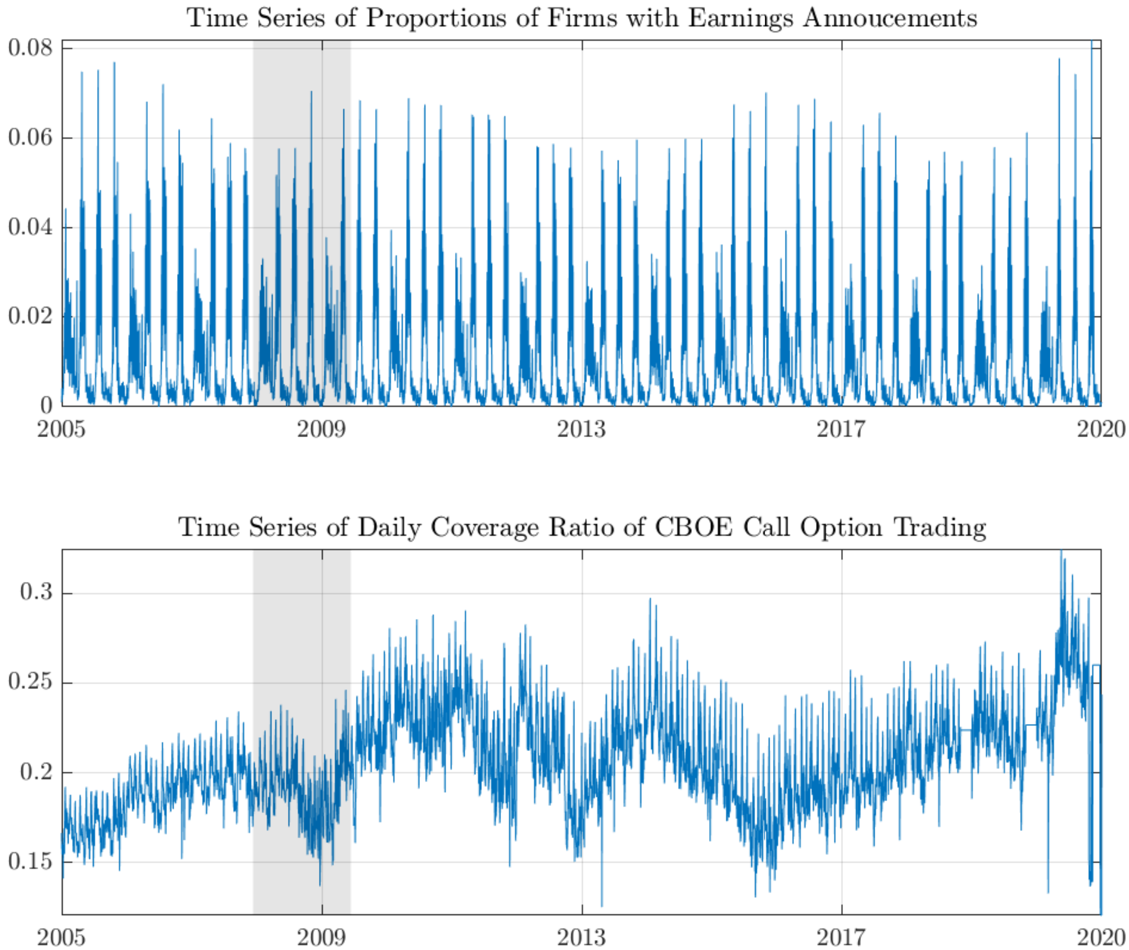

Figure 2. Dynamics of Regime Switching Variables. Figure 2 describes the two time-series variables used to decide the two regimes of equity option trading activities in Table 9. The first figure is the time-series proportion of firms with earnings announcements out of the total public firms. A higher proportion indicates more firms with earnings announcements and higher sentiment periods over time. The second figure is the coverage ratio of equity option trading activities using the CBOE database. It is defined as the total number of stocks with call option trading divided by the total number of trading stocks at each point in time. The sample period is from 2005 to 2020.

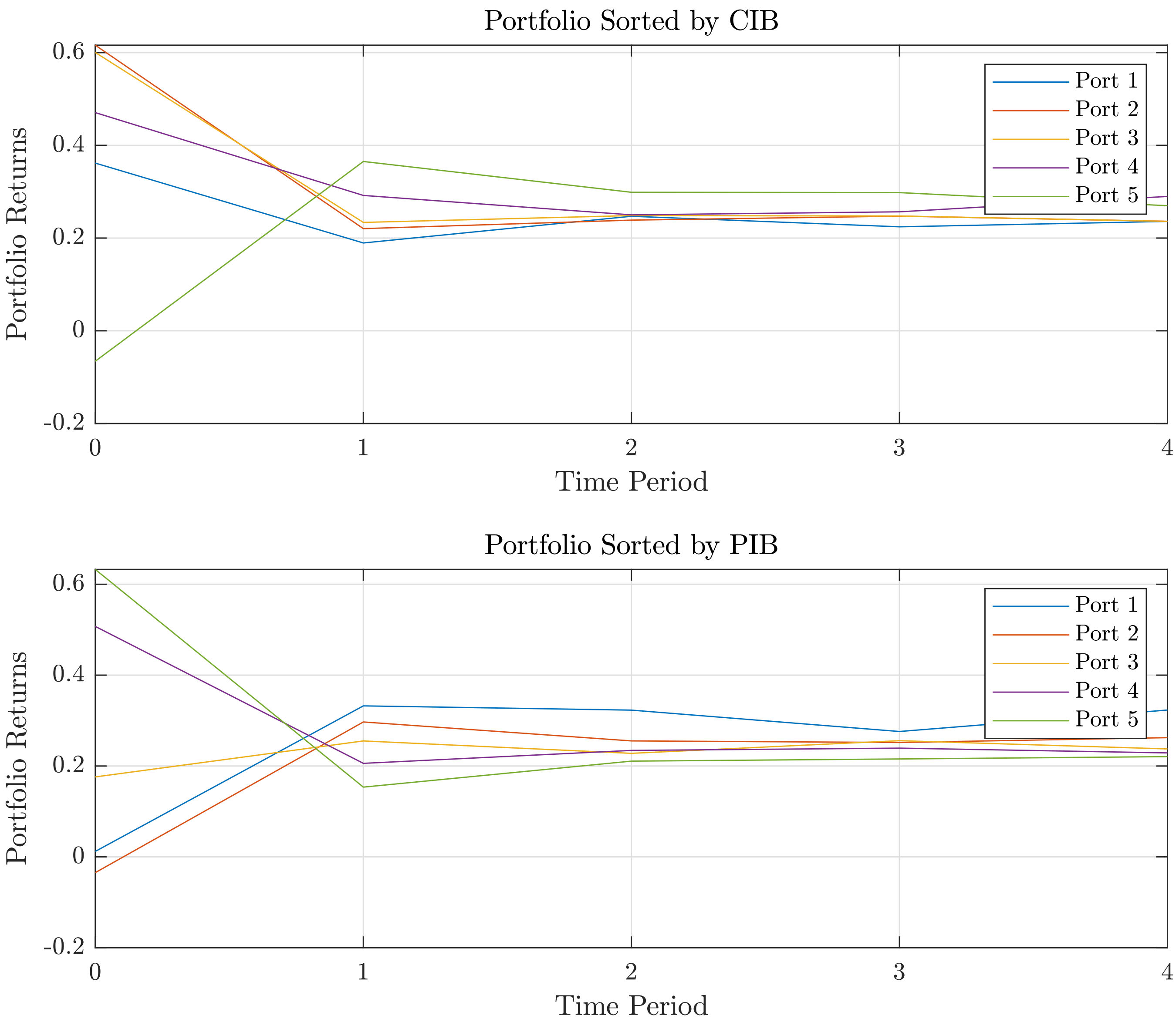

Figure 3. Sentiment Effect of Equity Option Trading in the Cross Section. Figure 3 compares the time series of portfolio returns sorted by call and put IB, namely CIB and PIB, over different time periods without overlaps at weekly frequency separately. At the end of each week, we sort all stocks with available CIB or PIB into quintiles based on the value of CIB or PIB. The portfolios are held in the current week, the next week without overlaps, the second week without overlaps, and so on and so forth until the fourth week after sorting. The portfolios' returns are equal-weighted average returns in percentile among all available stocks within each portfolio bin.