Betting Against the Crowd: Option Trading and Market Risk Premium

March 2025

ABSTRACT

We provide a comprehensive study on how option trading influences the equity market risk premium. Surprisingly, we find that trading of individual call options predicts the market index more strongly than index options. This predictability is both statistically significant and economically substantial, persisting from weeks to months. Individual option trading largely reflects investor sentiment and is primarily driven by retail investors. It also forms the key component in an ensemble learning model, combined with index option trading and other related predictors, respectively. Among all predictors examined, option trading emerges as the most powerful predictor of the market risk premium.

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

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

1 Introduction

In the presence of private information, trading options is known to be more profitable than trading the underlying asset due to the leverage options provide. Consistent with this view, Easley, O'Hara, and Srinivas (1998) and Cao, Chen, and Griffin (2005) show that option trading volume predicts stock returns. Subsequent studies, including Pan and Poteshman (2006), Bali and Hovakimian (2009), Cremers and Weinbaum (2010), An, Ang, Bali, and Cakici (2014), and Ge, Lin, and Pearson (2016), find that option price-based characteristics also predict the cross-section of stock returns. However, despite the importance of market predictability, the direct impact of option trading on the overall market has received little attention.[1] Notable exceptions are Chordia, Kurov, Muravyev, and Subrahmanyam (2021) and Henderson, Pearson, and Wang (2023), who use index put order flow to predict weekly market returns and construct investor sentiment measures based on the issuance of retail structured equity products, respectively. However, whether the market is predictable out-of-sample at the more common monthly frequency remains an open question. More importantly, the rich trading information embedded in individual options has not yet been explored in the context of market predictability.

In this paper, we bridge the gap in the literature by presenting a comprehensive analysis of how option trading affects the equity market risk premium. First, we construct our predictors using trading information embedded in individual options. Second, we compare these predictors with existing trading activity-based predictors and explore ensemble learning methods by combining all predictors, including other sentiment-based predictors. Third, inspired by Henderson, Pearson, and Wang (2023), we demonstrate that our proposed predictors are linked to investor sentiment, capturing patterns of overreaction followed by subsequent corrections that explain the negative predictability of our predictors. Our findings reveal that option trading conveys significant forward-looking information about the

[1] Cochrane (2008) highlights the significance of market predictability, particularly in its role in determining all investment returns.

stock market, making it one of the most powerful predictors of the market risk premium.[2]

Specifically, we construct two measures, ACIB and APIB, based on the aggregate order imbalance of individual call and put options, respectively. Distinguishing between calls and puts is crucial, as retail investors predominantly engage in buying call options. Bryzgalova, Pavlova, and Sikorskaya (2023) estimate that retail investors account for 62% of total equity option trading volume, suggesting that ACIB is more likely to capture retail buying activity than APIB. In contrast, Chordia et al. (2021), who also separate calls and puts, focus primarily on index put options due to their heavy use driven by hedging demand.

Empirically, we find that ACIB strongly and negatively predicts future stock market excess returns across various horizons, from days to months. A one-standard-deviation increase in ACIB is associated with a decline in stock market excess returns of 0.075% the next day, 0.240% the next week, 0.945% the next month, and 2.316% the next quarter on average. Out of sample, at the monthly level, the out-of-sample R^2 reaches 6.114%, almost doubling those of most existing predictors. Economically, a mean-variance-utility investor who allocates wealth between the market portfolio and T-bill can obtain an annualized Sharpe ratio of 1.360 if she follows a monthly portfolio rebalancing strategy based on the predictive signal of ACIB. In contrast, the aggregate equity put option order imbalance, APIB, shows no predictive power for market returns at any horizon.

These results support the interpretation of ACIB as a measure of investor sentiment, more so than APIB. Since ACIB reflects sentiment-driven retail trading, it is likely driven by investors' beliefs about future stock prices that are not justified by rational evaluation of available information, resulting in subsequent price corrections. This interpretation aligns with anecdotal evidence from financial media, which frequently reports large retail investor losses from speculative equity option trading.[3]

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

[3] 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).

Based on insights from Henderson, Pearson, and Wang (2023), we provide further evidence to show that ACIB captures sentiment. First, we show that ACIB is highly correlated with existing sentiment measures. Indeed, it has a correlation of 50% with the BW sentiment of Baker and Wurgler (2007) and 33% with SEP sentiment of Henderson, Pearson, and Wang (2023). Second, we decompose option orders into three groups by trading size, moneyness, and time to maturity, and construct ACIB by using the options only within each group. We find that the ACIB of small trading size has stronger market return predictability compared with the ACIB of median or large trading size, consistent with the view that trading smaller sizes is generally initiated by retail investors. Third, we find that ACIB from ATM call options has stronger market return predictability than ACIB from OTM or ITM options, consistent with the evidence documented by Bryzgalova, Pavlova, and Sikorskaya (2023) that retail investors prefer trading at-the-money call options.

Fourth, we examine the trading by market makers and professional customers, who are less likely to trade from sentiment. Consequently, we expect that the aggregate call option order imbalance (ACIB) constructed from their trading 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 for its forecasting power on market risk premium.

Fifth, we examine the predictability of ACIB conditional on the level of sentiment. Based on insights from Stambaugh, Yu, and Yuan (2012), the sentiment effect from ACIB (i.e., the predictive power of ACIB) should be more salient when market participants are more optimistic in general. Using the option sentiment developed by Henderson, Pearson, and Wang (2023) from the retail structured equity products (SEP), we split our sample into two regimes based on the level of SEP. We find that the predictability of ACIB is much stronger and significant only when SEP is high. The SEP results further support the view that our sentiment index extracted from equity call options reflects likely the retail investors' sentiment.

Finally, we compute an alternative ACIB using retail option trading data constructed by

Bryzgalova, Pavlova, and Sikorskaya (2023) through a single-leg price improvement mechanism (SLIM), which can effectively identify retail investors' option trading activity. We find that the alternative ACIB (i.e., SLIM ACIB) is also capable of predicting negatively the market return in multiple horizons, and the measure itself is highly correlated with ACIB (58% at weekly frequency). The close linkage between ACIB and the retail proxy SLIM ACIB based on Bryzgalova, Pavlova, and Sikorskaya (2023) provides further support that our ACIB measure captures investor sentiment in the option market.

Our results are robust to a number of controls. First, ACIB is a unique option investor sentiment, and cannot be resumed by other sentiment measures. To show this, we run standard predictive regressions by controlling for a comprehensive set of existing sentiment measures, which are the 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)). 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 or much 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 et al. (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.

It is important to note that our paper is about the time-series predictability of the market by trading activity, and this is entirely different from cross-sectional predictability of stock returns. A large body of literature documents that the cross-sectional variations in call and put option trading have important 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 these implications in our sample using stock-level data of call and put imbalance. Specifically, when sorting stocks into quintiles according to CIB (PIB), we find *positive* return predictability that stocks with high CIB (PIB) outperform (underperform) stocks with low CIB (PIB) in the cross-section. However, in the aggregate, the predictability is *negative*. The reason is that cross-sectional does not imply time-series predictability, because the market is removed which can either be independent or positively/negatively correlated over time conditionally or unconditionally. Hence, time-series predictability and its direction must be examined on a case-by-case basis. In our case, the time-series predictability is negative, consistent with, for example, the implied cost of capital and investor attention, where the cross-sectional predictability goes the opposite direction (see Li, Ng, and Swaminathan (2013) and Chen, Tang, Yao, and Zhou (2022)).

Our paper contributes to three stands of literature. First, it adds to the literature of using information of the option market to predict the stock market. Bollerslev, Tauchen, and Zhou (2009), Chen, Joslin, and Ni (2019), and Han and Li (2021) uncover variance risk premium, aggregate purchase of deep-out-of-the-money SPX index put options, and aggregate implied volatility spread as useful predictors of the market. Martin (2017) provides a lower bound on the market risk premium and shows that it has some degree of predictability. But Back, Crotty, and Kazempour (2022) find that the bound is unsatisfactory out-of-sample. Closely related, Chordia et al. (2021) and Henderson, Pearson, and Wang (2023) use index put order flow and an option investor sentiment as new predictor. However, all of the existing predictors are either statistically insignificant out of sample or have small predictability. Complimenting these studies, we find the first option-based predictor that has the most significant predictive power and that also links to retail trading and sentiment.

Second, our paper contributes to the literature by proposing a novel sentiment measure from equity options. Measuring investor sentiment is undeniably challenging.[4] Baker and Wurgler (2007) pioneered by constructing a stock market sentiment index. Recent literature 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 individual 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.

Third, our paper contributes to the recent important debate about market predictability. While Goyal and Welch (2008) argue against it, Campbell and Thompson (2008) argue for it, supported by subsequent studies such as Rapach, Strauss, and Zhou (2010), Henkel, Martin, and Nardari (2011), Pettenuzzo, Timmermann, and Valkanov (2014), Colacito, Ghysels, Meng, and Siwasarit (2016), and Chen, Da, and Huang (2022). However, in a recent study, Goyal, Welch, and Zafirov (2024) once again question the market predictability by examining the predictive power of a larger set of predictors published in top finance journals. Interestingly, none of which is related to option trading activity or what the retail investors

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

are doing. We contribute to the debate by showing that ACIB is a powerful predictor and the market predictability is even stronger than previously thought.

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.

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.[5] 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.[6] 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.[7] The CBOE open-close data documents detailed volume information

[5] 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).

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

[7] 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.

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.

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:[8]

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

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

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,

[8]The empirical results are robust if we use absolute delta-weighted or moneyness-weighted summation across all option contracts.

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:

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

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, Lee, Pearson, and Poteshman (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. To compare with index options order imbalance, we follow Chordia et al. (2021) to construct index call IB (ICIB) and index put IB (IPIB). While ICIB is highly related to ACIB with a correlation of 0.60, it has low correlation with sentiment index such as SEP (with a correlation of 0.02), indicating ICIB is not informative to sentiment trading, especially from retail investors. The low (or even negative) correlation between IPIB and the sentiment indices is also consistent with the finding by Chordia et al. (2021) that IPIB is not driven by sentiment trading but reflects risk protection strategies by retail traders.

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 multiperiod predictive regression follows Fama and French (1988, 1989):[9]

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

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, 0.945% next month, and 2.316% next quarter, with the corresponding t statistics of -3.36, -2.69, -2.89, and -3.63.[10] 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 senti-

[9] 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.

[10] 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.

ment 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)).

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:

$$\begin{cases} r_{t,t+k} = \alpha + \beta \times x_t + \epsilon_{t,t+K}, \ t = 1, \ldots, T_0 - K, \\ \hat{r}_{t,t+k} = \hat{\alpha} + \hat{\beta} \times x_t, \qquad\qquad t = T_0, \ldots, T, \end{cases} \tag{5}$$

$$Benchmark : r^B_{t,t+k} = \frac{1}{t-K} \sum_{s=1}^{t-K} r_{s,s+K}, \ t = T_0, \ldots, T, \tag{6}$$

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:

$$R^2_{OS} = 1 - \frac{MSFE_1}{MSFE_0}, \tag{7}$$

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:

$$w_{t,t+K} = \frac{1}{\gamma} \frac{\hat{r}_{t,t+k}}{\hat{\sigma}^2_{t,t+k}}, \tag{8}$$

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:

$$SR = \frac{R_p}{\sigma_p}, \tag{9}$$

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:

$$CER = R_p - 0.5\gamma\sigma_p^2. \tag{10}$$

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:

$$CER\ Gain = CER - \overline{CER}. \tag{11}$$

[**Insert Table 3**]

Panel A and Panel B in Table 3 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 to 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.[11]

To further demonstrate the benefit of ACIB's information, we compare it with the index option IPIB proposed by Chordia et al. (2021) in both Panel A and Panel B of Table 3, as both ACIB and IPIB are constructed by option trading activity. To investigate whether ACIB captures existing predictors in the literature, especially those predictors related to sentiment, we follow Huang et al. (2015) and Huang, Li, and Wang (2021) and construct a combined predictor with 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 (GW PCA).[12] 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 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

[11] 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.

[12] 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).

proposed by Chen, Joslin, and Ni (2019), aggregate implied volatility spread (IVS) by Han and Li (2021).[13] Finally, we run partial least square (PLS) regression and extract a single combined predictor (i.e., PLS (Existing Predictors)) using the whole sample period. We then conduct the out-of-sample test based on PLS (Existing Predictors) and compare its performance with ACIB. The empirical results are provided in Table 3.

In Table 3 we first confirm the finding by Chordia et al. (2021) that IPIB is a strong predictor at the daily and weekly frequency in the out-of-sample tests. For example, both the out-of-sample R^2 and the Sharpe ratio have significant improvement when investors use IPIB to timing the stock market at weekly frequency, with an out-of-sample R^2 of 0.717% and a Sharpe ratio of 0.345, significantly higher than the benchmark performance (i.e., the buy-and-hold strategy). However, the performance of IPIB is not as strong as that of ACIB, especially at the monthly frequency, when ACIB achieve an out-of-sample R^2 (Sharpe ratio) of 6.114% (1.360), while IPIB has negative numbers. Furthermore, we show that investors can benefit further from option market information when considering ACIB and IPIB. We find that the weekly out-of-sample R^2 (the market-timing Sharpe ratio) can be improved from 0.717% (0.345) when using IPIB alone to 1.957% (0.513) when considering both ACIB and IPIB together in the forecasting regression. Lastly, the performance by all existing predictors (i.e., PLS (Existing Predictors)) also demonstrates that ACIB has superior performance compared with all existing predictors. When combining information from ACIB, the forecasting performance by existing predictors can achieve significant improvements. In general, we show that investors can significantly benefit from using our variable ACIB to adjust positions of risky assets over time. Our paper complements existing studies of index option and other existing predictors and manifests the incremental value of the equity option market.[14]

[13] 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.

[14] The predictive power of ACIB remains strong and significant in an in-sample multiple regression with all available predictors listed in Section 3.2. The table is available upon request.

3.3 International Stock Market Return Predictability

We also examine whether ACIB can forecast international stock market returns. Baker, Wurgler, and Yuan (2012) document that there exists a global sentiment index that can spread across markets through private capital flows and functions as a contrarian predictor of country-level returns. Given that ACIB represents an option-based sentiment measure and is closely linked to stock market sentiment, it could also help identify such a global sentiment index and forecast other countries' stock market 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 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 4]

Table 4 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 5]

Table 5 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.[15]

In addition to this, Table 5 Panel B also shows that among options with different moneyness, ACIB constructed using ATM options has the best performance across different moneyness, further consistent with our sentiment explanation as Bryzgalova, Pavlova, and Sikorskaya (2023) find that retail traders prefer trading at-the-money options. The next well-performed type of 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 5 Panel C, the factor of time to maturity does not affect the predictive power of ACIB,

[15] 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.

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.[16] 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, 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 6 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

[16]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.

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, Pearson, Poteshman, and White (2021). The results are provided in Table 6 Panel D.

[**Insert Table 6**]

Table 6 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 6 Panel C shows that the closing position trading activities have some predictive power, although the results are not as strong as opening positions.[17] As discussed in Pan and 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 6 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

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

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), 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 7.

[Insert Table 7]

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.[18] 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 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 8 Panel A confirms this finding that stock market returns appear predictable by ACIB only when the level of SEP sentiment is above the median.

[18]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.

[Insert Table 8]

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.[19] 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 8 Panel B confirm this hypothesis.

[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

[19] 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.

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 8 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 8 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.

4.5 Retail Option Trading Proxy by Bryzgalova, Pavlova, and Sikorskaya (2023)

The recent seminal work of Bryzgalova, Pavlova, and Sikorskaya (2023) builds a proxy for retail option trading through a flag for price improvement mechanisms among transaction-level data, namely a single-leg price improvement mechanism (SLIM). To verify that our ACIB measure captures retail option trading activity, we construct a similar variable using the retail option trading data based on Bryzgalova, Pavlova, and Sikorskaya (2023). In particular, at the end of each day, we take a cross-sectional average of all available retail option trade imbalance weighted by the underlying stock's market capitalization for call and put options identified by SLIM based on Bryzgalova, Pavlova, and Sikorskaya (2023).[20] We name the new variables SLIM ACIB for call and SLIM APIB for put, in order to distinguish them from ACIB and APIB constructed by ourselves. We then run similar predictive regressions as in Section 3.1. The sample period for SLIM ACIB and SLIM APIB is from November 2019 to June 2021 (due to the data availability).

[**Insert Table 9**]

Comparing the time-series correlation between ACIB and SLIM ACIB, we find that they are highly correlated to each other. For example, daily (weekly) ACIB is significantly correlated with daily (weekly) SLIM ACIB with a correlation of 0.44 (0.58), indicating ACIB indeed captures well the dynamics of retail option trading activity. Furthermore, the predictive results in Table 9 show that SLIM ACIB is also able to forecast future stock market returns with negative signs at weekly frequency, although the significance is weaker than ACIB. Since the option trade direction to calculate order imbalance in Bryzgalova, Pavlova, and Sikorskaya (2023) is inferred based on transaction price (i.e., above or below the midpoint as described in Muravyev (2016)), the classification of buy and sell trade direction is not as accurate as that of ACIB using the CBOE database in our case, thus dampening its predictive power for stock market returns. Nevertheless, the close relationship between ACIB and SLIM ACIB demonstrates the validity of our variable ACIB and further supports the linkage of equity option trading to the aggregate stock market through a retail investors' sentiment channel.

[20]We thank greatly the authors of Bryzgalova, Pavlova, and Sikorskaya (2023) to make their data available online.

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:

$$Long - Short\ Return = \frac{1}{M}\sum_{i \in Port\ 5}^{M} R_{i,t} - \frac{1}{M}\sum_{j \in Port\ 1}^{M} R_{j,t}. \tag{12}$$

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 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 six 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), 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.

As further evidence to support the superior performance of ACIB compared with index call options, we run multiple predictive regressions by including both index call IB and ACIB 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.

[Insert Table 12]

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 (2025). We then run a similar predictive regression as in Section 3.1:

$$\sum_{k=1}^{K} \frac{\sigma_{t+k}}{K} \equiv \sigma_{t,t+K} = a + b \times X_t + \epsilon_{t,t+K}, \tag{13}$$

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.[21] The regression results are presented in Table 13.

[Insert Table 13]

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

[21] 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.

References

An, Byeong-Je, Andrew Ang, Turan G. Bali, and Nusret Cakici, 2014, The joint cross section of stocks and options, *Journal of Finance* 69, 2279–2337.

Andersen, Torben G, and Tim Bollerslev, 1998, Answering the skeptics: Yes, standard volatility models do provide accurate forecasts, *International Economic Review* 885–905.

Back, Kerry, Kevin Crotty, and Seyed Mohammad Kazempour, 2022, Validity, tightness, and forecasting power of risk premium bounds, *Journal of Financial Economics* 144, 732–760.

Baker, Malcolm, and Jeffrey Wurgler, 2006, Investor sentiment and the cross-section of stock returns, *Journal of Finance* 61, 1645–1680.

Baker, Malcolm, and Jeffrey Wurgler, 2007, Investor sentiment in the stock market, *Journal of Economic Perspectives* 21, 129–151.

Baker, Malcolm, Jeffrey Wurgler, and Yu Yuan, 2012, Global, local, and contagious investor sentiment, *Journal of Financial Economics* 104, 272–287.

Bali, Turan G., and Armen Hovakimian, 2009, Volatility spreads and expected stock returns, *Management Science* 55, 1797–1812.

Barber, Brad M, Terrance Odean, and Ning Zhu, 2008, Do retail trades move markets?, *Review of Financial Studies* 22, 151–186.

Black, Fischer, 1976, Studies of stock market volatility changes, *Proceedings of the American Statistical Association, Business & Economic Statistics Section, 1976* .

Bollen, Nicolas PB, and Robert E Whaley, 2004, Does net buying pressure affect the shape of implied volatility functions?, *Journal of Finance* 59, 711–753.

Bollerslev, Tim, George Tauchen, and Hao Zhou, 2009, Expected stock returns and variance risk premia, *Review of Financial Studies* 22, 4463–4492.

Bryzgalova, Svetlana, Anna Pavlova, and Taisiya Sikorskaya, 2023, Retail trading in options and the rise of the big three wholesalers, *Journal of Finance* 78, 3465–3514.

Campbell, John Y, and Samuel B Thompson, 2008, Predicting excess stock returns out of sample: Can anything beat the historical average?, *Review of Financial Studies* 21, 1509–1531.

Cao, Charles, Zhiwu Chen, and John M. Griffin, 2005, Informational content of option volume prior to takeovers, *Journal of Business* 78, 1073–1109.

Chan, Kalok, and Wai-Ming Fong, 2000, Trade size, order imbalance, and the volatility–volume relation, *Journal of Financial Economics* 57, 247–273.

Chen, Hui, Scott Joslin, and Sophie Xiaoyan Ni, 2019, Demand for crash insurance, intermediary constraints, and risk premia in financial markets, *Review of Financial Studies* 32, 228–265.

Chen, Jian, Guohao Tang, Jiaquan Yao, and Guofu Zhou, 2022, Investor attention and stock returns, *Journal of Financial and Quantitative Analysis* 57, 455–484.

Chen, Yong, Zhi Da, and Dayong Huang, 2022, Short selling efficiency, *Journal of Financial Economics* 145, 387–408.

Chordia, Tarun, Alexander Kurov, Dmitriy Muravyev, and Avanidhar Subrahmanyam, 2021, Index option trading activity and market returns, *Management Science* 67, 1758–1778.

Chordia, Tarun, Richard Roll, and Avanidhar Subrahmanyam, 2002, Order imbalance, liquidity, and market returns, *Journal of Financial Economics* 65, 111–130.

Chordia, Tarun, and Avanidhar Subrahmanyam, 2004, Order imbalance and individual stock returns: Theory and evidence, *Journal of Financial Economics* 72, 485–518.

Clark, Todd E., and Kenneth D. West, 2007, Approximately normal tests for equal predictive accuracy in nested models, *Journal of Econometrics* 138, 291–311.

Cochrane, John H, 2008, The dog that did not bark: A defense of return predictability, *Review of Financial Studies* 21, 1533–1575.

Colacito, Riccardo, Eric Ghysels, Jinghan Meng, and Wasin Siwasarit, 2016, Skewness in expected macro fundamentals and the predictability of equity returns: Evidence and theory, *Review of Financial Studies* 29, 2069–2109.

Corsi, Fulvio, 2009, A simple approximate long-memory model of realized volatility, *Journal of Financial Econometrics* 7, 174–196.

Cremers, Martijn, and David Weinbaum, 2010, Deviations from put-call parity and stock return predictability, *Journal of Financial and Quantitative Analysis* 45, 335–367.

Easley, David, Maureen O'Hara, and P. S. Srinivas, 1998, Option volume and stock prices: Evidence on where informed traders trade, *The Journal of Finance* 53, 431–465.

Fama, Eugene F., and Kenneth R. French, 1988, Dividend yields and expected stock returns, *Journal of Financial Economics* 22, 3–25.

Fama, Eugene F., and Kenneth R. French, 1989, Business conditions and expected returns on stocks and bonds, *Journal of Financial Economics* 25, 23–49.

Gao, Can, and Ian W. R. Martin, 2021, Volatility, valuation ratios, and bubbles: An empirical measure of market sentiment, *The Journal of Finance* 76, 3211–3254.

Ge, Li, Tse-Chun Lin, and Neil D. Pearson, 2016, Why does the option to stock volume ratio predict stock returns?, *Journal of Financial Economics* 120, 601–622.

Goyal, Amit, and Pedro Santa-Clara, 2003, Idiosyncratic risk matters!, *Journal of Finance* 58, 975–1007.

Goyal, Amit, and Ivo Welch, 2008, A comprehensive look at the empirical performance of equity premium prediction, *Review of Financial Studies* 21, 1455–1508.

Goyal, Amit, Ivo Welch, and Athanasse Zafirov, 2024, A comprehensive 2022 look at the empirical performance of equity premium prediction, *Review of Financial Studies* 37, 3490–3557.

Han, Bing, and Gang Li, 2021, Information content of aggregate implied volatility spread, *Management Science* 67, 1249–1269.

Han, Bing, and Gang Li, 2025, Idiosyncratic volatility and the icapm covariance risk, *Journal of Financial and Quantitative Analysis (Forthcoming)* .

Henderson, Brian J, Neil D Pearson, and Li Wang, 2023, Retail derivatives and sentiment: A sentiment measure constructed from issuances of retail structured equity products, *Journal of Finance* 78, 2365–2407.

Henkel, Sam James, J Spencer Martin, and Federico Nardari, 2011, Time-varying short-horizon predictability, *Journal of Financial Economics* 99, 560–580.

Hodrick, Robert J., 1992, Dividend yields and expected stock returns: Alternative procedures for inference and measurement, *Review of Financial Studies* 5, 357–386.

Hu, Jianfeng, 2014, Does option trading convey stock price information?, *Journal of Financial Economics* 111, 625–645.

Huang, Dashan, Fuwei Jiang, Jun Tu, and Guofu Zhou, 2015, Investor sentiment aligned: A powerful predictor of stock returns, *Review of Financial Studies* 28, 791–837.

Huang, Dashan, Jiangyuan Li, and Liyao Wang, 2021, Are disagreements agreeable? evidence from information aggregation, *Journal of Financial Economics* 141, 83–101.

Hvidkjaer, Soeren, 2008, Small trades and the cross-section of stock returns, *Review of Financial Studies* 21, 1123–1151.

Jiang, Fuwei, Joshua Lee, Xiumin Martin, and Guofu Zhou, 2019, Manager sentiment and stock returns, *Journal of Financial Economics* 132, 126–149.

Johnson, Travis L., and Eric C. So, 2012, The option to stock volume ratio and future returns, *Journal of Financial Economics* 106, 262–286.

Kandel, Shmuel, and Robert F. Stambaugh, 1996, On the predictability of stock returns: An asset-allocation perspective, *Journal of Finance* 51, 385–424.

Lakonishok, Josef, Inmoo Lee, Neil D. Pearson, and Allen M. Poteshman, 2007, Option market activity, *Review of Financial Studies* 20, 813–857.

Li, Yan, David T Ng, and Bhaskaran Swaminathan, 2013, Predicting market returns using aggregate implied cost of capital, *Journal of Financial Economics* 110, 419–436.

Martin, Ian, 2017, What is the expected return on the market?, *Quarterly Journal of Economics* 132, 367–433.

Muravyev, Dmitriy, 2016, Order flow and expected option returns, *Journal of Finance* 71, 673–708.

Newey, Whitney K., and Kenneth D. West, 1987, A aimple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703–708.

Ni, Sophie Xiaoyan, Neil D Pearson, Allen M Poteshman, and Joshua White, 2021, Does option trading have a pervasive impact on underlying stock prices?, *Review of Financial Studies* 34, 1952–1986.

Pan, Jun, and Allen M. Poteshman, 2006, The information in option volume for future stock prices, *Review of Financial Studies* 19, 871–908.

Pettenuzzo, Davide, Allan Timmermann, and Rossen Valkanov, 2014, Forecasting stock returns under economic constraints, *Journal of Financial Economics* 114, 517–553.

Rapach, David, and Guofu Zhou, 2022, Asset pricing: Time-series predictability .

Rapach, David E., Matthew C. Ringgenberg, and Guofu Zhou, 2016, Short interest and aggregate stock returns, *Journal of Financial Economics* 121, 46–65.

Rapach, David E., Jack K. Strauss, and Guofu Zhou, 2010, Out-of-sample equity premium prediction: Combination forecasts and links to the real economy, *Review of Financial Studies* 23, 821–862.

Rapach, David E, Jack K Strauss, and Guofu Zhou, 2013, International stock return predictability: What is the role of the united states?, *Journal of Finance* 68, 1633–1662.

Roll, Richard, Eduardo Schwartz, and Avanidhar Subrahmanyam, 2010, O/S: The relative trading activity in options and stock, *Journal of Financial Economics* 96, 1–17.

Stambaugh, Robert F, Jianfeng Yu, and Yu Yuan, 2012, The short of it: Investor sentiment and anomalies, *Journal of Financial Economics* 104, 288–302.

van Binsbergen, Jules H, Svetlana Bryzgalova, Mayukh Mukhopadhyay, and Varun Sharma, 2024, (almost) 200 years of news-based economic sentiment, *National Bureau of Economic Research* .

Table 1

Summary Statistics of Equity Option Trading Activities

This table 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 ICIB/IPIB (Chordia et al. (2021)), BW sentiment (Baker and Wurgler (2006)), SEP sentiment (Henderson, Pearson, and Wang (2023)), PLS sentiment (Huang et al. (2015)), GM sentiment (Gao and Martin (2021)), Manager sentiment (Jiang et al. (2019)), and Michigan sentiment based on University of Michigan consumer survey data.

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	ICIB	IPIB	BW Sentiment	SEP Sentiment	Michigan Sentiment	PLS Sentiment	GM Sentiment	Manager Sentiment
ACIB	0.43	0.60	−0.11	0.50	0.33	0.24	−0.24	0.55	0.19
APIB		0.42	−0.24	0.41	0.15	−0.03	−0.32	0.62	0.27
ICIB			0.06	0.40	0.02	0.33	−0.25	0.40	0.23
IPIB				0.07	−0.24	0.35	0.18	−0.41	−0.36
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

This table 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. When running daily and weekly regressions, we include the lagged stock market return as a regressor. $D/W/M$ represents the forecast horizon in the number of days/weeks/months. The slope coefficient on the predictor 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 in the parentheses is computed using the GMM standard errors with $D/W/M - 1$ Newey-West lag correction.

Predictor		D=1			D=3			D=6	
ACIB	−1.659		−1.831	−1.176		−1.217	−1.092		−1.091
	(−3.36)		(−2.78)	(−3.58)		(−2.87)	(−3.86)		(−3.09)
APIB		−0.331	0.401		−0.391	0.096		−0.439	−0.003
		(−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		W=1			W=2			W=3	
ACIB	−0.958		−0.844	−0.863		−0.747	−0.892		−0.804
	(−2.69)		(−1.67)	(−3.21)		(−1.95)	(−3.58)		(−2.37)
APIB		−0.627	−0.244		−0.587	−0.248		−0.553	−0.188
		(−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		M=1			M=2			M=3	
ACIB	−0.945		−0.949	−0.822		−0.779	−0.772		−0.701
	(−2.89)		(−2.42)	(−3.28)		(−2.35)	(−3.63)		(−2.47)
APIB		−0.413	0.010		−0.447	−0.099		−0.481	−0.168
		(−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

Out-of-sample Predictability by Option Trading Activity

For out-of-sample tests, 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 predictors are specified in the first column. "PLS (Existing Predictors)" is constructed following Huang et al. (2015) and Huang, Li, and Wang (2021). "Existing Predictors" include: ICIB, IPIB, GW PCA, SEP, BW, GM, Manager, Michigan, PLS, VRP, IVS, PNBO, HLW. The definitions are specified in Section 3.2. "ACIB+IPIB" stands for using ACIB and IPIB together in a multiple regression to forecast MKTRF. The out-of-sample R^2 statistic in Panel A and the certainty equivalent return and the Sharpe ratio (in the parentheses) in Panel B are specified in Section 3.2. The t-stat in the parentheses of Panel A is computed based on Clark and West (2007). Benchmark is the buy-and-hold strategy for the market portfolio.

Panel A. Out-of-sample R^2						
2010 to 2020	D=1	D=3	W=1	W=2	M=1	M=2
ACIB	2.225	0.672	0.756	1.757	6.114	9.833
	(2.55)	(2.63)	(1.93)	(2.65)	(2.84)	(3.11)
IPIB	1.779	0.062	0.717	0.695	−1.302	−0.233
	(2.25)	(1.99)	(2.24)	(1.79)	(−1.16)	(0.08)
PLS (Existing Predictors)	1.611	0.186	1.139	0.122	7.540	−5.812
	(2.12)	(1.73)	(1.64)	(2.43)	(2.16)	(1.25)
ACIB+ IPIB	2.250	0.688	1.957	2.177	4.250	8.343
	(2.58)	(3.13)	(3.37)	(2.74)	(2.33)	(2.95)
ACIB+ PLS (Existing Predictors)	1.873	0.766	0.725	0.264	9.502	−1.917
	(2.39)	(2.75)	(2.25)	(2.52)	(2.45)	(1.79)
Panel B. Sharpe Ratio and CER Gain						
2010 to 2020	D=1	D=3	W=1	W=2	M=1	M=2
ACIB	0.372	0.086	1.385	0.217	10.416	11.114
	(0.212)	(0.163)	(0.394)	(0.276)	(1.360)	(1.431)
IPIB	−0.117	−0.089	0.738	0.567	−5.618	−1.308
	(0.115)	(0.128)	(0.345)	(0.352)	(0.391)	(0.711)
PLS (Existing Predictors)	0.259	0.021	0.914	1.117	6.768	1.469
	(0.191)	(0.150)	(0.341)	(0.370)	(1.183)	(0.771)
ACIB+ IPIB	0.431	0.396	2.263	1.059	2.278	6.765
	(0.239)	(0.240)	(0.513)	(0.375)	(0.947)	(1.286)
ACIB+ PLS (Existing Predictors)	0.499	0.128	1.035	2.062	9.657	7.687
	(0.235)	(0.172)	(0.354)	(0.472)	(1.323)	(1.152)
Benchmark Sharpe Ratio	(0.147)	(0.155)	(0.252)	(0.258)	(0.725)	(0.687)

Table 4

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. The slope coefficient on the predictor is expressed as a percentage of the raw value (multiplied by 100). When $D/W/M > 1$, the t-stat in the parentheses 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	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	−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
	(−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	−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
	(−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	−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
	(−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	−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
	(−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	−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
	(−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	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
	(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 5

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 in the parentheses 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	D=1	D=3	D=6	D=1	D=3	D=6	D=1	D=3	D=6
ACIB	−1.882	−1.156	−1.084	−0.732	−0.471	−0.625	−0.188	−0.190	−0.333
	(−3.01)	(−2.84)	(−3.24)	(−1.47)	(−1.51)	(−2.60)	(−0.39)	(−0.64)	(−1.51)
APIB	0.437	0.012	0.016	−0.027	−0.401	−0.250	−0.332	−0.002	−0.090
	(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	D=1	D=3	D=6	D=1	D=3	D=6	D=1	D=3	D=6
ACIB	−0.656	−0.470	−0.561	−1.660	−1.042	−1.067	−1.159	−0.974	−0.844
	(−1.04)	(−1.09)	(−1.56)	(−2.76)	(−2.65)	(−3.29)	(−2.00)	(−2.67)	(−2.80)
APIB	−0.591	−0.382	−0.425	0.228	−0.028	0.028	−0.059	−0.136	−0.233
	(−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	D=1	D=3	D=6	D=1	D=3	D=6	D=1	D=3	D=6
ACIB	−0.901	−0.813	−0.590	−1.489	−1.149	−1.107	−1.375	−1.032	−0.952
	(−1.89)	(−2.48)	(−2.13)	(−2.89)	(−3.22)	(−3.69)	(−2.70)	(−3.07)	(−3.17)
APIB	0.085	0.251	0.113	0.021	0.374	0.214	0.181	0.245	0.216
	(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 6

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 in the parentheses 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	D=1	D=3	D=6	D=1	D=3	D=6	D=1	D=3	D=6
ACIB	0.643	−0.215	−0.035	1.817	0.421	0.544	1.160	0.233	0.144
	(1.23)	(−0.69)	(−0.15)	(2.60)	(1.04)	(1.73)	(1.72)	(0.56)	(0.40)
APIB	−0.321	−0.298	−0.205	−0.779	−0.010	−0.251	0.510	0.632	0.412
	(−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	D=1	D=3	D=6	D=1	D=3	D=6	D=1	D=3	D=6
ACIB	0.505	0.407	0.221	0.368	0.269	0.302	0.403	0.114	0.140
	(0.72)	(1.01)	(0.72)	(0.71)	(0.81)	(1.05)	(0.89)	(0.40)	(0.56)
APIB	0.635	0.070	−0.083	−0.574	−0.470	−0.098	−0.425	0.459	0.417
	(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	D=1	D=3	D=6	D=1	D=3	D=6	D=1	D=3	D=6
ACIB	−0.358	0.165	0.180	0.319	0.766	0.751	0.372	0.678	0.690
	(−0.70)	(0.49)	(0.63)	(0.62)	(2.44)	(2.89)	(0.82)	(2.04)	(2.39)
APIB	0.428	0.278	0.303	0.426	−0.200	−0.209	−0.190	−0.149	−0.069
	(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	D=1	D=3	D=6	D=1	D=3	D=6	D=1	D=3	D=6
ACIB	−0.384	−0.529	−0.569	−0.837	−0.828	−0.789	−1.128	−0.636	−0.591
	(−0.80)	(−1.54)	(−1.90)	(−1.45)	(−2.13)	(−2.46)	(−2.52)	(−2.20)	(−2.40)
APIB	−0.401	−0.261	−0.303	−0.094	0.009	−0.117	0.367	−0.024	−0.079
	(−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 7
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 in the parentheses 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		D=1			D=3			D=6	
ACOB/S	−1.752		−1.653	−1.004		−0.951	−1.175		−1.215
	(−2.40)		(−1.71)	(−1.56)		(−1.21)	(−1.95)		(−1.72)
ACOS/S	1.385		1.445	0.690		0.677	0.959		0.911
	(2.00)		(2.00)	(1.24)		(1.19)	(2.07)		(1.93)
APOB/S		−0.389	−0.146		−0.364	−0.101		−0.264	0.044
		(−1.04)	(−0.16)		(−1.13)	(−0.16)		(−0.86)	(0.08)
APOS/S		−0.034	−0.075		0.121	0.116		0.134	0.122
		(−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		D=1			D=3			D=6	
ACOB/S	−1.262		−1.480	−1.244		−1.537	−1.182		−1.268
	(−1.84)		(−2.12)	(−2.48)		(−2.95)	(−2.68)		(−2.81)
ACOS/S	0.616		0.209	0.675		0.245	0.666		0.413
	(0.98)		(0.27)	(1.47)		(0.45)	(1.70)		(0.90)
APOB/S		−0.991	−0.598		−0.756	−0.352		−0.884	−0.587
		(−1.55)	(−0.90)		(−1.62)	(−0.73)		(−2.19)	(−1.43)
APOS/S		0.445	1.181		0.336	1.080		0.393	0.860
		(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		D=1			D=3			D=6	
ACOB/S	−1.195		−0.938	−1.236		−1.128	−1.199		−1.052
	(−1.59)		(−1.07)	(−2.22)		(−1.75)	(−2.44)		(−1.83)
ACOS/S	0.811		0.941	0.879		0.972	0.835		0.880
	(0.88)		(0.87)	(1.27)		(1.23)	(1.41)		(1.28)
APOB/S		−0.699	−0.486		−0.568	−0.209		−0.624	−0.272
		(−1.52)	(−0.77)		(−1.61)	(−0.41)		(−1.86)	(−0.58)
APOS/S		0.277	0.019		0.234	−0.064		0.337	0.062
		(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 8

Predictive Power of ACIB in Different Regimes

In Panel A, the sample days from 2005 to 2020 are separated into two regimes: above and below the median of the level of the 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. The slope coefficient on the predictor is expressed as a percentage of the raw value (multiplied by 100). The t-stat in the parentheses 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	Coefficient	D=1	D=3	W=1	W=2	M=1	M=2
Regime of High SEP Sentiment	ACIB	−3.126	−1.491	−1.187	−1.172	−1.672	−1.188
		(−4.02)	(−2.94)	(−1.87)	(−2.76)	(−3.41)	(−3.43)
	APIB	1.451	0.577	0.329	0.291	0.444	0.145
		(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	−0.939	−0.910	−0.550	−0.529	−0.796	−0.723
		(−1.02)	(−1.54)	(−0.82)	(−0.99)	(−1.47)	(−1.53)
	APIB	−0.270	−0.187	−0.671	−0.720	−0.182	−0.137
		(−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	D=1	D=3	W=1	W=2	M=1	M=2
Regime of Many Earnings Announcements	ACIB	−3.297	−1.831	−1.632	−1.428	−1.147	−0.765
		(−3.43)	(−3.25)	(−1.99)	(−2.66)	(−2.53)	(−2.25)
	APIB	1.495	0.652	0.916	0.711	0.697	0.012
		(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	−0.059	−0.477	0.092	0.071	−0.688	−0.742
		(−0.07)	(−0.82)	(0.16)	(0.14)	(−1.15)	(−1.57)
	APIB	−1.071	−0.553	−1.566	−1.447	−0.619	−0.232
		(−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	D=1	D=3	W=1	W=2	M=1	M=2
Regime of High Coverage of Option Trading	ACIB	−3.565	−1.726	−0.759	−1.073	−0.969	−0.632
		(−4.20)	(−3.38)	(−1.18)	(−2.74)	(−2.09)	(−2.04)
	APIB	1.929	0.460	0.185	0.186	0.291	0.350
		(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	−0.418	−0.678	−0.812	−0.395	−0.916	−0.891
		(−0.43)	(−1.08)	(−1.08)	(−0.66)	(−1.47)	(−1.58)
	APIB	−0.603	−0.255	−0.782	−0.747	0.062	−0.112
		(−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 9

In-sample Predictability of SLIM ACIB and SLIM APIB

This table 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. We construct SLIM ACIB and SLIM APIB using the retail option trading data based on Bryzgalova, Pavlova, and Sikorskaya (2023). In particular, at the end of each day, we take a cross-sectional average of all available retail option trade imbalance (i.e. IB) for call and put options identified by SLIM based on Bryzgalova, Pavlova, and Sikorskaya (2023). The weekly (monthly) SLIM ACIBs or SLIM APIBs are constructed by taking the average of all the daily observations within each week (month). The sample period for SLIM ACIB and SLIM APIB is from November 2019 to June 2021. 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. When running daily and weekly regressions, we include the lagged stock market return as a regressor. The slope coefficient on the predictor 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 in the parentheses is computed using the GMM standard errors with $D/W/M - 1$ Newey-West lag correction.

Predictor		D=1			D=3			D=6	
SLIM ACIB	1.708		1.299	−0.169		−0.144	−1.027		−1.034
	(0.46)		(0.39)	(−0.07)		(−0.07)	(−0.54)		(−0.57)
SLIM APIB		−6.180	−6.071		0.390	0.378		−0.028	−0.113
		(−1.47)	(−1.53)		(0.14)	(0.14)		(−0.01)	(−0.05)
R^2 (%)	9.84	11.46	11.34	−0.03	0.00	−0.24	2.39	1.90	2.15

Predictor		W=1			W=2			W=3	
SLIM ACIB	−0.251		−0.320	−3.252		−3.277	−2.642		−2.691
	(−0.07)		(−0.10)	(−2.13)		(−2.10)	(−2.15)		(−2.10)
SLIM APIB		−0.921	−0.956		0.008	−0.345		−0.404	−0.693
		(−0.29)	(−0.32)		(0.00)	(−0.15)		(−0.23)	(−0.39)
R^2 (%)	−1.84	−1.64	−2.82	7.09	−2.31	6.02	6.48	−2.22	5.72

Predictor		M=1			M=2			M=3	
SLIM ACIB	−2.721		−2.506	−1.263		−0.948	−0.704		−0.367
	(−1.98)		(−1.70)	(−1.67)		(−1.49)	(−0.97)		(−0.67)
SLIM APIB		1.906	1.007		1.857	1.478		1.789	1.612
		(1.21)	(0.72)		(2.08)	(2.20)		(1.87)	(2.03)
R^2 (%)	7.47	−6.36	2.87	−1.02	0.20	−2.50	−6.16	2.29	−3.99

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 in the parentheses 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	W=1	W=2	W=3	Portfolio	W=1	W=2	W=3
CIB	−1.617	−1.348	−1.388	PIB	−0.622	−0.488	−0.353
Port 1	(−3.28)	(−3.45)	(−3.97)	Port 1	(−0.97)	(−0.91)	(−0.68)
R^2 (%)	1.27	2.02	2.73	R^2 (%)	0.10	0.17	−0.05
CIB	−1.591	−1.293	−1.342	PIB	−0.603	−0.500	−0.358
Port 2	(−3.13)	(−3.12)	(−3.70)	Port 2	(−0.98)	(−0.99)	(−0.73)
R^2 (%)	1.35	1.70	2.58	R^2 (%)	0.06	0.17	−0.03
CIB	−1.514	−1.235	−1.248	PIB	−0.599	−0.471	−0.353
Port 3	(−2.84)	(−2.85)	(−3.32)	Port 3	(−0.98)	(−0.96)	(−0.74)
R^2 (%)	1.22	1.38	2.12	R^2 (%)	0.29	0.03	0.08
CIB	−1.765	−1.466	−1.468	PIB	−0.542	−0.434	−0.298
Port 4	(−3.19)	(−3.24)	(−3.72)	Port 4	(−0.93)	(−0.90)	(−0.63)
R^2 (%)	1.47	1.83	2.76	R^2 (%)	0.26	0.07	−0.01
CIB	−1.693	−1.427	−1.407	PIB	−0.477	−0.369	−0.291
Port 5	(−3.14)	(−3.20)	(−3.63)	Port 5	(−0.80)	(−0.76)	(−0.61)
R^2 (%)	1.27	1.90	2.46	R^2 (%)	0.11	0.09	−0.07
CIB	−0.076	−0.078	−0.019	PIB	0.145	0.119	0.063
Port 5−1	(−0.57)	(−0.64)	(−0.17)	Port 5−1	(1.14)	(1.13)	(0.65)
R^2 (%)	0.22	−0.12	0.09	R^2 (%)	−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 six 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. The slope coefficient on the predictor is expressed as a percentage of the raw value (multiplied by 100). When $D > 1$, to adjust for the overlapping dependent variable, the t-stat in the parentheses is computed using the GMM standard errors with $D - 1$ Newey-West lag correction. The sample period is from 2005 to 2020.

		OTM			ATM			ITM		
Ticker	Predictor	D=1	D=3	D=6	D=1	D=3	D=6	D=1	D=3	D=6
RUT	ICIB	2.403	0.673	0.052	−0.049	0.090	−0.040	0.120	−0.105	0.066
		(1.85)	(0.89)	(0.08)	(−0.10)	(0.35)	(−0.19)	(0.29)	(−0.42)	(0.29)
	IPIB	−0.275	−0.182	−0.324	0.269	0.409	0.296	−0.643	−0.128	−0.212
		(−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	0.541	−0.706	0.635	−0.228	−0.220	−0.164	−0.591	−0.541	−0.513
		(0.28)	(−0.68)	(0.82)	(−0.55)	(−0.87)	(−0.87)	(−0.96)	(−1.45)	(−1.75)
	IPIB	0.828	−0.244	−0.119	0.890	0.822	0.597	−0.939	−0.664	−0.525
		(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	−6.315	−2.714	−3.082	−0.026	0.070	−0.074	−0.018	0.137	0.052
		(−1.59)	(−1.12)	(−2.20)	(−0.05)	(0.21)	(−0.34)	(−0.03)	(0.40)	(0.20)
	IPIB	5.811	3.055	2.579	−0.952	−0.280	−0.044	0.235	0.084	−0.189
		(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
SPX	ICIB	−1.000	−0.447	−0.411	−0.800	−0.102	−0.055	−0.173	−0.092	−0.021
		(−1.97)	(−1.56)	(−2.05)	(−1.44)	(−0.35)	(−0.23)	(−0.53)	(−0.46)	(−0.14)
	IPIB	0.857	0.336	0.343	−0.308	0.060	−0.089	−0.133	−0.171	−0.218
		(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	−4.756	−3.228	−1.606	−1.053	−0.784	−0.794	−0.070	−0.198	−0.213
		(−1.94)	(−2.42)	(−1.60)	(−2.09)	(−2.85)	(−3.77)	(−0.12)	(−0.56)	(−0.70)
	IPIB	2.193	1.708	0.545	0.179	0.069	0.141	0.449	−0.139	−0.211
		(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	−0.267	−0.520	−0.250	−0.323	0.203	0.030	0.405	−0.236	−0.526
		(−0.62)	(−1.96)	(−1.16)	(−0.75)	(0.78)	(0.15)	(0.74)	(−0.76)	(−1.87)
	IPIB	−0.581	0.078	0.149	−0.542	0.078	−0.047	−0.236	−0.590	−0.462
		(−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

Multiple Regressions with Index Options

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 5.2. 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. The slope coefficient on the predictor is expressed as percentage of the raw value (multiplied by 100). When $D/W/M > 1$, the t-stat in the parentheses 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	D=1	D=3	W=1	W=2	M=1	M=2
ACIB	−1.519	−1.009	−0.919	−0.710	−1.133	−0.866
	(−2.81)	(−2.64)	(−2.15)	(−2.36)	(−2.80)	(−3.30)
RUT CIB	0.029	−0.094	−0.347	−0.362	−0.200	0.065
	(0.06)	(−0.35)	(−0.92)	(−1.46)	(−0.56)	(0.26)
DJX CIB	0.213	0.112	0.568	0.188	0.411	−0.059
	(0.46)	(0.41)	(1.51)	(0.70)	(1.12)	(−0.28)
NDX CIB	0.029	0.054	0.039	−0.104	0.293	0.139
	(0.06)	(0.22)	(0.11)	(−0.38)	(0.97)	(1.27)
SPX CIB	−0.548	−0.024	0.338	0.097	0.117	0.055
	(−1.16)	(−0.09)	(0.84)	(0.33)	(0.35)	(0.24)
OEX CIB	−0.441	−0.349	−0.570	−0.547	−0.229	−0.239
	(−0.98)	(−1.32)	(−1.53)	(−1.88)	(−0.52)	(−0.84)
VIX CIB	0.321	0.274	0.352	0.286	1.125	0.611
	(0.71)	(1.07)	(0.89)	(1.07)	(3.14)	(2.56)
R^2 (%)	0.68	0.58	1.89	1.79	7.29	9.90

Table 13

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). The slope coefficient on the predictor is expressed as percentage of the raw value (multiplied by 100). When $D/W/M > 1$, the t-stat in the parentheses 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	D=1	D=3	W=1	W=2	M=1	M=2
ACIB	−0.006	−0.024	−0.621	−0.113	1.200	0.946
	(−0.29)	(−0.75)	(−1.49)	(−0.33)	(1.51)	(1.37)
APIB	0.060	0.123	1.455	1.245	0.595	0.681
	(2.92)	(4.10)	(3.50)	(3.30)	(0.92)	(0.86)
ICIB	0.004	0.046	0.480	0.336	0.737	1.447
	(0.20)	(2.06)	(1.71)	(1.44)	(1.00)	(2.24)
IPIB	0.011	0.030	−0.065	−0.255	−1.094	−1.185
	(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	D=1	D=3	W=1	W=2	M=1	M=2
ACIB	−0.010	−0.027	−0.141	−0.124	0.863	0.887
	(−0.52)	(−0.80)	(−1.39)	(−0.88)	(1.18)	(1.38)
APIB	0.098	0.204	0.530	0.774	1.244	1.036
	(5.49)	(6.56)	(4.44)	(4.75)	(1.57)	(1.23)
ICIB	0.013	0.056	0.130	0.170	0.678	1.216
	(1.02)	(2.85)	(1.61)	(1.81)	(1.15)	(2.05)
IPIB	−0.012	−0.003	−0.022	−0.057	−0.988	−1.093
	(−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

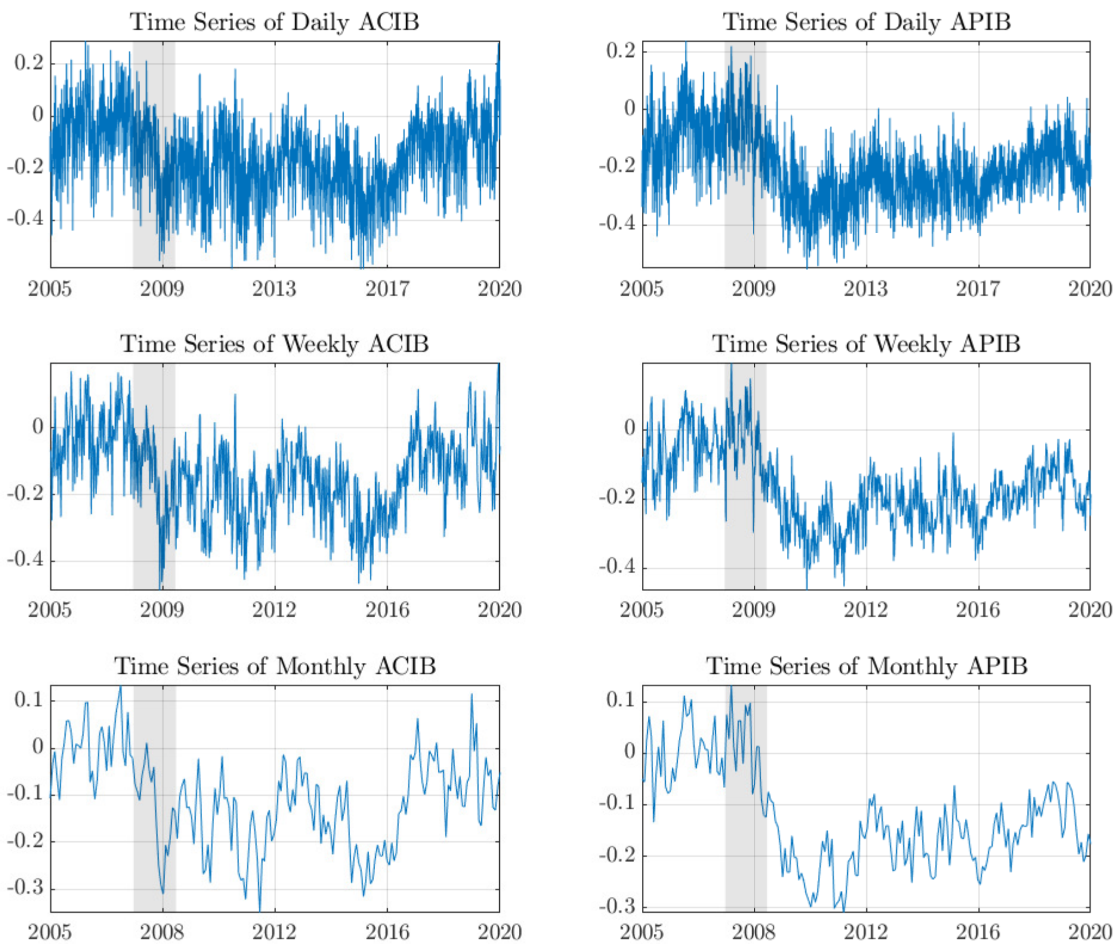


Figure 1. The Time Series of ACIB and APIB. Figure 1 depicts the time series of ACIB and APIB from 2005 to 2020 at daily, weekly, and monthly frequency. The option data is collected from the Chicago Board Options Exchange (CBOE). The grey areas indicate the National Bureau of Economic Research (NBER) 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.

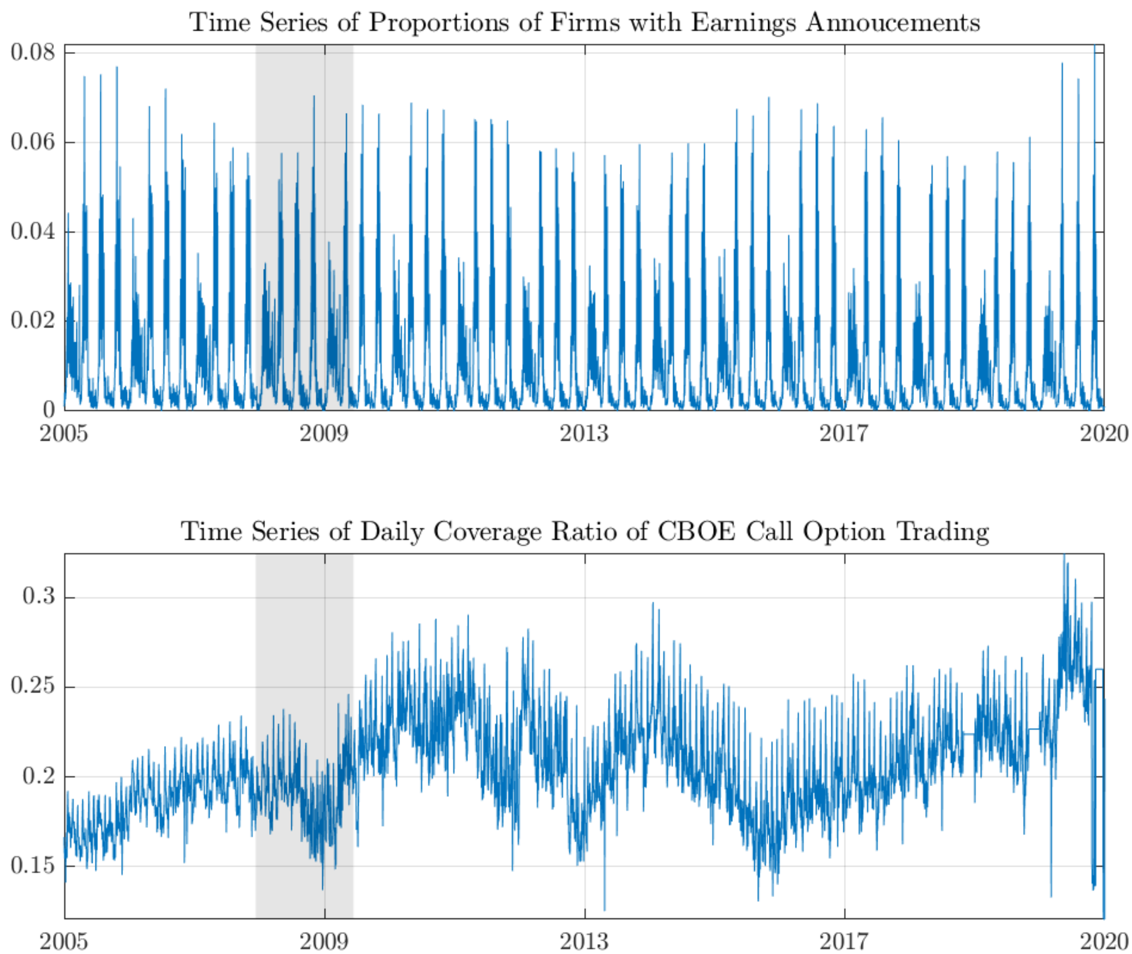
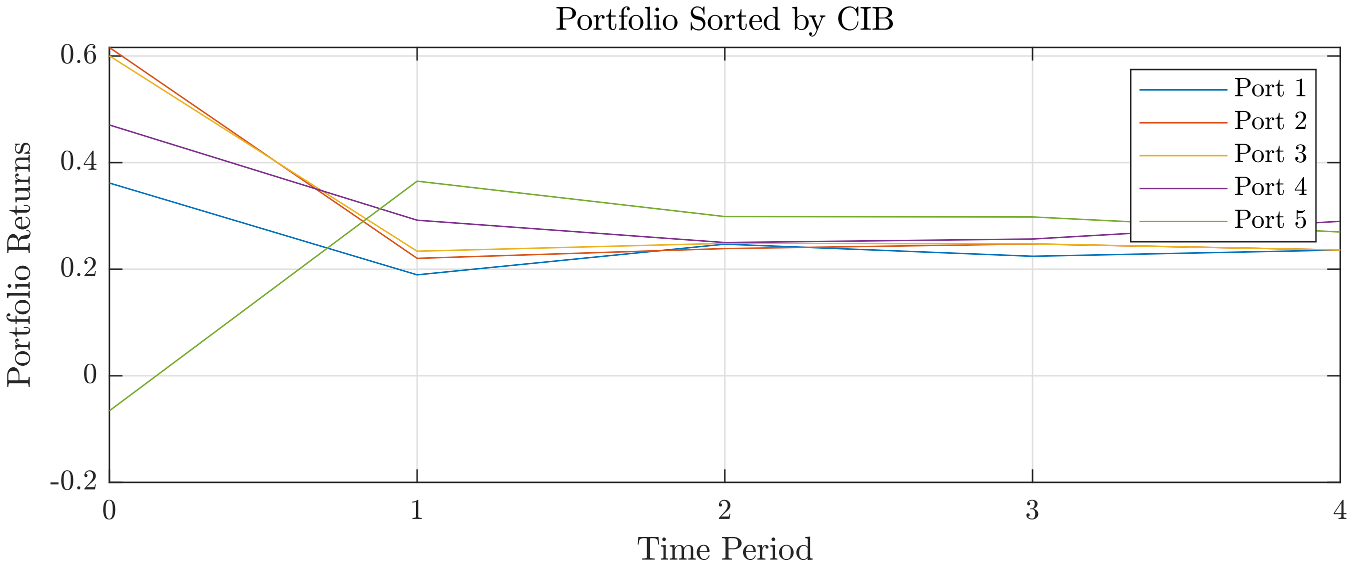


Figure 2. Dynamics of Regime Switching Variables. Figure 2 describes the two time-series variables used to decide the two regimes of equity option trading activities in Table 9. The first figure is the time-series proportion of firms with earnings announcements out of the total public firms. A higher 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.



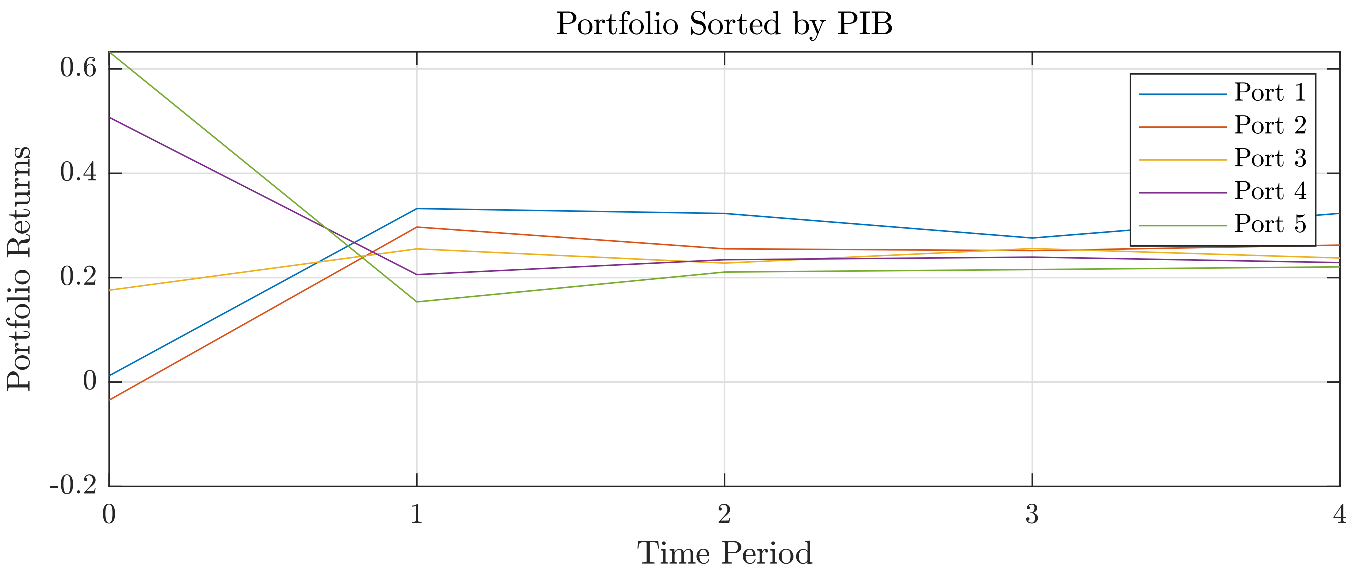


Figure 3. Sentiment Effect of Equity Option Trading in the Cross Section. Figure 3 compares the time series of portfolio returns sorted by call and put IB, namely CIB and PIB, over different time periods without overlaps at weekly frequency separately. At the end of each week, we sort all stocks with 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.