Investor sentiment and return predictability of the option to stock volume ratio

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Highlights

- The relation between future stock returns and option to stock volume ratio (O/S) varies over time.
- O/S has the explanatory power on future stock returns only during high investor sentiment periods.
- Investor sentiment has a unique effect on O/S-return relation after controlling consumer sentiment.
- Investor sentiment impacts differently on future stock returns from consumer sentiment.

Abstract

We study the effect of investor sentiment on the relation between the option to stock volume ratio (O/S) and future stock returns. Relative option volume has return predictability under short-sale constraints; in this regard, we expect and find that the O/S-return relation is only discovered during high investor sentiment periods. Our research also finds that Baker and Wurgler's (BW) investor sentiment index has a unique effect on the O/S-return relation after controlling for consumer sentiment indices and economic environment factors. Such indices are generally used as alternative measures of investor sentiment in the literature; however, we present evidence that investor sentiment differs from consumer sentiment.

JEL Classification: G12; G14.

Keywords: Investor sentiment; option to stock volume ratio; short-sale constraints; consumer sentiment; return predictability.

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Investor sentiment is one of the most significant financial issues among researchers and practitioners. In this regard, Baker and Wurgler's (2006), (2007) investor sentiment index is designed to capture the level of market-wide mispricing in the stock market. Baker and Wurgler (2006), (2007) study the direct relation between their sentiment index and future stock returns; they also emphasize that time-varying investor sentiment has a different impact on each individual asset because of the various levels of short-sale constraints. In addition, many other research papers investigate the indirect effect of investor sentiment on future stock returns (Yu and Yuan, 2011; Stambaugh et al., 2012; Shen and Yu, 2013). These studies present strong evidence that investor sentiment makes well-known anomalies predominant. In this current study, we investigate the effect of investor sentiment on the return predictive power of the option to stock volume ratio (O/S). Although prior studies usually adopt consumer sentiment indices as alternative measures of investor sentiment (Lemmon and Portniaguina, 2006; Antoniou et al., 2013), we demonstrate that Baker and Wurgler's (BW) investor sentiment index may also have a unique effect on future stock returns compared with consumer sentiment indices.

We focus on the effect of investor sentiment on the forecasting power of the O/S with regard to future stock returns. Johnson and So (2012) suggest a theoretical model whereby the O/S is negatively related to future stock returns when investors face short-sale constraints. In a multi-market asymmetric information world, the limitation of shorting stocks has an important effect on efficient investments. It is predicted that investors with negative private information frequently trade options rather than stocks when equity short-sale constraints are strong. Thus, relative option volume is informative on future stock returns. However, Johnson and So (2012) show mixed empirical results for their hypothesis that high short-sale costs cause the strong return predictive power of the O/S. In order to find robust empirical evidence, we investigate whether investor sentiment enhances the O/S-return relation. Our findings consistently support the prediction that the O/S has a significant relation with future stock returns only during high investor sentiment periods because investors experience strong short-sale impediments during such periods. We concentrate on market-wide short-sale constraints while Johnson and So (2012) focus on the short-sale costs of individual firms.

Baker and Wurgler (2006), (2007) base their investor sentiment index on direct stock market variables: trading volume (measured as total New York Stock Exchange (NYSE) turnover), the premium for dividend-paying stocks, the closed-end fund discount, the number of initial public offerings (IPOs) and the mean 1st-day IPO return, and the equity share in new issues. According to the literature (Zweig, 1973; Lee et al., 1991; Baker and Wurgler, 2000, 2004; Ritter, 2001; Baker and Stein, 2004), these six variables reflect market-wide mispricing. Baker and Wurgler (2007) state that such mispricing is caused by the

sentiment-based demand of irrational investors and a limit to arbitrage. Accordingly, both demand shock and the limit to arbitrage are necessary conditions for mispricing to occur. If investors have no limit to arbitrage, irrational demand shocks never lead to mis-valuation because rational investors take the full advantage of such shocks. Further, the limit to arbitrage is closely related to short-sale constraints, the usual limit to arbitrage of overpricing. Such short-sale constraint is also a key factor in determining the O/S-return relation; thus, we expect that investor sentiment has a strong effect on the return predictive power of the O/S. Further, we suggest that our expectation is supported by empirical results.

Many researchers and practitioners are interested in consumer sentiment indices such as the consumer confidence index provided by The Conference Board (CB), and the Michigan Consumer Sentiment Index (MCSI). Consumer sentiment indices are one of the most important variables that show current and future economic states; indeed, consumer sentiment is listed on the 10 leading economic indicators (Lemmon and Portniaguina, 2006). A consumer sentiment index is related to investor sentiment because consumers can also be potential investors. Consequently, such an index is used as a typical alternative measure of investor sentiment in prior research (Lemmon and Portniaguina, 2006; Antoniou et al., 2013). However, consumer sentiment differs from investor sentiment. First, the two aforementioned consumer sentiment indices use a survey-based methodology that involves U.S. households. Such households may not participate in the stock market as investors; thus, not all consumers are investors. Further, consumer sentiment surveys do not ask about stock market investments; consequently, consumer sentiment may not have a direct connection with investor sentiment. Second, consumer sentiment indices focus on consumer confidence about present and future economic states, and do not consider the limit to arbitrage. Thus, consumer sentiment is related to sentiment-based demand for stocks and has little relation to short-sale constraints. As aforementioned, the limit to arbitrage and irrational demand shocks on stocks are two key factors that cause mispricing. Accordingly, consumer sentiment may not have a direct connection with mis-valuation and an increase in the level of the BW investor sentiment index. Third, people's responses to a survey may differ from their actual behavior (Baker and Wurgler, 2007). In other words, households questioned by consumer sentiment surveys may not necessarily invest their capital in the stock market at the same level as they say in the surveys.

Lemmon and Portniaguina (2006) report that the CB index and the MCSI are highly correlated with each other. The authors further show that consumer sentiment is 85% correlated with key macroeconomic variables, suggesting that consumer sentiment is a good reflection of macroeconomic conditions. However, the BW investor sentiment index is little affected by macroeconomic variables. Baker and Wurgler (2006), (2007) state that such variables have negligible impacts on the common variation among

the six sentiment measures; thus, the "raw" investor sentiment index would qualitatively present the same results as those orthogonalized by several macroeconomic fundamentals. Consequently, we expect and find that the BW investor sentiment index covers that unique part of stock market information that consumer sentiment indices or economic environment variables do not capture. In other words, investor sentiment reflects the limit to arbitrage, although both consumer sentiment and investor sentiment indices measure irrational sentiment-based demand shock.

In order to study the effect of investor sentiment on the O/S-return relation, we investigate weekly portfolio returns sorted by the O/S. In a univariate analysis, we use the alphas calculated by various asset-pricing models in order to control risk and achieve robust results. These models are the capital asset pricing model (CAPM) alpha, Fama and French's three-factor model, and a four-factor model that includes the momentum factor. Decile portfolios are constructed by the O/S during high- and low-sentiment periods. We classify periods as high-sentiment if the BW investor sentiment index is higher than the median of the whole sample and as low-sentiment otherwise. Our findings suggest that the alpha differences between high and low O/S portfolios for the whole sample are 0.243% per week (12.636% annually) in the four-factor model. Additionally, the alpha differences during high investor sentiment periods are 0.415% per week (21.580% annually) in the four-factor model. These alpha differences during high investor sentiment periods are economically and statistically significant and almost twice as much as those during the whole sample period. By contrast, the alpha differences in the four-factor model during low investor sentiment periods are only 0.085% per week (4.420% annually) and not significantly different from zero. Thus, our findings confirm that the return predictive power of the O/S, in accordance with Johnson and So (2012), is driven by the results during high investor sentiment periods, thereby supporting our hypothesis. In order to investigate the unique effect of the BW investor sentiment index on the O/S-return relation further, we also conduct univariate and multivariate analyses after taking consumer sentiment indices and economic environment variables into account. Our results are qualitatively the same. Consequently, the BW investor sentiment index has an effect on future stock returns that consumer sentiment indices and other economic condition indicators are unable to match, thereby making the effect unique.

Our research contributes to two strands of literature. First, our findings extend the work of sentiment literature. Prior studies focus on the similarity of investor sentiment with consumer sentiment. Such research papers generally use the consumer sentiment indices as alternative measures of investor sentiment in the stock market. To the best of our knowledge, our research is the first to study the difference between investor sentiment and consumer sentiment. In this regard, it suggests important clues

to help fully understand the unique effect of investor sentiment on future stock returns that is not captured by consumer sentiment indices or macro-economic indicators. Second, this research presents additional insights for the literature about individual stock options. Johnson and So (2012) focus on the cross-sectional relation between short-sale costs and the return predictive power of the O/S. Their study considers residual institutional ownership (RI), loan fees, and loan supply. They calculate RI by using the residual from a cross-sectional regression of institutional ownership on firm sizes. The RI has some limitations as a measure of short-sale costs because it is an indirect measure of short-sale constraints. In addition, loan fee and loan supply data are presented for restricted periods from 2002 to 2009. Further, Johnson and So (2012, p. 278) explain that "Table 4 provides mixed support for Empirical Prediction 2," thereby suggesting that their short-sale cost measures have vague empirical relations with the predictive power of the O/S for future stock returns. We revisit this issue in order to address the clear relation between short-sale constraints and the return predictive power of the O/S by concentrating on market-wide and time-varying investor sentiment. Our research also differs from that of Johnson and So (2012) because we consider market-wide data while they focus on firm-level data.

The rest of the paper is organized as follows. Section I introduces our key variables including the O/S and investor and consumer sentiment measurements. In this section, we also describe main measures and summary statistics. Section II explains the data and reports the main empirical results. Section III describes the additional empirical results. Section IV concludes our research.

I. Variables and Summary Statistics

This section explains our key variables, including sentiment measures and the O/S. In Section I.A, we introduce sentiment measures such as Baker and Wurgler's (2006), (2007) investor sentiment and consumer sentiment (the CB index and the MCSI). Section I.B describes Johnson and So's (2012) O/S. Section I.C presents the summary statistics and the correlations among the key variables.

A. Investor and Consumer Sentiment Measures

1. Investor Sentiment Index of Baker and Wurgler (2006), (2007)

Baker and Wurgler (2006) propose an investor sentiment index to capture market-wide mispricing such as the tronics boom of the early 1960s, the Nifty Fifty bubble of the early 1970s, and the Internet bubble of the 1990s. However, it is hard to develop one perfect measure of mis-valuation although studies

suggest various mispricing measures such as trading volume (measured as total NYSE turnover), the premium for dividend-paying stocks, the closed-end fund discount, the number of IPOs and the mean 1st-day IPO return, and the equity share in new issues (Zweig, 1973; Lee et al., 1991; Baker and Wurgler, 2000, 2004; Ritter, 2001; Baker and Stein, 2004). These six variables measure the level of investor sentiment; however, they have advantages and disadvantages because of idiosyncratic variations that are unrelated to investor sentiment. In order to mitigate the concern about irrelevant aspects, Baker and Wurgler (2006) adopt principal component methodology in order to extract the common variation among the six variables. Further, Baker and Wurgler minimize the effect of macro-economic fundamentals on their sentiment index by using the residual from the regression of macro-economic factors on investor sentiment. These macro-economic factors are growth in industrial production, real growth in durable consumption, nondurable consumption, services consumption, growth in employment, and a National Bureau of Economic Research (NBER) recession indicator. Baker and Wurgler (2006), (2007) also report that macro-economic factors have unnoticeable impacts on investor sentiment, suggesting that the results of raw investor sentiment are consistent with those of the residuals from the regression of such factors.

2. Consumer Sentiment Indices

The CB index and the MCSI are two important consumer sentiment indices. Such indices differ from the BW investor sentiment index because they mainly depend on survey-based methodology among U.S. households in order to gauge the level of consumer sentiment. The MCSI is used as a more common measure of consumer sentiment than the CB index in academic research papers because the MCSI began before the CB index and offers data over a longer period (Ludvigson, 2004). Indeed, the MCSI began to report an annual consumer sentiment index in the 1940s by surveying U.S. households. Then, in 1952, the MCSI became a quarterly index, and since 1977 has been available monthly in order to meet the demand for consumer sentiment data. The MCSI questionnaire is delivered to 500 U.S. households. With regard to the CB index, Antoniou et al. (2013) describe it particularly well. They explain that the CB index survey started as a bimonthly measure in 1967 and become a monthly index in 1977. The CB index questionnaire is sent to 5,000 random households in the U.S. The literature utilizes the CB index to forecast household spending activities (Acemoglu and Scott, 1994; Ludvigson, 2004). Lemmon and Portniaguina (2006) also use the CB index as a measure of investor sentiment.

We present the details of the CB index and the MCSI questionnaires in the Appendix. The questions of both consumer sentiment indices are divided into two parts: the present situation component and the expectations component. The two consumer sentiment indices are very similar with regard to the

expectations component; however, the present conditions of consumer attitudes are measured differently. The MCSI's present situation component focuses on changes in macro-economic conditions, while the CB index's present situation component is particularly interested in economic activities such as labor market conditions, which are usually a late mover that follow other economic indicators. Thus, the MCSI captures changes in consumer sentiment sooner than the CB index.

B. The Option to Stock Volume Ratio

Johnson and So (2012) study the relation between the O/S and future stock returns. Order flow imbalances are usually unobservable or very hard to calculate in real time; thus, the authors utilize the O/S to predict future underlying equity returns and find the negative O/S-return relation, which suggests that a high O/S implies bad news for stockholders. We adopt Johnson and So's (2012) O/S measure in order to investigate the effect of investor sentiment on the relation between relative option volume and future stock returns. Investors with negative private information prefer to trade options under conditions of severe equity short-sale impediments; thus, option volumes are increased by such informed trading. Consequently, the relative option volume measure becomes informative to predict future stock returns.

We need options data to construct the O/S. Such options data are obtained from OptionMetrics, which provides daily option volumes, quoted closing prices, and option Greeks on all exchange-listed options for U.S. equities. We gather information about underlying stocks from the Center for Research in Security Prices (CRSP). Following Johnson and So (2012), we include options that expire between five and thirty trading days. We also include firm-weeks with at least 25 call and 25 put contracts that are traded to mitigate problems associated with illiquid options markets. We eliminate closed-end funds, real estate investment trusts, American depository receipts (ADRs), and firms with stock prices below $1.

We calculate the O/S in a manner that was developed by Roll, Schwartz, and Subrahmanyam (2010) and further studied by Johnson and So (2012). Specifically, for each stock *i* and for each week *w*, we calculate $O/S_{i,w}$ as the options contract volume per 100 shares of stock volume:

$$O / S_{i,w} = \frac{OPVOL_{i,w}}{STVOL_{i,w}}, \tag{1}$$

where $OPVOL_{i,w}$ is the weekly sum of the total number of contracts traded across all options listed for stock *i*, and $STVOL_{i,w}$ is the weekly sum of the total stock volume in units of 100.

C. Summary Statistics and Correlations

This section presents the summary statistics for the O/S, the volumes of call and put options, equity volume, firm size, book-to-market ratio, momentum, and investor sentiment index. We also show the correlation table for the BW investor sentiment index, the consumer sentiment indices, the Chicago Fed National Activity Index (CFNAI), and past market returns. Our sample periods cover 1996 to 2010 because OptionMetrics provides options data from 1996. The final data include 603,754 firm-weeks that satisfy the data restrictions. Panel A of Table I shows the sample characteristics and O/S descriptive statistics by year. The firm-week observations increase during the whole period, a finding that is consistent with Johnson and So (2012). The mean of O/S is 4.976% for the whole sample, suggesting that on average the stock trading volumes are 20 times larger than the options trading volumes.

[Table I here]

In Panel B of Table I, we describe the various volume measures by O/S deciles. VLC (VLP) is defined as the total call (put) options trading volume for the corresponding week in units of 100 shares. OPVOL is the total options trading volume that is the sum of VLC and VLP. The average of options trading volumes such as VLC, VLP, and OPVOL tend to be high for the high O/S groups. EQVOL is defined as the total equity trading volume in units of 100 shares. The mean of EQVOL is larger for high O/S firms than low O/S ones. LSIZE is a measure of firms' sizes judged by the log of market capitalization at the firms' most recent quarterly earnings announcements in COMPUSTAT. BM is the log of book-to-market ratio. Panel B shows that high O/S firms are more likely to have low BM. MOMEN is defined as the market-adjusted stock returns for the last six months. High O/S firms tend to have high MOMEN in our sample.

Panels C and D account for the investor sentiment index. Panel C presents the mean (the standard deviation) of the BW investor sentiment index as 0.185 (0.591). Further, the minimum (maximum) of the index is -0.902 (2.497). The median is 0.055; thus, high-(low-)sentiment periods have a sentiment index above (below) 0.055. Panel D shows the O/S descriptive statistics during high- and low-sentiment periods. The characteristics of O/S during high-sentiment periods are similar with those during low-sentiment periods. The numbers of firms and firm-week observations are 4,402 (4,282) and 300,579 (298,986) during high-(low-)sentiment periods. The difference in the O/S mean between high- and low-sentiment periods is also very small: -0.264 (= 4.827-5.091). Thus, we confirm that investor sentiment has a negligible impact on the O/S.

Table II presents the correlations among investor sentiment, consumer sentiment, and economic condition indicators. BW_SENTI is the BW investor sentiment index. Table II includes the two consumer sentiment indices: the CB index and the MCSI. CULMKT is defined as the past market return over the last 12 months. The CFNAI is the weighted average of 85 indicators of economic activity and inflationary pressure used as a measure of real economic activities taken from the Federal Reserve Bank of Chicago. CULMKT and CFNAI are important measures of economic state indicators. The correlation between BW_SENTI and the MCSI (the CB index) is 38% (56%), suggesting that investor sentiment has an economically significant relation with consumer sentiment. Thus, following the literature, we confirm that consumer sentiment is a good alternative measure of investor sentiment. However, the remaining 62% (44%) of the irrelevant variation in investor sentiment is still unexplained by the MCSI (the CB index). In the following sections of this research, we concentrate on this irrelevant part of investor sentiment with regard to consumer sentiment. The correlation between the two consumer sentiment indices is much higher (85%) than the correlation between investor sentiment and consumer sentiment. Further, consumer sentiment is positively related with the CFNAI, which is used as a measure of economic conditions. The correlation between the MCSI (the CB index) and the CFNAI is 14% (17%). In contrast to consumer sentiment, BW_SENTI has a negative relation with the CFNAI of -10%. This is indicative of the difference between the information contained in investor and consumer sentiment.

[Table II here]

II. Empirical Analysis

In this section, we verify our hypothesis that investor sentiment has an effect on the trading profits based on the O/S. In Section II.A, we check the differences in the profits of the O/S long-short strategy between high- and low-sentiment periods. Section II.B shows the unique information presented by the BW investor sentiment index for the stock and options markets beyond other consumer sentiment measures.

A. Investor Sentiment and Profits in O/S Long-Short Strategy

We investigate the effect of investor sentiment on the profits of an O/S-based strategy. Following Stambaugh et al. (2012), we employ various factor model regressions of O/S long-short trading profits for two sub-periods determined by the level of investor sentiment. Table III shows the alphas of various time-series factor models for each O/S decile portfolio: the CAPM, Fama and French's three-factor model, and a four-factor model that includes the momentum factor. To calculate the alphas, we regress weekly excess returns of each O/S decile portfolio on the contemporaneous market factor, the small-minus-big market capitalization (SMB) factor, the high-minus-low book-to-market ratio (HML) factor, and the momentum factor. Specifically, we estimate four variants of the following four-factor model corresponding to each O/S decile:

$$r^p - r^f = \alpha + \beta_m \left(r_{mkt} - r^f \right) + \beta_{SMB} SMB + \beta_{HML} HML + \beta_{UMD} UMD + \varepsilon, \quad (2)$$

where r^p is the weekly equal-weighted portfolio return in each O/S decile using the O/S in the prior week, r^f is the risk-free rate, and r_{mkt} is the market return. SMB, HML, and UMD are the weekly returns associated with small-minus-big capitalization, high-minus-low book-to-market ratio, and high-minus-low momentum strategies, respectively. Excess returns are calculated based on the model, omitting all factors, and the CAPM alphas are derived from the factor model, omitting all factors except for the market factor. Further, the three-factor alpha is calculated based on the factor model, omitting only UMD.

[Table III here]

Table III reports the average excess returns and the alphas from these factor regressions corresponding to each O/S decile. We also present the differences of the average excess returns and the alphas between low and high O/S portfolios during the whole sample periods, high-sentiment periods, and low-sentiment periods. The results indicate that high O/S portfolios underperform low O/S portfolios, especially during high-sentiment periods. In the four-factor model, the "All" column shows that the lowest O/S portfolio has an alpha of -0.003%, and the highest O/S portfolio has an alpha of -0.25% in the following week, during the whole sample period. These empirical results are consistent with the results from Johnson and So (2012). During high-sentiment periods, the lowest O/S portfolio has an alpha of -0.23% in the following week while the highest O/S portfolio has an alpha of -0.64%. However, during low-sentiment periods, the lowest O/S portfolio has an alpha of 0.16%, and the highest O/S portfolio has an alpha of 0.08% in the following week. The "1-10" row shows the statistical significance of the difference between

the alphas of the lowest and highest O/S portfolios. Thus, the differences between the alphas of the lowest and highest O/S portfolios are 0.24% with a *t*-statistic of 3.04 during the whole sample period, 0.42% with a *t*-statistic of 3.04 during high-sentiment periods, and 0.09% with a *t*-statistic of 0.98 during low-sentiment periods. This supports our hypothesis that the return predictability of the O/S only exists during high investor sentiment periods. Further, we confirm that the empirical findings from Johnson and So (2012) are mostly driven by the results during high-sentiment periods. In addition, the final "(1 + 2) - (9 + 10)" row shows the statistical significance of the difference between the alphas of the two lowest and two highest O/S decile portfolios. Consistent with the results in the "1-10" row, the size and magnitude of the *t*-statistic for the alphas are larger during high-sentiment periods than those during the whole sample period and low-sentiment periods. The common pattern of the four-factor model alpha decreasing with the O/S is observed in the whole sample period, high-sentiment periods, and low-sentiment periods. However, the statistical and economic significances of the differences in the alphas of the four-factor models among O/S portfolios during the whole sample period are mostly attributed to those during high-sentiment periods. The results for the excess returns, the CAPM alphas, and the three-factor model are similar to those of the four-factor model.[1]

As mentioned in Johnson and So (2012), a high (low) O/S implies bad (good) news; thus, we observe relatively bad future stock returns after a high O/S. We further expect and find that this O/S-return relation becomes pronounced during high-sentiment periods because short-sale constraints bind more strongly during such periods than others. During high-sentiment periods with strong short-sale constraints, investors prefer to trade options in order to exploit their negative private information rather than stocks because of expensive short-sale costs, which makes the O/S more useful. The "1-10" and "(1 + 2) - (9 + 10)" rows in Table III reveal consistent results with our argument. This additionally suggests that the profits of short-leg positions generally drive the differences of a long-short strategy's profits based on the O/S between high-sentiment and low-sentiment periods. For example, the four-factor alphas of high O/S portfolios (short legs) change by 0.72% per week (= 0.077% - (-0.643%)) from low-sentiment periods to high-sentiment periods. However, those of low O/S portfolios (long legs) vary only 0.39% per week (= 0.162% - (-0.228%)). These results indicate that informed traders influence the profitability of short legs

[1] Although the untabulated result for the ΩO/S (the percentile rank in the firm-specific time-series of the O/S) is somewhat weaker than the results for the O/S, the results for the ΔO/S (the change in the O/S relative to a rolling average of the past O/S for each firm) and the ΩO/S are consistent with our hypothesis. The weakness of the patterns for the ΩO/S is consistent with the results in Johnson and So (2012). Johnson and So (2012) imply that the weak predictive power of the ΩO/S is attributed to its sensitiveness to market-wide variation in option or equity volumes that are not related to private information.

more than long legs during high-sentiment periods. The results for the four-factor model are qualitatively the same for the excess returns, the CAPM alpha, and the three-factor model alpha. Our findings associated with economically and statistically significant profits in the short leg of an O/S strategy are also consistent with Stambaugh et al.'s (2012) second hypothesis.

To check the persistency of the O/S-return relation during high-sentiment periods, we explore the duration of the predictive power based on the O/S for future stock returns. Figure 1 shows the alphas from the four-factor model based on an O/S long-short strategy during high- and low-sentiment periods. Following Johnson and So (2012), we plot the alphas of an O/S long-short strategy during the 1-12 weeks after portfolio formation. The O/S is measured 1-12 weeks prior to the realized return window during high- and low-sentiment periods. The top graph shows the weekly alphas from the four-factor model and the 95% confidence interval for the alphas. The bottom graph shows the cumulative alphas calculated by the four-factor model.

[Figure 1 here]

The top graph in Figure 1 indicates that the predictive power of the O/S for the future stock returns during high-sentiment periods is short-lived and quickly disappears within a few weeks. We find that this predictive power during high-sentiment periods remains significant at the 5% level for the three weeks following the portfolio formation week. This pattern during high-sentiment periods is very similar to those of Johnson and So (2012). Meanwhile, the predictive power of the O/S during low-sentiment periods presents different shapes from the predictive power of the O/S during high-sentiment periods. Further, the predictive power of the O/S during low-sentiment periods always presents insignificant results during the 1-12 weeks after the portfolio formation week. These findings regarding high- and low-sentiment periods are consistent with the results from Table III; thus also indicating that the O/S-return relation during the whole sample period is mostly determined by the O/S-return relation during high-sentiment periods. The bottom graph in Figure 1 shows that the cumulative 12-week alphas from the four-factor model during low-sentiment periods are negative while the cumulative 12-week alphas during high-sentiment periods are positive. This suggests that investor sentiment has a critical effect on the profits of an O/S long-short strategy. Johnson and So (2012) report mixed empirical findings for their hypothesis that short-sale constraints have a relation with future stock returns. Our findings confirm that the mixed results from Johnson and So (2012) are mainly driven by the results during high-sentiment

periods. Further, our findings suggest that investor sentiment has the ability to distinguish between two regimes based on the return predictive power of the O/S.

B. Does the BW Investor Sentiment Index Contain Unique Information?

With regard to the sentiment measurement, the literature employs three representative sentiment indices: the BW investor sentiment index, the CB index, and the MCSI.[2] As aforementioned, the two consumer sentiment indices (the CB index and the MCSI) are based on a survey methodology that uses U.S. households. The BW investor sentiment index directly measures investors' sentiment by using financial data that are available in the stock market. Thus, we argue that the BW investor sentiment index contains unique information about financial markets that is not included in consumer sentiment indices. In order to confirm the uniqueness of such information, we first check the effect of consumer sentiment indices on the profitability of an O/S long-short strategy. We then examine the profitability of an O/S trading strategy in different states that are defined by independent double-sorting by the BW investor sentiment index and one of the consumer sentiment indices. Finally, we design a regression model in order to present the uniqueness of the BW investor sentiment index after controlling for the consumer sentiment indices simultaneously.

One problem in using a raw consumer sentiment index is its correlation with macroeconomic conditions. In order to remove macroeconomic information from the raw consumer sentiment indices, we follow the approach used in the literature. Specifically, with regard to the CB index, we follow Antoniou et al. (2013) and first regress the raw CB index series on growth in industrial production; real growth in durable, nondurable, and services consumption; growth in employment; and an NBER recession indicator. Next, we calculate a weighted three-month rolling average of the residuals from this regression, using a weight of 3/6 for month *t*, a weigh of 2/6 for month *t*-1, and a weight of 1/6 for month *t*-2. With regard to the MCSI, we follow Fong and Toh (2014) and use the residuals from the regression of the raw MCSI series on the aforementioned macroeconomic variables.

We use one of these orthogonalized consumer sentiment indices and define a high (low) consumer sentiment period as one in which the consumer sentiment index is above (below) the sample median value,

[2] With regard to the CB index, Antoniou et al. (2013) evaluate the effect of sentiment on momentum profits, and Arif and Lee (2014) investigate the relation between corporate investment and market-wide investor sentiment. With regard to the MCSI, Lemmon and Portniaguina (2006) explore the relationship between investor sentiment and the small-stock premium, and McLean and Zhao (2014) show that economic recessions and low investor sentiment increase external financial costs.

following the same approach as the BW investor sentiment index periods. Table IV presents the average excess returns and the alphas from the factor regressions in each O/S decile portfolio during high and low consumer sentiment periods. Panel A reports the results using the CB index and Panel B reports the results using the MCSI. We find that the CB index and the MCSI are able to distinguish between two regimes based on the profitability of an O/S long-short strategy in a similar way to the BW investor sentiment index. For instance, in Panel A of Table IV, the differences of the four-factor alphas between the lowest and highest O/S portfolios are 0.36% with a *t*-statistic of 2.45 during high CB index periods and 0.14% with a *t*-statistic of 1.88 during low CB index periods. Panel B of Table IV further shows that the differences of the four-factor alphas between the lowest and highest O/S portfolios are 0.37% with a *t*-statistic of 2.55 during high MCSI periods and 0.11% with a *t*-statistic of 1.56 during low MCSI periods. During high consumer sentiment periods, the profits of an O/S long-short strategy are larger and more strongly significant than those during low consumer sentiment periods. These results are consistent with empirical evidence in the literature that utilizes consumer sentiment indices as alternative measures of investor sentiment. The results also show that the profits of an O/S long-short strategy with the CB index and the MCSI during low consumer sentiment periods are larger and more strongly significant than those with the BW investor sentiment index during low-sentiment periods. In addition, these results suggest another implication for our empirical results in Section II.A. Stambaugh et al. (2012) express a concern about the misleading conclusion induced by the asymmetry in the sentiment index. They repeat the empirical analyses with the CB index and the MCSI instead of the BW investor sentiment index in order to alleviate the effect of the asymmetry in the sentiment index on the asymmetry in pricing.[3] Similarly, we repeat the analysis in Table III with the CB index and the MCSI and gain qualitatively the same results with the BW investor sentiment index. Thus, the results in Table IV address the potential concern of Stambaugh et al. (2012).

[Table IV here]

[3] Stambaugh et al. (2012) show that the BW investor sentiment index is positively skewed (0.19) and the MCSI is negatively skewed (-0.30) during their sample periods from August 1965 to January 2008. They are concerned that the difference in the skewness of sentiment indices has an impact on the asymmetry in pricing. During our sample periods, the BW investor sentiment index is positively skewed (1.61), and the CB index and the MCSI are negatively skewed (-0.49 and -0.56).

We use investor and consumer sentiment in our model simultaneously in Tables V and VI. These tables present the profits of an O/S long-short strategy in four combinations of investor sentiment and consumer sentiment state: a low consumer sentiment state with low or high investor sentiment and a high consumer sentiment state with low or high investor sentiment. In Table V, we conduct analyses of the O/S trading profits during high and low investor sentiment periods after controlling for the CB index. We find that the CB index cannot weaken the effect of the BW investor sentiment index on the profitability of an O/S long-short strategy. The profits of an O/S long-short strategy during high and low CB index periods still vary with the BW investor sentiment index. For example, during high CB index periods, the differences of the four-factor alphas between the lowest and highest O/S portfolios are 0.46% with a *t*-statistic of 2.68 during high-sentiment periods and -0.14% with a *t*-statistic of -0.45 during low-sentiment periods. We also discover consistent results with the MCSI in Table VI. An O/S long-short strategy is still more profitable during high-sentiment periods than during low-sentiment periods even after controlling for the MCSI. During high MCSI periods, the differences of the four-factor alphas between the lowest and highest O/S portfolios are 0.53% with a *t*-statistic of 2.53 during high investor sentiment periods and 0.07% with a *t*-statistic of 0.39 during low investor sentiment periods. Overall, the BW investor sentiment index has a significant influence on the profitability of an O/S long-short strategy after considering the CB index and the MCSI. Thus, these empirical results in Tables V and VI confirm that the BW investor sentiment index contains unique information on the stock and options markets beyond consumer sentiment indices.

[Table V here]

[Table VI here]

In order to check the robustness of our results, we establish a regression model to control the information of consumer sentiment indices simultaneously. The following regression model is estimated:[4]

[4] Table 5 in Stambaugh et al. (2012) shows the predictive power of investor sentiment for future returns from a long-short strategy based on market anomalies after controlling for market factors, SMB, and HML. In a similar way to the predictive regressions in Stambaugh et al. (2012), we perform a predictive regression for adjusted returns on an O/S long-short strategy.

$$R_{p,t} - \beta_p^{'} F_t = \gamma_0 + \gamma_1 BW\_SENTI_{t-1} + \gamma_2 CON\_SENTI_{t-1} + \varepsilon_t, \quad (3)$$

where $R_{p,t}$ is the return on an O/S decile 1-10 spread portfolio, F_t are factors, and β_p are factor loadings. BW_SENTI_t is the BW investor sentiment index, and CON_SENTI_t is a consumer sentiment index such as the CB index and the MCSI.

Table VII reports the results of the predictive regressions with the BW investor sentiment index and consumer sentiment indices. The coefficient estimates for *BW_SENTI* are always positive and significant, supporting our hypothesis that O/S return predictability becomes strong during high investor sentiment periods. For instance, in the univariate regression for the four-factor risk-adjusted spread returns, the coefficient estimate for *BW_SENTI* is 0.003 with a *t*-statistic of 2.08. After controlling for the CB index and the MCSI, the coefficient estimates for *BW_SENTI* are also 0.003 with a *t*-statistic of 1.89 and 0.003 with a *t*-statistic of 2.23 in columns (6) and (7), respectively. However, the coefficient estimates for the CB index and the MCSI are not significant in the regression with the BW investor sentiment index. These results are consistent with the findings of independent double-sorting by the BW investor sentiment index and consumer sentiment indices in Tables V and VI. Additionally, the coefficient estimate for *BW_SENTI* still remains significantly positive after controlling for the CB index and the MCSI in column (8). Columns (1)-(4) also show the results of the raw spread returns (not risk-adjusted). These are similar to the results of the four-factor risk-adjusted spread returns. In the unreported results, the coefficient estimates for *BW_SENTI* are always positively significant in the predictive regressions of the market risk-adjusted spread returns and the three-factor risk-adjusted spread returns. Taken together, Tables V, VI, and VII present empirical evidence that confirms the superior informativeness of the BW investor sentiment index with regard to the predictive power of O/S compared with consumer sentiment indices. These findings are consistent with Berger and Turtle (2015) and Huang et al. (2015), which report that an investor sentiment index differs from consumer sentiment indices.

[Table VII here]

III. Additional Analyses

In this section, we conduct additional analyses in order to strengthen the robustness of our main findings. In Section III.A, we check whether economic environments can also have a significant effect on asymmetric pricing in order to dispel the concern that investor sentiment is contaminated by factors

related to economic environments. Section III.B investigates the interactive effect of investor sentiment and cross-sectional short-sale constraints on the O/S-return relation. In order to conduct this investigation, we adopt residual institutional ownership as a measure of the short-sale costs of individual firms.

A. Investor Sentiment, Profits in O/S Long-Short Strategy, and Economic Environments

Baker and Wurgler (2007) express a concern that the BW investor sentiment index is affected by fundamental economic risk. In order to alleviate this concern, we show that economic risk factors do not have an impact on the ability of investor sentiment index to distinguish the asymmetric pricing effect. In this context, Antoniou et al. (2013) investigate whether the market states described by past market returns have an effect on the ability of a consumer sentiment index to distinguish momentum profits. Further, Fong and Toh (2014) examine whether the dependence of the max effect on investor sentiment is driven by economic states.

Our empirical results support the hypothesis derived from the argument that during high-sentiment periods, informed traders tend to utilize options rather than stocks in order to exploit negative information because of high short-sale constraints in the stock market. In a similar way to concerns in the literature, an alternative explanation for our results is that informed traders decide to use options based on information about economic environments, such as past market returns or economic indicators, in order to exploit market anomalies, such as momentums and reversals. Under this alternative explanation, the profits of an O/S long-short strategy may be attributed to economic environments, not the asymmetric relationship between the O/S and future stock returns, depending on the level of investor sentiment. In order to verify whether economic environments explain the profits of an O/S long-short strategy, we show that the variables related to economic environments do not affect the relation between investor sentiment and the return predictability of the O/S. Following Antoniou et al. (2013) and Fong and Toh (2014), we employ past market returns and CFNAI as the variables that reflect economic environments.

In a similar way to the methodology in Antoniou et al. (2013), we define UP (DOWN) market states when the cumulative returns of the CRSP value-weighted index that includes dividends for the months t-k to t-1 are non-negative (negative). Based on the market states, Table VIII reports the average excess returns and the alphas from the four-factor model. These are conditional on two market states with 12-month cumulative returns (k = 12) and two investor sentiment states.[5] For DOWN market states, as

[5] We also compute the alphas in the CAPM and three-factor model. These results are similar to the results in Table VIII. The unreported results for the CAPM and three-factor model are available upon request.

shown in Table VIII, the profits based on an O/S long-short strategy (see the "1-10" row) for the average excess returns and the alphas in the four-factor model during high-sentiment periods are positive and highly significant, while those during low-sentiment periods are negative and insignificant. For instance, the average excess returns and alphas in the four-factor model conditional on DOWN market states and high-sentiment states are 0.54% with a *t*-statistic of 3.17 and 0.50% with a *t*-statistic of 2.43, respectively. However, when conditional on DOWN market states and low-sentiment states, the average excess returns and alphas in the four-factor model are -0.01% with a *t*-statistic of -0.05 and -0.25% with a *t*-statistic of -1.50, respectively.

[Table VIII here]

The profits of an O/S long-short strategy during high-sentiment periods are also positive and significant in UP market states. In a similar way to the results in DOWN market states, the profits of an O/S long-short strategy during low-sentiment periods are insignificant. For an O/S long-short strategy that includes the second-lowest and second-highest O/S decile portfolios (see the "(1 + 2) - (9 + 10)" row), the results are quantitatively the same as the results in the "1-10" row. We also conduct the same analysis using the 24-month (k = 24) and 36-month (k = 36) cumulative returns. Owing to space limitations, the results associated with market states of 24-month and 36-month cumulative returns are omitted; however, the results are consistent with those in Table VIII. Thus, the results in Table VIII support our hypothesis that the return predictive power of the O/S becomes strong during high-sentiment periods compared with those during low-sentiment periods after controlling for economic state variables.

In addition, following Fong and Toh (2014), we define two economic states by classifying periods with non-negative (negative) values of CFNAI as periods of economic expansion (contraction). Based on economic states that depend on the level of CFNAI, Table IX presents the average excess returns and the alphas from the four-factor model, using independent double-sorting by two economic states and two investor sentiment states.

[Table IX here]

For economic expansion periods in Table IX, the profits based on an O/S long-short strategy (see the "1-10" row) are larger and more strongly significant during high-sentiment periods than those during low-sentiment periods. The profits for the excess returns and the alphas in the four-factor model, conditional on economic expansion and high-sentiment states, are 0.44% with a *t*-statistic of 1.81 and 0.79% with a *t*-statistic of 3.00, respectively. For economic expansion and low-sentiment states, the profits for the excess returns and the alphas in the four-factor model are 0.07% with a *t*-statistic of 0.57 and 0.09% with a *t*-statistic of 0.61, respectively. The results for economic contraction are similar to those for economic expansion. The profits for the excess returns and the alphas from the four-factor model in economic contraction and high-sentiment states are 0.33% with a *t*-statistic of 2.53 and 0.34% with a *t*-statistic of 2.35, respectively, while those in economic contraction and low-sentiment states are 0.03% with a *t*-statistic of 0.25 and -0.06% with a *t*-statistic of -0.54, respectively. Taken together, Tables VIII and IX present empirical evidence confirming that the difference between the O/S profits in high- and low-sentiment periods cannot be explained by the phenomena related to economic environments.

Further, we report the regression results in order to examine the explanatory power of investor sentiment after controlling for consumer sentiment and economic environments.[6] In order to conduct this examination, we estimate the following regression model:

$$R_{p,t} - \beta_p^{'} F_t = \gamma_0 + \gamma_1 BW\_SENTI_{t-1} + \gamma_2 ECOEN_{t,k} + \gamma_3 ECOEN_{t,k}^2 + \gamma_4 CON\_SENTI_{t-1} + \varepsilon_t, \quad (4)$$

where $R_{p,t}$ is the return on the O/S decile 1-10 spread portfolio, F_t are factors, and β_p are factor loadings. BW_SENTI_t is the BW investor sentiment index, and $ECOEN_{t,k}$ is the variable for economic environments. CON_SENTI_t is the consumer sentiment indices.

As shown in Panel A of Table X, the regression results that involve the 12-month lagged market returns show the magnitudes and the significances of the coefficient estimates for *BW_SENTI*. With regard to the raw spread returns, the coefficient estimates for *BW_SENTI* are still positive and highly significant after controlling for 12-month lagged market returns, the square of 12-month lagged market returns, and consumer sentiment indices. After considering 12-month lagged market returns (see column (1)), the coefficient estimate for *BW_SENTI* is 0.003 with a *t*-statistic of 2.31, which is a similar result to the one in

[6] Cooper et al. (2004) use market states in the regression model in order to check whether momentum profits are related to market states. In addition, Antoniou et al. (2013) add investor sentiment to the regression model of Cooper et al. (2004) in order to explain the effect of sentiment on momentum profits after controlling for market states. In a similar way to the regression model in Antoniou et al. (2013), we verify the asymmetric pricing effect of investor sentiment on the profits of an O/S long-short strategy after controlling for the economic environment variables.

Table VII. After controlling for the square of 12-month lagged market returns, the CB index, and the MCSI, the results are similar to the result in column (1). The significantly positive signs of the coefficient estimates for *BW_SENTI* are consistent with our hypothesis that investor sentiment affects the profits of an O/S long-short strategy. Further, we find that the coefficient estimates for consumer sentiment indices are always insignificant after controlling for the BW investor sentiment index, a result that is consistent with those in Section II.B. The coefficient estimate for *BW_SENTI* still remains significantly positive after controlling for the 12-month lagged market returns, the square of 12-month lagged market returns, the CB index, and the MCSI simultaneously. With regard to the four-factor risk-adjusted spread returns, the patterns in the coefficient estimates for *BW_SENTI* are similar to those for the raw spread returns.[7]

[Table X here]

We also run the regression with regard to the 24-month and 36-month lagged market returns.[8] The results show that the coefficient estimates for *BW_SENTI* are all positive and significant after controlling for various factors that can affect the O/S profits. Specifically, with regard to the four-factor risk-adjusted spread returns, the coefficient estimates for *BW_SENTI* in the regression that involves the past market returns, the square of past market returns, and the MCSI are 0.003 with a *t*-statistic of 2.10 for the 12-month lagged market returns, 0.003 with a *t*-statistic of 2.01 for the 24-month lagged market returns, and 0.004 with a *t*-statistic of 2.45 for the 36-month lagged market returns. Overall, the results in Panel A of Table X show that after considering market states and consumer sentiment indices, the BW investor sentiment index contains additional information that further explains the time-series variation of the profits of an O/S long-short strategy.

In Panel B of Table X, we take CFNAI into account instead of the past market returns in Panel A. In a similar way to the results in Panel A, the coefficient estimates for *BW_SENTI* are always positive and highly significant. For the four-factor risk-adjusted spread returns, the coefficient estimates for *BW_SENTI* are 0.004 with a *t*-statistic of 2.10 in column (8) and 0.004 with a *t*-statistic of 2.46 in column (9). In addition, the coefficient estimate for *BW_SENTI* is 0.003 with a *t*-statistic of 1.94 in the regression model that includes CFNAI, the square of CFNAI, the CB index, and the MCSI. After controlling for the

[7] The results for the CAPM and three-factor model are similar to the results in Panel A of Table X. These results are available upon request.

[8] The results for the regression with the 24-month and 36-month lagged market returns are available upon request.

BW investor sentiment index, the consumer sentiment index presents an insignificant effect on the profits of an O/S long-short strategy. The results in Table X also confirm that investor sentiment captures variation in the profits of an O/S long-short strategy compared with economic environments and consumer sentiment.

B. Short-Sale Constraints and Profits in an O/S Long-Short Strategy

Our hypothesis argues that informed traders exploit options rather than stocks when they have negative news about the stocks during high-sentiment periods owing to equity short-sale constraints. This situation causes significantly larger profits for an O/S long-short strategy during high-sentiment periods compared with low-sentiment periods. Thus, we expect that the average pricing effects of an O/S on future stock returns are strong during high-sentiment periods, because during such periods, short-sale constraints bind strongly. Our research focuses on the time-series of the variation in the stock market's short-sale constraints while Johnson and So (2012) discuss the cross-sectional variation of short-sale constraints across firms. Johnson and So (2012) show that firms with low residual institutional ownership (RI) have a strong O/S-return relation. Low RI leads to a small amount of stock loans, which makes short selling costly. In this section, we further investigate the effect of investor sentiment on the cross-sectional relation between RI and the return predictive power of O/S. Following Nagel (2005), we use RI as the measure of short-sale costs. This measure shows the differences in short-sale costs among individual firms. Specifically, the RI is calculated by the residual from the following cross-sectional regression:

$$\log\left(\frac{INST_{i,q}}{1-INST_{i,q}}\right)=\alpha_q+\beta_q SIZE_{i,q}+\gamma_q\left(SIZE_{i,q}\right)^2+\varepsilon_{i,q}, \tag{5}$$

where $INST_{i,q}$ is the fraction of shares outstanding held by institutions for firm i in quarter q reported in the Thomson Financial Institutional Holdings (13F) database, and $SIZE_{i,q}$ is the market capitalization of firm i in quarter q. We winsorize $INST_{i,q}$ at 0.01% and 99.99%, following Nagel (2005) and Johnson and So (2012).

The RI is defined as the percentage of shares held by institutions adjusted by firm sizes in the cross-sectional regression. Stock with a high (low) value of RI faces less (more) binding short-sale constraints in the stock market. When institutional ownership is high, investors can easily borrow stocks, causing lower short-sale costs compared with stocks that have low institutional ownership.

Table XI presents O/S raw spread returns and O/S risk-adjusted spread returns adjusted by the four-factor model for portfolios. These return spreads are sorted by RI and investor sentiment. Panel A (short-sale cost terciles) of Table XI shows that the four-factor risk-adjusted spread returns during the whole sample period increase when investors experience high short-sale constraints. The four-factor risk-adjusted spread returns are 0.54% with a *t*-statistic of 4.79 for portfolios with the lowest RI and -0.02% with a *t*-statistic of -0.16 for portfolios with the highest RI. During low-sentiment periods, the four-factor risk-adjusted spread return for portfolios with the highest RI is negative and insignificant, while the return for portfolios with the lowest RI is significantly positive. During high-sentiment periods, the four-factor risk-adjusted spread return for portfolios with the highest RI is more significant and larger than during low-sentiment periods. More interestingly, the four-factor risk-adjusted spread return for portfolios with RI (2) is positive and significant during high-sentiment periods. Meanwhile, the return for portfolios during low-sentiment periods is negative and insignificant, which causes mixed results in Johnson and So (2012). As the level of investor sentiment increases, the magnitude and significance of O/S profits grow larger and stronger. The results of the raw spread returns are similar to those for the four-factor risk-adjusted spread returns. Panel B reports the results based on the RI quantiles. In a similar way to the results in Panel A, the four-factor risk-adjusted spread return for portfolios with RI (3) is positive and significant only during high-sentiment periods. The results in Section III.B indicate that the relationship between O/S and future stock returns tends to strengthen as the level of investor sentiment increases.

[Table XI here]

IV. Concluding Remarks

Investor sentiment has a crucial role with regard to future stock returns when investors have equity short-selling constraints. Classical models predict that irrational demand shocks have no impact on equity valuation because rational investors take full advantage of arbitrage in such circumstances. However, Baker and Wurgler (2006), (2007) state that sentiment-based demand causes overvaluation when rational investors face strong short-sale impediments. In addition to Baker and Wurgler's work, many researchers study the direct and indirect impact of investor sentiment on future stock returns (Yu and Yuan, 2011; Stambaugh et al., 2012; Shen and Yu, 2013). In this regard, we explore the unique effect of investor sentiment on the O/S-return relation. Our findings present evidence that the O/S-return relation reported by Johnson and So (2012) is only observed during high-sentiment periods because short-sale constraints

are strong during such periods. The literature focuses on the similarity between investor and consumer sentiment by using consumer sentiment as an alternative measure of investor sentiment. However, this research explores the difference between investor and consumer sentiment, and studies the unique effect of investor sentiment on future stock returns beyond consumer sentiment.

We find that investor sentiment makes the return predictive power of O/S prominent. An investment strategy based on the O/S presents 0.415% of alpha per week (21.580% annually), calculated by a four-factor model during high-sentiment periods. However, the strategy shows only 0.085% of alpha per week (4.420% annually) during low-sentiment periods. In addition, the alpha from the factor regressions during high-sentiment periods is significantly different from zero, although the alpha during low-sentiment periods is not. We also present evidence that the profitability of an O/S long-short strategy during high-sentiment periods lasts for only the first three weeks. After this, the significance of the alphas disappears, implying that the O/S-return relation is fully reflected on the stock market within a few weeks. Our additional empirical results also show that this effect of investor sentiment on the O/S-return relation is still found after controlling for consumer sentiment and economic environment factors. This suggests that the investor sentiment of Baker and Wurgler (2006), (2007) has its own unique impact on future stock returns, which consumer sentiment and macro-economic fundamentals do not. Thus, we expect that practitioners can utilize the effect of investor sentiment on future stock returns when constructing their efficient investment strategy.

One of our limitations is that the current research does not consider culture; thus, we will incorporate culture into our model in the future research. With regard to future research, Rieger et al. (2014) document the real effect of culture on risk preferences among various nations. Their findings prompt the research question of whether culture may affect the relation between option-implied information and future stock returns in a similar way to investor sentiment. Following this line of research, we are interested in investigating the direct and indirect effects of culture on financial markets.

Appendix. Questions of the CB index and the MCSI

The CB index's questions are as follows (Antoniou et al., 2013):

Q1) How would you rate present general business conditions in your area?

Q2) What would you say about available jobs in your area right now?

Q3) Six months from now, do you think that the business conditions in your area will be better, the same, or worse?

Q4) Six months from now, do you think there will be more, the same, or fewer jobs available in your area?

Q5) Would you guess your total family income to be higher, the same, or lower six months from now?"

The MCSI's questions are as follows (Ludvigson, 2004):

Q1) Do you think now is a good or bad time for people to buy major household items? (Good time to buy/uncertain/depends/bad time to buy.)

Q2) Would you say that you (and your family living with you) are better off or worse off financially than you were a year ago? (Better/the same/worse.)

Q3) Now turning to business conditions in the country as a whole—do you think that during the next 12 months, we'll have good times financially or bad times, or what? (Good times/uncertain/bad times.)

Q4) Looking ahead, which would you say is more likely—that in the country as a whole we'll have continuous good times during the next five years or so or that we'll have periods of widespread unemployment or depression, or what? (Good times/uncertain/bad times.)

Q5) Now looking ahead—do you think that a year from now, you (and your family living with you) will be better off financially, or worse off, or just about the same as now? (Better/the same/worse.)

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Table I. Descriptive statistics

Panel A provides sample size information and the O/S descriptive statistics by year, where the O/S is the options contract volume per 100 shares of stock volume. Panel B presents average firm characteristics by the O/S deciles. The sample consists of 603,754 firm-weeks spanning 1996 through 2010. VLC (VLP) is defined as the total call (put) options trading volume for the corresponding week in units of 100 shares. OPVOL is total options trading volume that is the total of VLC and VLP. EQVOL is defined as the total equity trading volume in units of 100 shares. LSIZE is a measure of firm sizes and is the log of market capitalization at the firms' most recent quarterly earnings announcements from COMPUSTAT. BM is the log of book-to-market ratio. MOMEN is defined as the past market-adjusted stock returns for the last six months. Panel C presents summary statistics for Baker and Wurgler's investor sentiment index. Panel D provides sample size information and the O/S descriptive statistics of during high- and low-sentiment periods.

Panel A: Sample characteristics and the O/S descriptive statistics by year

Year	Firms	Firm-weeks	MEAN	P25	P50	P75	SKEW
1996	1,403	23,267	5.423	1.585	3.176	6.260	4.460
1997	1,710	28,414	5.270	1.548	3.077	6.264	4.378
1998	1,911	31,437	4.606	1.361	2.740	5.559	4.489
1999	1,959	34,926	4.573	1.379	2.905	5.882	4.519
2000	2,021	43,407	4.177	1.397	2.816	5.336	4.320
2001	1,779	36,887	3.603	1.063	2.176	4.335	5.734
2002	1,665	34,133	3.449	0.959	2.080	4.307	4.663
2003	1,586	34,033	4.179	1.042	2.313	5.055	6.988
2004	1,775	39,947	4.995	1.217	2.743	6.145	4.419
2005	1,819	42,888	5.580	1.209	2.849	6.534	6.025
2006	1,963	50,725	5.988	1.332	3.202	7.248	5.982
2007	2,087	55,590	5.939	1.263	3.054	6.943	5.639
2008	1,968	53,088	5.147	1.056	2.572	5.970	5.435
2009	1,801	47,158	5.594	1.194	2.862	6.493	5.484
2010	1,850	47,854	6.102	1.202	2.952	6.868	5.747
ALL		603,754	4.976	1.254	2.768	5.948	5.218

Panel B: Firm characteristics by O/S deciles

	VLC	VLP	OPVOL	EQVOL	LSIZE	BM	MOMEN
1 (Low)	177	111	288	84,599	8.199	0.541	0.935
2	351	207	558	74,481	7.968	0.499	3.036
3	587	340	926	79,842	7.928	0.483	4.757
4	928	537	1,465	89,308	7.941	0.468	5.469
5	1,431	827	2,258	99,985	7.988	0.455	6.433
6	2,254	1,331	3,585	117,590	8.073	0.442	7.096
7	3,576	2,206	5,782	138,526	8.179	0.427	8.067
8	5,373	3,445	8,818	153,741	8.267	0.419	8.933
9	7,928	5,385	13,313	159,091	8.337	0.406	11.081
10 (High)	15,685	10,904	26,589	140,629	8.309	0.381	14.893
High-Low	15,508	10,793	26,301	56,029	0.110	-0.160	13.958

Panel C: Summary statistics for Baker and Wurgler's investor sentiment index

N	MEAN	STD.	MINIMUM	P25	P50	P75	MAXIMUM
180	0.185	0.591	-0.902	-0.129	0.055	0.346	2.497

Panel D: Sample characteristics and the O/S descriptive statistics during high- and low-sentiment periods

Sentiment period	Firms	Firm-weeks	MEAN	P25	P50	P75	SKEW
High sent.	4,402	300,579	4.827	1.289	2.771	5.814	4.930
Low sent.	4,282	298,986	5.091	1.214	2.754	6.052	5.469

Table II. Correlations

This table presents correlations among the investor sentiment index, consumer sentiment indices, and economic condition indicators. BW_SENTI is Baker and Wurgler's investor sentiment index. CB is the consumer confidence index provided by The Conference Board. MCSI is the Michigan Consumer Sentiment Index. CULMKT is 12-months cumulative return of the value-weighted index. CFNAI is the Chicago Fed National Activity Index. The p-values are shown in parentheses.

	BW_SENTI	MCSI	CB	CULMKT
MCSI	0.39			
(p-value)	(0.000)			
CB	0.56	0.85		
(p-value)	(0.000)	(0.000)		
CULMKT	-0.20	0.04	0.02	
(p-value)	(0.006)	(0.625)	(0.828)	
CFNAI	-0.10	0.14	0.17	0.75
(p-value)	(0.183)	(0.071)	(0.019)	(0.000)

Table III. The profits of an O/S long-short strategy and Baker and Wurgler's investor sentiment index

This table presents the average excess returns and alphas from factor regressions across O/S deciles and for an O/S long-short strategy, where the O/S is the ratio of option volume to equity volume. Decile portfolios are formed at the end of each week, ranging from 1 to 10 with the highest (lowest) values located in the 10th (1st) decile. The sample consists of 603,754 firm-weeks spanning 1996 through 2010. Portfolio returns are measured in the following week and regressed in four models: the excess return model, CAPM, the Fama-French three-factor model, and the four-factor model (including the three-factor model and the momentum factor). The average excess returns and alphas from the four models for the whole sample period (All), the high-sentiment periods (High), and the low-sentiment periods (Low) are reported. All excess returns and alphas are shown as percentages; *t*-statistics are shown in parentheses.

	Excess return			CAPM			Three-factor			Four-factor		
	All	High	Low	All	High	Low	All	High	Low	All	High	Low
1 (Low)	0.310	0.171	0.447	0.032	-0.156	0.242	-0.046	-0.250	0.148	-0.003	-0.228	0.162
	(2.47)	(0.93)	(2.59)	(0.26)	(-0.85)	(1.37)	(-0.37)	(-1.38)	(0.83)	(-0.02)	(-1.23)	(0.93)
2	0.272	0.122	0.421	-0.010	-0.200	0.208	-0.076	-0.269	0.128	-0.047	-0.275	0.140
	(2.05)	(0.61)	(2.37)	(-0.08)	(-1.01)	(1.14)	(-0.57)	(-1.36)	(0.70)	(-0.35)	(-1.36)	(0.77)
3	0.273	0.095	0.450	-0.008	-0.228	0.243	-0.086	-0.322	0.150	-0.064	-0.329	0.159
	(1.97)	(0.45)	(2.51)	(-0.06)	(-1.07)	(1.33)	(-0.62)	(-1.53)	(0.82)	(-0.46)	(-1.53)	(0.87)
4	0.220	-0.046	0.484	-0.061	-0.369	0.277	-0.134	-0.460	0.173	-0.107	-0.482	0.186
	(1.54)	(-0.21)	(2.64)	(-0.43)	(-1.69)	(1.47)	(-0.94)	(-2.11)	(0.92)	(-0.74)	(-2.16)	(1.00)
5	0.227	-0.062	0.517	-0.060	-0.383	0.280	-0.123	-0.453	0.192	-0.091	-0.462	0.205
	(1.56)	(-0.28)	(2.79)	(-0.41)	(-1.71)	(1.48)	(-0.84)	(-2.01)	(1.01)	(-0.62)	(-2.00)	(1.09)
6	0.112	-0.205	0.427	-0.174	-0.524	0.205	-0.243	-0.591	0.091	-0.212	-0.600	0.103
	(0.73)	(-0.86)	(2.24)	(-1.14)	(-2.20)	(1.06)	(-1.58)	(-2.47)	(0.47)	(-1.38)	(-2.44)	(0.54)
7	0.197	-0.107	0.497	-0.089	-0.427	0.277	-0.144	-0.490	0.185	-0.121	-0.509	0.195
	(1.27)	(-0.44)	(2.60)	(-0.57)	(-1.76)	(1.42)	(-0.92)	(-2.00)	(0.94)	(-0.77)	(-2.03)	(1.00)
8	0.116	-0.151	0.385	-0.174	-0.465	0.172	-0.242	-0.542	0.072	-0.217	-0.564	0.084
	(0.74)	(-0.61)	(1.99)	(-1.11)	(-1.88)	(0.87)	(-1.54)	(-2.19)	(0.36)	(-1.37)	(-2.23)	(0.43)
9	0.152	-0.168	0.474	-0.139	-0.481	0.256	-0.197	-0.545	0.168	-0.178	-0.581	0.179
	(0.95)	(-0.67)	(2.40)	(-0.87)	(-1.91)	(1.27)	(-1.22)	(-2.15)	(0.82)	(-1.09)	(-2.24)	(0.89)
10 (High)	0.092	-0.209	0.396	-0.194	-0.529	0.170	-0.260	-0.597	0.067	-0.246	-0.643	0.077
	(0.61)	(-0.89)	(2.03)	(-1.28)	(-2.28)	(0.86)	(-1.71)	(-2.56)	(0.34)	(-1.60)	(-2.69)	(0.39)
1-10	0.218	0.379	0.052	0.227	0.373	0.071	0.213	0.347	0.081	0.243	0.415	0.085
	(2.77)	(2.86)	(0.61)	(2.88)	(2.81)	(0.83)	(2.69)	(2.59)	(0.93)	(3.04)	(3.04)	(0.98)
(1+2) - (9+10)	0.169	0.334	-0.001	0.177	0.327	0.011	0.167	0.311	0.020	0.186	0.360	0.022
	(2.58)	(3.03)	(-0.02)	(2.71)	(2.96)	(0.16)	(2.52)	(2.79)	(0.28)	(2.79)	(3.16)	(0.31)

Table IV. The profits of an O/S long-short strategy and consumer sentiment indices

Panel A presents the average excess returns and alphas from factor regressions with consumer confidence published by The Conference Board (CB) across O/S decile portfolios, where the O/S is the ratio of option volume to equity volume. Decile portfolios are formed at the end of each week, ranging from 1 to 10 with the highest (lowest) values located in the 10th (1st) decile. The sample consists of 603,754 firm-weeks spanning 1996 through 2010. Portfolio returns are measured in the following week and regressed in four models: the excess return model, CAPM, the Fama-French three-factor model, and the four-factor model (including the three-factor model and the momentum factor). The average excess returns and alphas from the four models during high CB index periods (High) and low CB index periods (Low) are reported. Panel B presents the average excess returns and alphas from factor regressions with the Michigan Consumer Sentiment Index (MCSI). All excess returns and alphas are shown as percentages; *t*-statistics are shown in parentheses.

Panel A: CB index

	Excess return		CAPM		Three-factor		Four-factor	
	High	Low	High	Low	High	Low	High	Low
1 (Low)	0.210	0.405	-0.161	0.212	-0.196	0.151	-0.175	0.130
	(1.22)	(2.20)	(-0.93)	(1.16)	(-1.15)	(0.78)	(-0.99)	(0.68)
2	0.200	0.340	-0.178	0.146	-0.194	0.111	-0.206	0.093
	(1.04)	(1.82)	(-0.93)	(0.78)	(-1.02)	(0.56)	(-1.05)	(0.48)
3	0.198	0.343	-0.175	0.146	-0.199	0.080	-0.231	0.064
	(0.97)	(1.81)	(-0.85)	(0.78)	(-0.98)	(0.40)	(-1.10)	(0.32)
4	0.061	0.372	-0.312	0.173	-0.334	0.111	-0.378	0.091
	(0.29)	(1.92)	(-1.47)	(0.90)	(-1.58)	(0.55)	(-1.73)	(0.45)
5	0.100	0.348	-0.280	0.145	-0.289	0.103	-0.319	0.081
	(0.45)	(1.82)	(-1.26)	(0.77)	(-1.30)	(0.51)	(-1.39)	(0.41)
6	-0.010	0.224	-0.389	0.023	-0.391	-0.029	-0.419	-0.049
	(-0.04)	(1.14)	(-1.64)	(0.12)	(-1.66)	(-0.14)	(-1.71)	(-0.24)
7	0.017	0.366	-0.365	0.172	-0.381	0.140	-0.415	0.125
	(0.07)	(1.84)	(-1.53)	(0.87)	(-1.59)	(0.67)	(-1.67)	(0.60)
8	-0.037	0.264	-0.421	0.062	-0.437	0.026	-0.465	0.009
	(-0.15)	(1.33)	(-1.71)	(0.32)	(-1.78)	(0.13)	(-1.83)	(0.04)
9	0.042	0.256	-0.347	0.058	-0.364	0.023	-0.406	0.007
	(0.17)	(1.27)	(-1.38)	(0.29)	(-1.45)	(0.11)	(-1.56)	(0.03)
10 (High)	-0.083	0.263	-0.463	0.065	-0.477	0.010	-0.537	-0.005
	(-0.35)	(1.34)	(-1.98)	(0.33)	(-2.04)	(0.05)	(-2.22)	(-0.02)
1-10	0.292	0.142	0.303	0.148	0.281	0.141	0.362	0.135
	(2.05)	(2.10)	(2.13)	(2.17)	(1.96)	(1.96)	(2.45)	(1.88)
(1 + 2) - (9 + 10)	0.225	0.113	0.236	0.117	0.226	0.114	0.281	0.111
	(1.86)	(2.15)	(1.96)	(2.23)	(1.86)	(2.05)	(2.24)	(1.99)

Panel B: MCSI								
	Excess return		CAPM		Three-factor		Four-factor	
	High	Low	High	Low	High	Low	High	Low
1 (Low)	0.387	0.226	0.072	-0.050	-0.005	-0.107	0.039	-0.087
	(2.22)	(1.24)	(0.41)	(-0.27)	(-0.03)	(-0.58)	(0.22)	(-0.48)
2	0.324	0.214	0.007	-0.057	-0.063	-0.102	-0.040	-0.087
	(1.68)	(1.16)	(0.04)	(-0.31)	(-0.33)	(-0.55)	(-0.20)	(-0.47)
3	0.351	0.189	0.035	-0.094	-0.035	-0.151	-0.034	-0.137
	(1.72)	(1.00)	(0.17)	(-0.50)	(-0.17)	(-0.80)	(-0.16)	(-0.72)
4	0.238	0.193	-0.077	-0.092	-0.150	-0.141	-0.152	-0.123
	(1.12)	(1.00)	(-0.36)	(-0.48)	(-0.70)	(-0.73)	(-0.69)	(-0.64)
5	0.227	0.220	-0.090	-0.071	-0.146	-0.114	-0.140	-0.094
	(1.02)	(1.17)	(-0.40)	(-0.38)	(-0.65)	(-0.60)	(-0.61)	(-0.50)
6	0.136	0.077	-0.181	-0.210	-0.235	-0.265	-0.222	-0.248
	(0.58)	(0.39)	(-0.76)	(-1.08)	(-0.99)	(-1.35)	(-0.91)	(-1.27)
7	0.198	0.184	-0.119	-0.093	-0.169	-0.137	-0.168	-0.122
	(0.83)	(0.92)	(-0.50)	(-0.46)	(-0.70)	(-0.68)	(-0.68)	(-0.61)
8	0.115	0.111	-0.202	-0.180	-0.278	-0.218	-0.272	-0.202
	(0.47)	(0.56)	(-0.83)	(-0.90)	(-1.13)	(-1.09)	(-1.08)	(-1.01)
9	0.201	0.095	-0.118	-0.184	-0.178	-0.229	-0.183	-0.214
	(0.80)	(0.47)	(-0.47)	(-0.91)	(-0.71)	(-1.12)	(-0.71)	(-1.05)
10 (High)	0.070	0.110	-0.247	-0.174	-0.318	-0.213	-0.328	-0.202
	(0.30)	(0.56)	(-1.06)	(-0.88)	(-1.36)	(-1.07)	(-1.37)	(-1.02)
1-10	0.317	0.116	0.319	0.124	0.314	0.106	0.367	0.114
	(2.28)	(1.60)	(2.29)	(1.69)	(2.22)	(1.43)	(2.55)	(1.56)
(1 + 2) - (9 + 10)	0.220	0.118	0.222	0.125	0.214	0.116	0.255	0.121
	(1.85)	(2.09)	(1.88)	(2.21)	(1.79)	(2.03)	(2.08)	(2.11)

Table V. The profits of an O/S long-short strategy independently sorted by the CB index and the BW investor sentiment index

This table reports the average excess returns and alphas from the four-factor model using independent sorting by the CB index and the BW investor sentiment index across O/S deciles and for an O/S long-short strategy, where O/S is the ratio of option volume to equity volume. Decile portfolios are formed at the end of each week, ranging from 1 to 10 with the highest (lowest) values located in the 10th (1st) decile. The sample consists of 603,754 firm-weeks spanning 1996 through 2010. Portfolio returns are measured in the following week. The average excess returns and alphas from the four-factor model during high-sentiment periods (High) and low-sentiment periods (Low) are reported for the top 50% of the CB index and the bottom 50% of the CB index. All excess returns and alphas are shown as percentages; *t*-statistics are shown in parentheses.

	Bottom 50% of the CB index				Top 50% of the CB index			
	Excess return		Four-factor		Excess return		Four-factor	
	High	Low	High	Low	High	Low	High	Low
1 (Low)	-0.038	0.545	-0.023	0.216	0.235	0.123	-0.218	-0.255
	(-0.09)	(2.75)	(-0.04)	(1.05)	(1.19)	(0.35)	(-1.07)	(-0.64)
2	-0.073	0.470	-0.093	0.150	0.182	0.259	-0.264	-0.203
	(-0.16)	(2.34)	(-0.16)	(0.72)	(0.82)	(0.68)	(-1.16)	(-0.47)
3	-0.135	0.494	-0.101	0.172	0.166	0.304	-0.312	-0.264
	(-0.29)	(2.45)	(-0.17)	(0.82)	(0.70)	(0.78)	(-1.27)	(-0.60)
4	-0.207	0.554	-0.272	0.229	0.004	0.251	-0.489	-0.231
	(-0.44)	(2.66)	(-0.45)	(1.06)	(0.02)	(0.64)	(-1.90)	(-0.53)
5	-0.284	0.547	-0.289	0.197	0.006	0.415	-0.451	-0.117
	(-0.63)	(2.65)	(-0.49)	(0.92)	(0.02)	(1.01)	(-1.67)	(-0.25)
6	-0.495	0.451	-0.434	0.085	-0.115	0.347	-0.568	-0.198
	(-1.04)	(2.15)	(-0.70)	(0.39)	(-0.42)	(0.79)	(-1.97)	(-0.41)
7	-0.178	0.538	-0.149	0.222	-0.085	0.361	-0.561	-0.125
	(-0.36)	(2.57)	(-0.23)	(1.01)	(-0.30)	(0.80)	(-1.93)	(-0.24)
8	-0.331	0.452	-0.350	0.121	-0.096	0.162	-0.579	-0.263
	(-0.69)	(2.14)	(-0.56)	(0.55)	(-0.33)	(0.35)	(-1.94)	(-0.51)
9	-0.412	0.467	-0.513	0.149	-0.093	0.499	-0.594	0.241
	(-0.82)	(2.19)	(-0.78)	(0.66)	(-0.32)	(1.04)	(-1.95)	(0.44)
10 (High)	-0.318	0.446	-0.409	0.119	-0.175	0.230	-0.679	-0.111
	(-0.65)	(2.15)	(-0.64)	(0.55)	(-0.66)	(0.47)	(-2.46)	(-0.20)
1-10	0.280	0.099	0.385	0.097	0.410	-0.106	0.461	-0.144
	(1.71)	(1.36)	(1.77)	(1.27)	(2.47)	(-0.39)	(2.68)	(-0.45)
(1 + 2) - (9 + 10)	0.309	0.051	0.403	0.048	0.342	-0.173	0.395	-0.295
	(2.20)	(0.96)	(2.16)	(0.87)	(2.48)	(-0.71)	(2.76)	(-1.01)

Table VI. The profits of an O/S long-short strategy independently sorted by the MCSI and the BW investor sentiment index

This table reports the average excess returns and alphas from the four-factor model using independent sorting by the MCSI and the BW investor sentiment index across O/S decile portfolios, where the O/S is the ratio of option volume to equity volume. Decile portfolios are formed at the end of each week, ranging from 1 to 10 with the highest (lowest) values located in the 10th (1st) decile. The sample consists of 603,754 firm-weeks spanning 1996 through 2010. Portfolio returns are measured in the following week. The average excess returns and alphas from the four-factor model during high-sentiment periods (High) and low-sentiment periods (Low) are reported for the top 50% of the MCSI and the bottom 50% of the MCSI. All excess returns and alphas are shown as percentages; *t*-statistics are shown in parentheses.

	Bottom 50% of the MCSI				Top 50% of the MCSI			
	Excess return		Four-factor		Excess return		Four-factor	
	High	Low	High	Low	High	Low	High	Low
1 (Low)	0.045	0.337	-0.167	-0.060	0.245	0.631	-0.299	0.450
	(0.15)	(1.45)	(-0.54)	(-0.25)	(1.05)	(2.52)	(-1.24)	(1.73)
2	0.002	0.343	-0.269	-0.024	0.192	0.551	-0.339	0.352
	(0.01)	(1.47)	(-0.85)	(-0.10)	(0.73)	(2.04)	(-1.25)	(1.25)
3	0.010	0.298	-0.163	-0.088	0.145	0.704	-0.421	0.467
	(0.03)	(1.26)	(-0.50)	(-0.36)	(0.52)	(2.59)	(-1.43)	(1.65)
4	-0.054	0.343	-0.263	-0.044	-0.041	0.719	-0.625	0.488
	(-0.17)	(1.42)	(-0.81)	(-0.17)	(-0.14)	(2.59)	(-2.03)	(1.70)
5	-0.098	0.413	-0.281	0.007	-0.041	0.689	-0.566	0.454
	(-0.32)	(1.75)	(-0.88)	(0.03)	(-0.13)	(2.31)	(-1.75)	(1.47)
6	-0.224	0.260	-0.448	-0.175	-0.194	0.704	-0.732	0.456
	(-0.69)	(1.06)	(-1.33)	(-0.69)	(-0.59)	(2.33)	(-2.11)	(1.47)
7	-0.099	0.356	-0.351	-0.026	-0.111	0.732	-0.655	0.486
	(-0.29)	(1.45)	(-0.97)	(-0.10)	(-0.34)	(2.39)	(-1.88)	(1.53)
8	-0.197	0.299	-0.447	-0.090	-0.124	0.528	-0.702	0.287
	(-0.59)	(1.20)	(-1.30)	(-0.34)	(-0.36)	(1.71)	(-1.96)	(0.90)
9	-0.250	0.306	-0.501	-0.079	-0.120	0.755	-0.695	0.558
	(-0.72)	(1.24)	(-1.37)	(-0.30)	(-0.35)	(2.30)	(-1.91)	(1.64)
10 (High)	-0.157	0.272	-0.424	-0.116	-0.239	0.602	-0.824	0.382
	(-0.46)	(1.13)	(-1.19)	(-0.46)	(-0.77)	(1.82)	(-2.52)	(1.12)
1-10	0.201	0.065	0.257	0.056	0.484	0.029	0.525	0.067
	(1.59)	(0.74)	(1.90)	(0.61)	(2.46)	(0.17)	(2.53)	(0.39)
(1 + 2) - (9 + 10)	0.227	0.051	0.244	0.055	0.398	-0.088	0.440	-0.069
	(2.12)	(0.80)	(2.13)	(0.83)	(2.43)	(-0.57)	(2.55)	(-0.43)

Table VII. Regression of O/S spread returns on the BW investor sentiment index and consumer sentiment indices

This table reports the coefficient estimates in two variants of the regression

$$R_{p,t} - \beta_p^{'} F_t = \gamma_0 + \gamma_1 BW\_SENTI_{t-1} + \gamma_2 CON\_SENTI_{t-1} + \varepsilon_t,$$

where $R_{p,t}$ is the return on the O/S decile 1-10 spread portfolio, F_t are factors, and β_p are factor loadings. BW_SENTI_t is the BW investor sentiment index and CON_SENTI_t is the consumer sentiment indices such as the CB index and the MCSI. All *t*-statistics calculated using Newey-West (1987) standard errors are shown in parentheses.

	Raw spread return				Four-factor risk-adjusted spread return			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002
	(1.90)	(1.93)	(1.88)	(1.83)	(2.33)	(2.34)	(2.32)	(2.24)
BW_SENTI	0.003	0.004	0.004	0.004	0.003	0.003	0.003	0.003
	(2.42)	(2.41)	(2.69)	(2.17)	(2.08)	(1.89)	(2.23)	(1.65)
CB		-4.0×10^{-5}		3.0×10^{-5}		-1.0×10^{-5}		5.0×10^{-5}
		(-0.74)		(0.40)		(-0.30)		(0.64)
MCSI			-1.1×10^{-4}	-1.6×10^{-4}			-7.0×10^{-5}	-1.6×10^{-4}
			(-1.18)	(-1.01)			(-0.82)	(-1.00)
Adj. R^2 (%)	0.75	0.82	0.93	0.95	0.55	0.57	0.64	0.69

Table VIII. The profits of an O/S long-short strategy independently sorted by market states and investor sentiment

This table reports the average excess returns and alphas from the four-factor model using independent sorting by market states and the BW investor sentiment index across O/S decile portfolios, where the O/S is the ratio of option volume to equity volume. Decile portfolios are formed at the end of each week, ranging from 1 to 10 with the highest (lowest) values located in the 10th (1st) decile. The sample consists of 603,754 firm-weeks spanning 1996 through 2010. Portfolio returns are measured in the following week. The average excess returns and alphas from the four-factor model during high-sentiment periods (High) and low-sentiment periods (Low) are reported for the UP market state and the DOWN market state. UP (DOWN) market state is defined as a month in which the cumulative returns of the value-weighted CRSP index over the past months *t*-12 to *t*-1 are non-negative (negative). All excess returns and alphas are shown as percentages; *t*-statistics are shown in parentheses.

	DOWN market state				UP market state			
	Excess return		Four-factor		Excess return		Four-factor	
	High	Low	High	Low	High	Low	High	Low
1 (Low)	-0.296	0.497	-0.625	-0.469	0.390	0.431	0.038	0.140
	(-0.76)	(0.95)	(-1.38)	(-0.86)	(1.97)	(2.83)	(0.18)	(0.86)
2	-0.409	0.533	-0.806	-0.266	0.371	0.384	-0.097	0.086
	(-1.00)	(1.01)	(-1.66)	(-0.48)	(1.69)	(2.38)	(-0.41)	(0.50)
3	-0.460	0.382	-0.835	-0.440	0.356	0.472	-0.110	0.148
	(-1.05)	(0.73)	(-1.63)	(-0.79)	(1.52)	(2.88)	(-0.43)	(0.84)
4	-0.713	0.532	-1.103	-0.409	0.268	0.468	-0.222	0.178
	(-1.56)	(1.01)	(-2.04)	(-0.74)	(1.12)	(2.73)	(-0.86)	(0.97)
5	-0.720	0.726	-0.948	-0.131	0.247	0.448	-0.242	0.119
	(-1.62)	(1.35)	(-1.79)	(-0.23)	(0.97)	(2.61)	(-0.87)	(0.65)
6	-1.002	0.557	-1.304	-0.303	0.170	0.384	-0.270	0.054
	(-2.08)	(1.03)	(-2.26)	(-0.54)	(0.64)	(2.13)	(-0.93)	(0.28)
7	-0.761	0.586	-1.145	-0.184	0.201	0.467	-0.304	0.162
	(-1.56)	(1.07)	(-1.95)	(-0.31)	(0.73)	(2.59)	(-1.02)	(0.84)
8	-0.945	0.514	-1.290	-0.370	0.222	0.342	-0.285	0.029
	(-1.93)	(0.94)	(-2.22)	(-0.64)	(0.79)	(1.86)	(-0.94)	(0.15)
9	-0.871	0.456	-1.238	-0.342	0.162	0.481	-0.411	0.183
	(-1.79)	(0.84)	(-2.12)	(-0.59)	(0.56)	(2.48)	(-1.30)	(0.88)
10 (High)	-0.835	0.505	-1.123	-0.216	0.086	0.360	-0.479	0.036
	(-1.91)	(0.99)	(-2.16)	(-0.39)	(0.31)	(1.82)	(-1.61)	(0.17)
1-10	0.539	-0.008	0.498	-0.253	0.304	0.071	0.518	0.104
	(3.17)	(-0.05)	(2.43)	(-1.50)	(1.71)	(0.72)	(2.73)	(0.98)
(1 + 2) - (9 + 10)	0.500	0.034	0.464	-0.088	0.257	-0.013	0.416	0.003
	(3.16)	(0.32)	(2.42)	(-0.75)	(1.78)	(-0.15)	(2.68)	(0.03)

Table IX. The profits of an O/S long-short strategy independently sorted by economic states and investor sentiment

This table reports the average excess returns and the alphas from the four-factor model using independent sorting by economic conditions and the BW investor sentiment index across O/S deciles and for an O/S long-short strategy, where the O/S is the ratio of option volume to equity volume. Decile portfolios are formed at the end of each week, ranging from 1 to 10 with the highest (lowest) values located in the 10th (1st) decile. The sample consists of 603,754 firm-weeks spanning 1996 through 2010. Portfolio returns are measured in the following week. The average excess returns and alphas from the four-factor model during high-sentiment periods (High) and low-sentiment periods (Low) are reported for economic expansion and economic contraction. Economic expansion (contraction) is defined as a month with non-negative (negative) values of the CFNAI. All excess returns and alphas are shown as percentages; *t*-statistics are shown in parentheses.

	Economic contraction				Economic expansion			
	Excess return		Four-factor		Excess return		Four-factor	
	High	Low	High	Low	High	Low	High	Low
1 (Low)	-0.142	0.563	-0.408	-0.007	0.520	0.354	0.151	0.112
	(-0.55)	(1.74)	(-1.49)	(-0.02)	(1.99)	(2.07)	(0.52)	(0.61)
2	-0.271	0.589	-0.562	0.097	0.561	0.285	0.013	0.015
	(-1.00)	(1.81)	(-1.91)	(0.27)	(1.93)	(1.55)	(0.04)	(0.08)
3	-0.241	0.522	-0.563	-0.015	0.471	0.391	-0.092	0.084
	(-0.82)	(1.60)	(-1.78)	(-0.04)	(1.54)	(2.09)	(-0.27)	(0.41)
4	-0.407	0.578	-0.694	0.002	0.358	0.408	-0.195	0.144
	(-1.32)	(1.74)	(-2.09)	(0.01)	(1.15)	(2.09)	(-0.56)	(0.69)
5	-0.428	0.685	-0.656	0.171	0.347	0.380	-0.209	0.072
	(-1.40)	(2.08)	(-1.97)	(0.46)	(1.05)	(1.87)	(-0.56)	(0.33)
6	-0.609	0.533	-0.868	-0.003	0.247	0.340	-0.320	0.048
	(-1.87)	(1.56)	(-2.44)	(-0.01)	(0.70)	(1.66)	(-0.81)	(0.22)
7	-0.506	0.641	-0.804	0.154	0.339	0.380	-0.321	0.107
	(-1.51)	(1.88)	(-2.20)	(0.40)	(0.96)	(1.82)	(-0.80)	(0.47)
8	-0.585	0.573	-0.802	0.024	0.334	0.232	-0.300	-0.060
	(-1.75)	(1.67)	(-2.21)	(0.06)	(0.91)	(1.09)	(-0.72)	(-0.26)
9	-0.609	0.542	-0.867	0.047	0.325	0.420	-0.389	0.184
	(-1.80)	(1.59)	(-2.34)	(0.12)	(0.86)	(1.83)	(-0.91)	(0.74)
10 (High)	-0.471	0.537	-0.744	0.054	0.084	0.281	-0.643	0.027
	(-1.57)	(1.66)	(-2.27)	(0.15)	(0.23)	(1.19)	(-1.57)	(0.11)
1-10	0.329	0.026	0.336	-0.061	0.436	0.073	0.794	0.085
	(2.53)	(0.25)	(2.35)	(-0.54)	(1.81)	(0.57)	(3.00)	(0.61)
(1 + 2) - (9 + 10)	0.333	0.036	0.320	-0.006	0.336	-0.032	0.598	-0.043
	(2.74)	(0.50)	(2.38)	(-0.07)	(1.76)	(-0.28)	(2.81)	(-0.35)

Table X. Regression of O/S spread returns on the BW investor sentiment index and economic environments

This table reports the coefficient estimates in two variants of the regression

$$R_{p,t} - \beta_p' F_t = \gamma_0 + \gamma_1 BW\_SENTI_{t-1} + \gamma_2 ECO\_EN_t + \gamma_3 ECO\_EN_t^2 + \gamma_4 CON\_SENTI_{t-1} + \varepsilon_t,$$

where $R_{p,t}$ is the return on the O/S decile 1-10 spread portfolio, F_t are factors, and β_p are factor loadings. BW_SENTI_t is the BW investor sentiment index. ECO_EN_t is the variables related to the economic environments such as 12-months cumulative returns of the value-weighted index and the CFNAI. CON_SENTI_t is the consumer sentiment indices such as the CB index and the MCSI. Panel A reports the coefficient estimates with 12-months cumulative returns of the value-weighted index (12-months CULMKT) and Panel B reports the coefficient estimates with the CFNAI. All *t*-statistics calculated using Newey-West (1987) standard errors are shown in parentheses.

Panel A: 12-months cumulative return of the value-weighted index

	Raw spread return					Four-factor risk-adjusted spread return				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Intercept	0.002	0.002	0.002	0.002	0.002	0.002	0.003	0.003	0.003	0.002
	(1.82)	(1.93)	(1.95)	(1.81)	(1.73)	(1.92)	(2.28)	(2.29)	(2.19)	(2.08)
BW_SENTI	0.003	0.003	0.004	0.004	0.004	0.003	0.003	0.003	0.003	0.003
	(2.31)	(2.20)	(2.25)	(2.46)	(2.06)	(2.10)	(1.95)	(1.87)	(2.10)	(1.71)
12-months	-0.001	-2.5×10^{-4}	3.5×10^{-4}	2.3×10^{-4}	6.0×10^{-5}	0.001	0.003	0.003	0.003	0.003
CULMKT	(-0.28)	(-0.06)	(0.08)	(0.06)	(0.01)	(0.33)	(0.65)	(0.73)	(0.73)	(0.66)
12-months		-0.012	-0.013	-0.011	-0.010		-0.019	-0.019	-0.018	-0.017
$CULMKT^2$		(-0.79)	(-0.86)	(-0.71)	(-0.62)		(-1.24)	(-1.28)	(-1.18)	(-1.05)
CB			-0.4×10^{-4}		-1.3×10^{-4}			-2.0×10^{-5}		3.0×10^{-5}
			(-0.78)		(-0.81)			(-0.48)		(0.30)
MCSI				-1.0×10^{-4}	2.0×10^{-5}				-7.0×10^{-5}	-1.1×10^{-4}
				(-1.10)	(0.24)				(-0.78)	(-0.69)
Adj. R^2 (%)	0.76	0.84	0.92	1.00	1.00	0.57	0.76	0.79	0.84	0.85

Panel B: CFNAI										
	Raw spread return					Four-factor risk-adjusted spread return				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Intercept	0.002	0.001	0.001	0.001	0.001	0.002	0.002	0.002	0.002	0.002
	(1.83)	(1.64)	(1.67)	(1.55)	(1.48)	(2.44)	(2.22)	(2.25)	(2.14)	(2.05)
BW_SENTI	0.003	0.003	0.004	0.004	0.004	0.003	0.003	0.004	0.004	0.003
	(2.39)	(2.40)	(2.40)	(2.76)	(2.23)	(2.15)	(2.17)	(2.10)	(2.46)	(1.94)
CFNAI	-1.2×10^{-4}	4.8×10^{-4}	0.001	0.001	0.001	0.001	0.001	0.002	0.002	0.002
	(-0.13)	(0.26)	(0.53)	(0.72)	(0.67)	(0.76)	(0.72)	(0.90)	(1.08)	(1.03)
$CFNAI^2$		2.5×10^{-4}	5.4×10^{-4}	0.001	0.001		2.6×10^{-4}	5.0×10^{-4}	0.001	0.001
		(0.38)	(0.57)	(0.77)	(0.77)		(0.39)	(0.54)	(0.72)	(0.72)
CB			-4.0×10^{-5}		4.0×10^{-5}			-3.0×10^{-5}		4.0×10^{-5}
			(-0.84)		(0.40)			(-0.65)		(0.45)
MCSI				-1.3×10^{-4}	-1.8×10^{-4}				-1.1×10^{-4}	-1.7×10^{-4}
				(-1.35)	(-1.13)				(-1.15)	(-1.05)
Adj. R^2 (%)	0.75	0.77	0.86	1.00	1.02	0.63	0.65	0.70	0.82	0.85

Table XI. Returns in an O/S long-short strategy sorted by short-sale costs and investor sentiment states

This table presents the average raw spread returns and the risk-adjusted spread returns in an O/S long-short strategy for portfolios double-sorted by short-sale costs (RI) and the BW investor sentiment index. RI (residual institutional ownership) is obtained from the cross-sectional regressions as detailed in Nagel (2005). In Panel A (B), firms are sorted each week into RI terciles (quintiles) for the whole sample period (All), the high-sentiment periods (High), and the low-sentiment periods (Low), and returns are measured in the following week. Within each RI portfolio, returns are computed for a long-short strategy based on the extreme O/S decile (quintile) portfolios for raw returns and risk-adjusted returns using the time-series regression on the three Fama-French factors and the momentum factor. All returns are shown as percentages; *t*-statistics are shown in parentheses.

Panel A: O/S decile spread returns by RI terciles

	Raw spread return			Four-factor risk-adjusted spread return		
	All	High	Low	All	High	Low
RI (1): High short-sale costs	0.519	0.710	0.323	0.542	0.754	0.342
	(4.70)	(4.24)	(2.26)	(4.79)	(4.34)	(2.30)
RI (2)	0.172	0.429	-0.093	0.198	0.487	-0.064
	(1.82)	(2.77)	(-0.89)	(2.07)	(3.04)	(-0.60)
RI (3): Low short-sale costs	-0.020	0.029	-0.072	-0.015	0.024	-0.045
	(-0.22)	(0.19)	(-0.68)	(-0.16)	(0.15)	(-0.42)
High-low short-sale costs	0.540	0.681	0.395	0.557	0.730	0.387
	(4.21)	(3.41)	(2.47)	(4.25)	(3.53)	(2.34)

Panel B: O/S quintile spread returns by RI quintiles

	Raw spread return			Four-factor risk-adjusted spread return		
	All	High	Low	All	High	Low
RI (1): High short-sale costs	0.318	0.535	0.095	0.331	0.579	0.103
	(2.86)	(3.23)	(0.65)	(2.91)	(3.37)	(0.68)
RI (2)	0.303	0.463	0.139	0.346	0.527	0.222
	(3.42)	(3.27)	(1.32)	(3.83)	(3.59)	(2.06)
RI (3)	0.087	0.237	-0.066	0.111	0.270	-0.073
	(1.02)	(1.71)	(-0.67)	(1.27)	(1.88)	(-0.72)
RI (4)	0.112	0.212	0.009	0.117	0.209	0.036
	(1.40)	(1.56)	(0.11)	(1.45)	(1.49)	(0.43)
RI (5): Low short-sale costs	-0.025	0.056	-0.108	-0.013	0.060	-0.099
	(-0.30)	(0.41)	(-1.11)	(-0.16)	(0.43)	(-0.98)
High-low short-sale costs	0.343	0.479	0.203	0.344	0.518	0.202
	(2.62)	(2.35)	(1.24)	(2.57)	(2.45)	(1.20)

Figure 1. The time-series of the O/S-return relation during high- and low-sentiment periods

This figure presents alphas associated with O/S long-short portfolios depending on the level of investor sentiment. The top graph shows weekly alphas, where the surrounding error bars represent the 95% confidence interval. The bottom graph shows the cumulative alphas. Alphas are calculated by the intercept in time-series regression weekly strategy returns on contemporaneous weekly factor returns for the three Fama-French factors and the momentum factor. The sample consists of 603,754 firm-weeks spanning 1996 through 2010. Alphas are shown as percentages.