The predictability of option-implied skewness: shorting cost and investor sentiment

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ABSTRACT

Option-implied skewness (OIS) has significant and positive relation with future stocks returns in the cross-section. We hypothesize that the predictability of option-implied skewness would be stronger when mispricing is more likely to occur, under the conjecture that the predictability stems from a delayed response of stock prices to information observable in the options market. In particular, we investigate whether the OIS-return relation varies with shorting costs and investor sentiment, and document supporting evidence for our hypothesis. First, we find that the OIS-return relation is stronger among stocks with high shorting costs, where we measure the shorting costs based on changes in breadth of ownership and price impacts for down market. Second, we observe that the predictability of OIS is more prominent and persistent when investor sentiment is higher.

1 Introduction

Previous studies suggest that equity and derivatives markets can have a separating equilibrium due to distinct characteristics of each market. For example, Easley et al. (1998) propose a model where informed investors are allowed to trades in both option and equity markets, and document that the options market is more attractive venues for investors who are willing to exploit private information. Since options enable more levered and refined trades that are aligned with investors' strategies, informed traders prefer to trade in the options market relative to the stock market, resulting in option trades being informative for future stock returns.

This argument is thereafter empirically supported in several studies which show that a particular information implied in the options market significantly predicts subsequent stock returns (Ofek et al., 2004; Pan and Poteshman, 2006; Ni et al., 2008; Roll et al., 2010; Xing et al., 2010; Johnson and So, 2012). If information-based trading mainly occurs in the options market, that is, if informed investors enter in the options market first, option prices would first incorporate new information, and thereafter stock prices would absorb such information. This process of price discovery results in the predictability of information embedded in options for future stock returns. In other words, the segmentation between the stock and option market allows option-implied information to have the predictive power for future movements of stock prices.

Consistent with prior literature, we also find option-implied skewness predicts future stock returns. In particular, we find that the lower option-implied skewness predicts lower stock returns in the cross-section, where we estimate option-implied skewness as a risk-neutral skewness following Bakshi et al. (2003). Over our sample period, the strategy selling high skewed stocks and buying low skewed stocks earns significant positive profits. This finding is not new; it just confirms the results in the work of Rehman and Vilkov (2012), which document that currently observed option-implied skewness is positively related to future stock returns. In the similar context, Xing et al. (2010) also show that steeper smirks in the traded options, which inherently correspond to lower risk-neutral skewness, predict lower subsequent returns.[1]

Our study is clearly differentiated from those studies in that we verify the source of the predictability of option-implied skewness for stock return, not just documenting the predictability. In this study, we provide confirming evidence that the predictive power stems from stock mispricing relevant to a delayed response of the stock prices to new information, by taking two concepts that are presumably associated with the mispricing into account – shorting cost and market sentiment.

First, we hypothesize that the predictability of option-implied skewness is stronger among stocks with higher shorting costs. High arbitrage costs in the stock market may force informed investors to choose the options market, and moreover, can deter arbitrageurs from exploiting option-implied information. Notable finding in recent literature is that arbitrage costs for arbitrageur who exploit overpricing are higher than those for arbitrageurs who exploit underpricing. For example, Brennan et al. (2012) document that price impacts for seller-initiated trades are greater than those for buyer-initiated trades. Brennan et al. (2013) show that illiquidity costs for down markets are higher than those for up markets by decomposing the Amihud (2002) price impact measure into elements that correspond to

[1] Rehman and Vilkov (2012) argue that the risk-neutral skewness has informational advantage relative to the steepness of implied volatility used in Xing et al. (2010) in that the former is extracted from all available options while the latter is based on two point of the volatility smile.

positive and negative return days.

Motivated by these results, we conjecture that shorting costs mainly play a role in speeding down the incorporation of the information in the options market into stock prices. High shorting costs can discourage arbitrages that involve sales, and thereby deter negative information from being absorbed into stock prices. This conjecture is consistent with previous studies including Easley et al. (1998) and Johnson and So (2012). Easley et al., 1998 argue that the shortsale constraint makes informed investors more likely to use options for bad news than for good ones. Johnson and So (2012) also argue that bad news, rather than good news, embedded in options is the one that has not yet been impounded into stock prices. They document that the option to stock volume ratio is negatively related to future stock returns, and argue that the negative relation is attributed to the shortsale impediment - an obstacle to the incorporation of bad news.

The role of the shortsale constraint on mispricing has been extensively explored in previous studies. From Miller (1977), who argue that impediments to shortselling play a role in limiting the ability of arbitrageurs to exploit overpricing, a number of studies document a significant relation between the shortsale constraint and overpricing.[2] For example, Chen et al. (2002) find that change in breadth of ownership are positively related to future return, and argue that since low breadth signals that the shortsales constraint is binding tightly, stocks with greater reduction in breadth earn lower average returns. Shortsales ban can be an extreme case of the constraint. Ni and Pan (2010) show that only within the sample of banned stocks, high put-call ratios in transactions predict low future stock returns, suggesting that shortsales ban plays a role in preventing information transmission across markets.

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2 The idea of Miller (1977) is empirically examined by a number of studies including Chen et al. (2002), Diether et al. (2002), Sadka and Scherbina (2007), and Stambaugh et al. (2012).

On the other hand, the literature suggests that there is a directional tendency of mispricing - investor sentiment.[3] For example, Baker and Wurgler (2006) construct the sentiment index using six variables known to proxy the market-wide investor sentiment, and present evidence that the index exhibits predictive power for stock returns. Interestingly, the literature that examines the effect of sentiment on asset prices in common document that the return predictive effect of sentiment varies with stock characteristics such as firm size.[4] For example, Baker and Wurgler (2006) find that the sentiment effect is prominent among small, high volatile and young stocks. Lemmon and Portniaguina (2006) also find that investor sentiment can predict the returns on small stocks.

This finding can be explained in the context of limit-to-arbitrage. As Shleifer (2000) argue, for stock prices being affected by investor sentiment, arbitrage should be limited. Even though investor sentiment induces mispricing, it cannot persist in the presence of arbitrageurs exploiting the mispricing. It implies that investor sentiment may exert more influences on stock prices when they are more costly to arbitrage. In other words, the effect of sentiment can vary across stocks depending on the difficulty of arbitrage. Recent evidence of Stambaugh et al. (2012) also supports this conjecture. They examine the role of investor sentiment in a wide set of asset-pricing anomalies, and find that the sentiment exhibits no relation to returns on long-legs of anomaly-based long-short strategies, indicating that the sentiment effect can be different across stocks.

Another notable finding of Stambaugh et al. (2012) is that each long-short strategy is

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[3] The effect of sentiment on asset prices is documented by previous studies including Shleifer (2000), Baker and Wurgler (2006), Baker and Wurgler (2007), Kumar and Lee (2006), Han (2008), Yu and Yuan (2011), and Stambaugh et al. (2012).

[4] The role of limit-to-arbitrage in the effect of investor sentiment on asset prices is suggested in previous studies including De Long et al. (1990), Shleifer and Summers (1990), Shleifer and Vishny (1997), Shleifer (2000), Hirshleifer (2001), Kumar and Lee (2006), Dorn et al. (2008), and Barber et al. (2009).

more profitable following high sentiment than following low sentiment. This evidence is consistent with the notion that sentiment-induced overpricing of the short-leg, rather than the underpricing of the long-leg, is the primary source of the anomaly profits. When arbitrageurs who exploit overpricing face greater difficulty than those who exploit underpricing, the short-leg, presumably costly to short, could be overpriced while the long-leg, presumably less costly to purchase, could not be underpriced. It leads to greater anomaly profits for high-sentiment periods than for low-sentiment periods.

The empirical results of Stambaugh et al. (2012) lead us to conjecture that the option-implied skewness will exhibit stronger relation to future stock returns when investor sentiment is high. When there is a tendency of overpricing, bad news would be relatively difficult to get incorporated into stock prices, and the delayed response of stock prices would be more prominent among stocks that are costly to short. In contrast, even though there is a tendency of underpricing, good news would easily to get impounded into stock prices since arbitrage exploiting underpricing is less costly, resulting in less significant predictability of the option-implied information. Combining these two cases, we hypothesize that option-implied skewness exhibit stronger predictive power during high-sentiment periods, especially among stocks with high shorting costs. By testing this hypothesis, we can find the evidence of whether the relation between option-implied skewness and stock returns stems from the delay response of the stock market.

In sum, in this paper, we answer the question of whether the mispricing of the stock market is the primary source of the predictive power of option-implied skewness for future stock returns by examining whether the predictive power varies with shorting costs and investor sentiment. In particular, we expect that the predictive power is stronger among stocks with higher shorting cost in high-sentiment periods to the extent that it is associated with overpricing, provided that shorting costs allows the overpricing in the stock market.

Our empirical findings support our hypotheses. First, we confirm the predictive power of option-implied skewness, where we use the implied skewness of the risk-neutral distribution as in Bakshi et al. (2003). Stocks in the lowest quintile of option-implied skewness underperform the highest quintile by 0.90 percent in the month following portfolio formation on a risk-adjusted basis using the Fama-French (1993) three factors. The return predictability is robust to controls of exposure to cross-sectional effects such as size, book-to-market, and momentum. Furthermore, we observe that stocks with lower skewness exhibit higher short interest, which supports the notion that lower skewness is associated with overvaluation as argued in previous studies.

Second, we find that the predictive power of option-implied skewness is significantly stronger among stocks with higher shorting costs. Among stocks in the highest tercile of shorting costs, a strategy long stocks in the lowest skewness quintile and short stocks in the highest skewness quintile yields risk-adjusted return of 1.73 percent. In contrast, in the lowest shorting cost tercile, the long-short strategy based on the skewness produce no significant profits. This evidence confirms that the predictability of the option-implied skewness is associated with overpricing to the extent that arbitrage impediments are relevant.

Third, we find that option-implied skewness exhibit stronger predictability during high-sentiment periods than during low-sentiment periods. Stocks in the lowest skewness quintile significantly underperform the highest quintile by 0.78 percent per month on a risk-adjusted basis following high sentiment, while the return difference is insignificant following low sentiment. The asymmetry in the return predictability across investor sentiment is also consistent with our hypothesis that the overpricing of stocks is the source of the predictability.

Lastly, we observe that short interest of stocks in the lowest skewness quintile is increasing even in the following month of portfolio formation, suggesting that informed investors attempt to exploit the negative information that has not got incorporated into stock prices.

To summarize, we document that the predictive power of option-implied skewness for future stock returns is stronger within the subsample of stocks that are costly to short, and moreover, when market sentiment is high. Collectively considered, we argue that the overpricing in the stock market is the primary source of the predictability, which implies the delayed response of stock prices to the information embedded in option skewness.

As mentioned, our study is an extension of the literature that documents a relation between option-implied skewness and future stock returns. One of the closest studies to ours is that of Rehman and Vilkov (2012), which document that the implied skewness is positively related to future stock returns, where they use the risk-neutral skewness following Bakshi et al. (2003)'s procedure. They interpret this result to indicate that the skewness is able to identify the misvaluation, and therefore, the observed positive skewness-return relation arises from a value correction process. In particular, the most overvalued stocks have the lowest ex ante skewness, and their price correction leads to lower returns. As mentioned before, we extend their work by investigating how the skewness-return relation varies with limits of arbitrage as well as the sentiment effect. Our finding that the predictability of option-implied skewness is stronger among stocks that are more susceptible to mispricing is consistent with the argument of Rehman and Vilkov (2012). On the other hand, Xing et al. (2010) find that steeper option volatility smirks lead to lower stock returns.[5] Their finding is in line with that of Rehman and Vilkov (2012) since a steeper slope of implied volatility equals to lower risk-

[5] In particular, they demonstrate that steeper option volatility smirks lead to lower stock returns, where the volatility smirk is defined as a difference in implied volatilities between an out-of-the-money put option and an in-the-money call option.

neutral skewness, everything else being equal (Bakshi et al., 2003).

What differentiate our study from these studies is that we focus on what underlies the return predictability. Our analysis reveals that the relation between option-implied skewness and stock returns stems from stock mispricing to the extent that arbitrage impediments allow the mispricing. By offering the evidence that a delayed response of stock prices to information in the options market lead to the return predictability, we contribute to the literature that examine the connection between the stock market and the options market returns (Ofek et al., 2004; Pan and Poteshman, 2006; Ni et al., 2008; Roll et al., 2010; Xing et al., 2010; Johnson and So, 2012).

Another contribution of our study is that we document the return predictability of option-implied skewness varies with investor sentiment. To our knowledge, we are the first to take investor sentiment account into in order to investigate the source of the return predictability. We find that the predictability of option-implied skewness is more prominent with higher market sentiment, and furthermore, this asymmetry is stronger among stocks with high shorting costs. It is consistent with the literature that relates the asymmetry in arbitrage impediments to the asymmetry in mispricing.

The remainder of this paper is organized as follows. Section 2 discusses the information content of option-implied skewness. Section 3 and describes the estimation procedure for the skewness and present and discuss the main empirical results. Section 4 concludes.

2 Option-implied skewness

2.1 Option-implied skewness in the literature

Our study begins with the presumption that option-implied skewness has information for the future movement of underlying stock prices. This presumption is based on the notion that the implied skewness can reflect investors' price pressure for options, as argued in previous studies. For instance, Rehman and Vilkov (2012) argue that more negative (positive) risk-neutral skewness indicates stronger buying pressure for out-of-the-money puts (calls), and hence, the skewness can serve as a forward-looking measure of option traders' belief.[6] The work of Xing et al. (2010) is also accordance with this point of view. In particular, they argue that since the steeper implied volatility smirk indicates investors' worries for the possibility of future negative jump, it predicts lower returns.

Besides, a number of studies document the relation between the risk-neutral skewness and investors' belief. For instance, Bollen and Whaley (2004) argue that net buying pressure determines a shape of the volatility smirk by demonstrate that the skewness is more sensitive to belief differences for the less liquid options. Toft and Prucyk (1997) find the more levered firms exhibit negative skewness. Buraschi and Jiltosv (2006) propose a model predicting that belief differences can affect the skewness of the risk-neutral density function. In their model, optimistic investors demand out-of-the-money calls, while pessimistic investors demand out-of-the-money puts. In particular, negative dividend shock induces optimistic investors to be more risk averse, and thereby reduces stock prices by more than what would be caused

[6] Buss and Vilkov (2012) also use risk-neutral distribution to estimate forward-looking market betas from current option prices and find that a monotonically increasing risk-return relation, which is not detectable with historical betas.

simply by a dividend reduction. This effect leads the left tail to extend towards more negative values. More recently, Birru and Figlewski (2012) argue that the risk neutral probability density contains information about investors' price expectations and risk preferences.

There exists a strand of literature that argues that lower skewness indicates higher systematic risk (Harvey and Siddique, 2000; Conrad et al., 2013) For example, Conrad et al. (2013) show the presence of skewness risk premium using the risk-neutral skewness extracted from 90-days options. Notably, their empirical results are opposite to those of Rehman and Vilkov (2012), even though they both use measures based on Bakshi et al. (2003). As for this issue, Rehman and Vilkov (2012) document that the difference arises due to either a periods used for skewness estimation or a portfolio rebalancing frequency. Conrad et al. (2013) construct portfolios based on a time series average of skewness over the last three months and rebalance the portfolios once every quarter, while Rehman and Vilkov (2012) construct portfolios based on skewness on each day and rebalance them each month.[7]

2.2 Positive OIS-return relation

Our sample consists of all firms listed on NYSE, AMEX, and NASDAQ during the period of 1996 through 2010. We obtain stock return, market capitalization, and trading volume data from CRSP, and accounting data, such as book value of assets, from Compustat. The risk-free rate and the three Fama-French (1993) factor mimicking portfolio returns are from the online data library of Ken French. We collect institutional ownership data from the CDA Spectrum database of Thomson Financial, which consists of institutional 13F filings.

[7] Furthermore, Rehman and Vilkov (2012) argue that their results are not contradicting, but rather complementary to those of Conrad et al. (2013), given that a short-term skewness-relation can be associated with option traders' beliefs while a long-term relation can be related to investor preferences.

Option-implied skewness is estimated according to the procedure of the Bakshi et al. (2003), using the daily option data from 1996 to 2010 available through Optionmetrics Ivy Database. Specifically, we sample all out-of-the-money calls and puts on individual stocks that have expiration date are closest to 30 days to maturity, and estimate risk-neutral skewness for each firm on each day that data are available.[8]

<Insert Table 1>

At the end of each month, we sort stocks into quintile portfolios based on the OIS as of the last day of a given month.[9] Table 1 provides average firm characteristics and monthly returns for the equal-weighted OIS portfolios. SIZE is the logarithm of the firm's market capitalization, and BM is the ratio of the book value of the firm's equity to the market value of equity. MOM is the momentum variable for each stock is defined as the cumulative return on the stock over the previous 6 months starting one month ago following Jegadeesh and Titman (1993). TURN is the logarithm of the firm's share turnover, measured as the trading volume divided by the number of shares outstanding. HS is the return skewness calculated using the previous month's daily stock returns. AD is the standard deviation of all outstanding current fiscal year earnings forecasts scaled by the absolute value of the mean forecast (with zero-mean-forecast observations excluded from the sample), computed as in Diether et al. (2002). IO is the fraction of institutional ownership computed by summing the stock holdings

[8] The details are given in Appendix.

[9] In order to investigate the relation between risk-neutral skewness and stock returns, Rehman and Vilkov (2012) conduct portfolio sorts base on the skewness estimate as of the last date, while Conrad et al. (2013) use an average of daily skewness estimates over past month. Rehman and Vilkov (2012) document that the effect of the skewness on stock returns are sensitive to the period used for the estimation of the skewness. Moreover, they find that the skewness effect weakens when the skewness is averaged over longer periods.

of all reporting institutions for each stock in each quarter.[10]

AMIHUD is the illiquidity measure suggested by Amihud (2002), computed as the ratio of the absolute monthly stock return to its dollar trading volume.[11] AMIDOWN is the half-Amihud measure for down days as the Amihud measure that is calculated using only data from negative return days following Brennan et al. (2013), who the half-Amihud measures inspired by the presence of asymmetry in price impacts between sales and purchases.[12] DBREADTH is the change in breadth of ownership measured as the ratio of the number of institutions that hold a long position in the stock to the total number of institutions in the sample for that quarter, following Lehavy and Sloan (2008). Note that institutional holding data are provided on a quarterly basis, so DBREADTH and IO in each quarter is assigned to each month in that quarter.

Several interesting observations can be made. First, individual stocks have negatively skewed risk-neutral return distribution, confirming the finding of previous studies including Conrad et al. (2013) and Rehman and Vilkov (2012). Most importantly, the last four rows in Table 1 reveals that OIS has positive predictability for future returns of the underlying stocks, consistent with Rehman and Vilkov (2012). The equal-weighted average excess return difference between the highest OIS quintile (OIS 5) and the lowest OIS quintile (OIS 1) is

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[10] A 1978 amendment to the Securities and Exchange Act of 1934 required all institutions with greater than $100 million of securities under discretionary management to report their holdings to the SEC. Holdings are reported quarterly on the SEC's form 13F.All common-stock positions greater than 10,000 shares or $200,000 must be disclosed.

[11] Amihud (2002) propose the illiquidity measure for each stock i for each month t computed as follows: ILLIQi,t = |Ri,t|/VOLi,t where Ri,t is the return on stock i in month t, and VOLi,t is the respective monthly trading volume in dollars.

[12] Brennan et al., 2012 find that the average difference between sell- and buy-order illiquidity measures is generally positive for a large cross-section of stocks over 26 years, and also find that it co-moves with the TED spread which is a measure of funding illiquidity. Brennan et al. (2013) conjecture that illiquidity in up markets and down markets can be different, and decompose the Amihud (2002) illiquidity measure into two elements that correspond to up and down days. In particular, they define the half-Amihud measure for up (down) days as the Amihud measure that is calculated using only data from positive (negative) return days.

1.02% per month with a corresponding Newey-West (1987) t-statistic of 4.40. This positive relation between OIS and future returns holds after controlling risk factors such as market, size, and book-to-market factors. As shown in the last two rows of Panel A, OIS 1 underperforms OIS 5 by 0.90% per month with Newey-West (1987) t-statistic of 3.98. This difference is economically significant and statistically significant at all conventional levels.

Rehman and Vilkov (2012) argue that the information content of OIS explain its positive predictability. In particular, they argue that OIS to have the positive predictability because it reflects the valuation of option traders, presumably most informed investors, for future performance of underlying stocks. Given their conjecture that bearish (bullish) valuation in the options market is associated with higher (lower) OIS, OIS can have predictive power for future stock returns to the extent that there is a delayed response of stock prices to the information of OIS. Put differently, they argue that stocks with lower OIS earn lower future returns since they do not fully incorporate the bearish valuation observable in the options market, and thereby, are overpriced.

2.3 Information content of OIS

As mentioned before, our result, shown in Table 1, confirms their finding to some extent. OIS is positively related with subsequent stock returns in the cross-section. However, it does not exclusively support their interpretation of market segmentation. According to the literature on investor’s skewness preference, the significant relation between skewness and average returns can be interpreted as evidence of skewness premium (Harvey and Siddique, 2000; Conrad et al., 2013; Chang et al., 2013).

<Insert Table 2>

To investigate this further, we examine whether the predictive power last over a long period. If the predictability of OIS is allowed by market segmentation, it should be temporary and unlikely to persist over a long period. Table 2 presents cumulative holding period returns for the next 12 months. Note that each portfolio returns are annualized for the sake of comparison. We report monthly returns in excess of the risk-free rate and characteristics-adjusted returns suggest by Daniel et al. (1997).

Table 2 shows that the predictability of OIS remains significant, at the least, over nine months and weakens thereafter. The difference in characteristics-adjusted return declines from 11.17% in the first month following portfolio formation and become statistically insignificant beyond the nine month. For example, for a holding period of three month, the return difference between stocks with OIS 5 and OIS 1 is 5.48% with t-statistics of 4.64, which is almost 50% smaller than the return if we hold the portfolio for one month. The return difference drops to 1.33% when we extend the holding period to nine month. The result may indicates that the predicative power of OIS diminish with time as the information of OIS is gradually incorporated.

<Insert Figure 1>

Figure 1 provides evidence consistent with the earlier finding. We explore changes in short interest of each OIS decile portfolio in order to verify the relation between OIS and future stock returns. Panel A depicts changes in short interest in the month prior to the portfolio formation month t, and Panel B illustrates those in the following month t+1. First, in Panel A, we find that short interest rises disproportionately in the month when a stock falls into the lowest OIS decile. More interestingly, we observe that short interest on the lowest

OIS portfolio continues to increase in the next month in Panel B, which indicates that there are traders to shortsell the stock, even after its low OIS is observed in the options market. In other words, it can be interpreted as evidence that informed investors attempt to exploit the negative information embedded in options that has not been yet incorporated into stock prices.

Another interesting result here is that stocks with high OIS, on average, have features that might be relevant to overpricing. In particular, OIS 5 exhibits high dispersion in analyst earnings forecast and low institutional ownership, as shown Table 1. Given the literature documenting that stocks with greater analyst disagreement or lower institutional ownership are more likely to be overpriced in the presence of short-sale constraints, and thereby earn lower future returns, our results may seem to be inconsistent.[13] However, we note that it is evidence supporting the information content of OIS. Even though stocks with low OIS are, on average, less susceptible to overpricing compared to those with high OIS, they underperform in the following month. It suggests that the predictability of OIS is not driven by a specific relation between OIS and other firm characteristics.

To summarize, in this section, we confirm the predictability and the information content of OIS, and moreover, present evidence that the predictability may stem from the delayed response of stock prices to OIS, as documented in Rehman and Vilkov (2012).

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[13] Since the earlier model of Miller (1977) in which stocks can be overpriced under short-sale constraints, the presence of overpricing is extensively discussed in the literature (Diether et al., 2002; Nagel, 2005; Sadka and Scherbina, 2007). For example, Diether et al. (2002) argue that stocks with high dispersion in investors' opinion are more likely to be overpriced, since short-sales constraints keep investors with the lowest valuations out of the market. Nagel (2005) also provide evidence of overpricing under the conjecture that short-sale constraints are more likely to bind among stocks with low institutional ownership. Since institutional constraint deters professional investors from trading against overpricing of stocks that do not own, low institutional ownership can proxy greater impediments to shortsell.

3 Empirical results

3.1 The predictability of OIS and shorting costs

The thrust of our paper is to investigate the source of the predictability of OIS. The literature has argued that the predictability comes from the delayed response of stock prices to the information observed in option market. To verify this argument, first, we take the role of arbitrage impediment on stock mispricing into account.

If the predicative power of OIS is associated with mispricing of stocks, OIS exhibit stronger predictive power for those that are difficult or costly to arbitrage. Greater arbitrage impediments deter arbitrageurs from exploiting mispricing, and thereby allow the mispricing to persist. In this regards, we expect that the stronger predictive power among stocks with higher arbitrage costs can shed light on the source of the predictability. On the other hand, the literature document that overpricing is more prevalent than underpricing due to the relative difficulty of short-selling versus purchasing. This phenomenon is also documented in the literature on short-selling constraints. Inspired by these findings, we hypothesize that the predictability of OIS is stronger among stocks that are more costly to short.

We measure shorting costs in two ways – the illiquidity cost for down markets (AMIDOWN) and change in breath of institutional ownership (DBREADTH). Brennan et al. (2013) decompose the Amihud (2002) illiquidity measure into two elements that correspond to up and down days under the conjecture that illiquidity in up markets and down markets can be different. We employ AMIDOWN as our first proxy for shorting costs, expecting that high AMIDOWN indicates higher costs.[14] The second proxy is change in breadth suggested by

[14] Kumar and Lee (2006) also use the liquidity costs as an arbitrage cost proxy, under the assumption that arbitrage costs are

Chen et al. (2002). They propose a model that predicts breadth of ownership proxies how tightly short-sale constraints bind, and show that low change in breadth predict lower subsequent returns. In accordance with their findings, we expect lower DBREADTH indicates greater difficulty of shorting.

<Insert Table 3>

To test our first hypothesis, we verify whether the return difference between high and low OIS varies with shorting costs. In particular, we sort stocks first into quintiles by our shorting cost measure and then form five portfolios within each quintile by OIS. Table 3 presents the subsequent months' average excess returns as well as adjusted returns for these equal-weighted portfolios. The risk-adjusted returns are those from the time-series regression of the portfolio returns on the three Fama-French (1993) factors. Panel A pertains to DBREADTH, and Panel B pertains to AMIDOWN.

We find that the positive OIS-return relation is stronger among stocks with higher shorting cost. In Panel A, the lowest OIS quintile underperforms the highest OIS quintile by 1.48% per month in the lowest DBREDTH quintile, but by 0.72% in the highest DBREADTH, on a risk-adjusted basis using the Fama-French (1993) three factors. This pattern is also observed in Panel B. The return difference between the highest and lowest OIS quintile portfolios is on average 1.41% with t-statistics of 3.04 among stocks in the highest AMIDOWN quintile, while the difference is 0.34% with t-statistics of 1.18 in the lowest AMIDOWN quintile. This evidence supports our hypothesis that the predictability of OIS stems from the mispricing of underlying stocks due to the delayed incorporation of the

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higher for less liquid stocks.

information contained in OIS.

One may have concern that our measures, DBREADTH and AMIDOWN, can serve as a good proxy for the difficult of shorting. To avoid this concern, we repeat the analysis using other plausible proxies suggested in the literature. For example, Nagel (2005) argue that short-sale constraints are more likely to bind among stocks with low institutional ownership. Institutional constraint deters professional investors from trading against overpricing of stocks that do not own, and therefore, low institutional ownership can indicate greater impediments to shortsell. Idiosyncratic volatility, used as a measure of the difficulty of arbitrage in the literature, also appears to be closely related to shorting costs (Kumar and Lee, 2006, Wurgler and Zhuravskaya, 2002). Hence, we conduct double sorts in the analogous manner as in Table 3, using institutional ownership or idiosyncratic volatility as a proxy for shorting costs. In unreported results, we observe qualitatively the same results as those of Table 3, suggesting that our results are not driven by a specific measure for shorting costs.

While each measure is itself a proxy of shorting costs, it does not imply that their information contents are the same. Hence, we combine the measures to produce a univariate monthly measure that correlates with shorting costs in the cross section of stocks. We expect this approach can diversify away some noise in each measure and thereby increases precision. For each measure, we assign a rank to each stock that reflects the sorting on that given measure, where the highest rank is assigned to the value of the measure associated with high shorting costs. More specifically, we rank stocks each month by DBREADTH (AMIDOWN) so that those with the highest DBREADTH (the lowest AMIDOWN) receive the highest rank. We then define a stock's SCORE as the average of its ranks for DBREADTH and AMIDOWN.

Panel C of Table 3 presents the monthly return on double-sorted portfolios based on

SCORE and OIS. We repeat the sequential sort in which we sort first into quintiles by SCORE and then form five portfolios within each quintile by OIS. The result confirms our earlier finding. For the highest SCORE stocks, the average returns are positive and monotonically increasing in OIS, with the difference between the highest and lowest OIS portfolios is 1.65% per month (t-statistic 3.64), on a risk-adjusted basis. In contrast, for the lowest SCORE stocks, the average returns are less monotonic in OIS, with the difference in risk-adjusted returns between the highest and lowest OIS portfolios equal to 0.50% per month (t-statistic 1.72).

<Insert Table 4>

Compared to portfolio sorts, the Fama-MacBeth (1973) cross-sectional regression has advantage in controlling the multiple effects at the same time (Fama and French, 2008). Hence, we now examine the cross-sectional relation between OIS and returns at the individual firm level using Fama-MacBeth regression. Table 4 present the time-series averages of the coefficients from the regressions of excess stock returns on OIS and other variables of interest. To investigate whether the OIS-return relation varies with shorting costs, we include two interaction dummy variables, OIS×D_DBREADTH and OIS×D_AMIDOWN, where D_DBREADTH (D_AMIDOWN) is set to one for stocks of which DBREADTH (AMIDOWN) above (below) the median value for the sample, or zero otherwise. We also various control variables such as firm size (SIZE), book-to-market ratio (BM), past returns (MOM), turnover (TURN), historical skewness (HS), analyst disagreement (AD), and institutional ownership (IO) in the regression.

As expected, the univariate regression results in Column 1 show a positive and significant relation between OIS and future stocks returns. The average slope from the regression of excess returns on OIS alone is 1.82 with a t-statistic of 4.81. The positive coefficient is robust to controls of other cross-sectional effects. The regression coefficient on OIS remains positive and significant, as shown in Columns 2 and 3. Moreover, we observe that the signs of coefficients on DBREADTH and AMIDOWN are consistent with the prediction of previous studies.

Of main interest are the coefficients on interaction dummies in Columns 4 through 6, which show results for the specification with interaction dummies. Consistent with earlier finding, the both OIS×D_DBREADTH and OIS×D_AMIDOWN have positive regression coefficients. It ensures that stocks with high shorting costs exhibit more strong positive OIS-return relation.[15]

To summarize, in this subsection, we provide evidence that the relation between option-implied skewness and future stock returns is stronger among stocks that are difficulty or costly to short. This evidence support the hypothesis that the predictive power of option-implied skewness stems from the mispricing, especially overpricing, induced by the delayed response of the stock market.

3.2 The predictability of OIS and investor sentiment

In this subsection, we investigate whether the predictability of OIS varies with investor sentiment. If the overpricing of the stock market is the source of the predictive power, it becomes stronger when there is a market-wide tendency of overpricing.

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[15] We conduct the analogous cross-sectional regression, where the dependent variables are risk-adjusted returns as in Brennan et al. (1998). We observe that the pattern is qualitatively the same in unreported results.

<Insert Table 5>

For this purpose, we first identify periods when a given mispricing direction is more likely, based on the monthly sentiment index constructed by Baker and Wurgler (2006). Specifically, we classify a high-sentiment month as the one in which the sentiment index values in the previous month is above the sample median, while a low-sentiment month is that with below-median value, following prior studies.[16] Panel A of Table 5 presents returns on OIS portfolios for high- and low-sentiment periods, respectively. We report excess returns as well as risk-adjusted returns using the three Fama-French factors. Note that the risk-adjusted returns following high- and low-sentiment periods are estimates of a_H and a_L in the following regression:

$$r_{i,t} = a_H d_{H,t} + a_L d_{L,t} + bMKT_t + sSMB_t + hHML_t + \varepsilon_{i,t} \quad (1)$$

where $d_{H,t}$ and $d_{L,t}$ are dummy variables indicating high- and low-sentiment periods, and $r_{i,t}$ is the excess return in month t on each portfolio.

Notably, we observe that the return difference between the highest and lowest OIS portfolio is more prominent following high sentiment. The lowest OIS underperforms the highest OIS by 0.78% with t-statistics of 2.92 per month following high sentiment, but by 0.05% with t-statistics of 0.21 following low sentiment, on a risk-adjusted basis. It apparently supports the conjecture that the positive OIS-return relation arises from the stock mispricing. The Fama-MacBeth regression also yields the same results. In Panel B, the average of regression coefficients on OIS is more negative and significant following high sentiment. In

[16] The Baker and Wurgler (2006) sentiment index is constructed as the first principal component of six underlying measures of investor sentiment: the average closed-end fund discount, the number and the first-day returns of IPO's, NYSE turnover, the equity share of total new issues, and the dividend premium (log difference of average market/book of dividend payers vs. nonpayers). The approach that splits a whole sample period into a binary state, which is a high- and a low-sentiment period, is used in the studies including Stambaugh et al. (2012) and Chen et al. (2002)

the full specification with OIS and the other control variables, the coefficient on OIS is 1.25 with t-statistics of 2.44 following high sentiment, but it is 0.31 with t-statistics of 0.73 following low sentiment (Columns 3 and 6).

This asymmetry in the return predictability between different sentiment periods is consistent with our hypothesis that relates the overpricing of stocks to the predictability of OIS. Increased noise trader risk in the stock market, suggested by previous studies including De Long et al. (1990), may drive most of arbitrageurs to choose to trade in the options market (Ofek et al., 2004; Pan and Poteshman, 2006; Ni et al., 2008; Roll et al., 2010; Xing et al., 2010; Johnson and So, 2012). Provided that increased noise trading in high-sentiment periods, overpricing are more difficult to be eliminated, and as a result, OIS has stronger predictability in those periods. In other words, high sentiment may increase noise trading in the stock market, and thereby can encourage market segmentation between stocks and options.

3.3 Shorting costs and investor sentiment

So far, we find evidence that the positive relation between option-implied skewness and future stock returns is attributed to the mispricing accompanied with a delayed response of stock prices to information in the options market. In particular, we take two concepts - the difficulty of shorting and investor sentiment - into account, and verify that the predictive power of OIS is stronger either when shorting is costly or when investor sentiment is high.

<Insert Table 6>

In this subsection, we consider two conditions together. Table 6 shows that monthly returns on double-sorted portfolios based on SCORE and OIS. Each month, quintile portfolios are formed by sorting first on SCORE, and then by sorting within each of those quintiles by OIS, again forming five portfolios. We report monthly excess returns and risk-adjusted returns on the resulting 25 equal-weighted portfolios following high-sentiment months, and those following low-sentiment months in Panels A and B, respectively.

Indeed, the results in Table 6 confirm that the predictive power of OIS is stronger where overpricing is more likely. The return difference between the highest and lowest OIS portfolio is the largest in among stocks with the highest SCORE during both periods. More interestingly, the predictability of OIS appears to be more prominent following high-sentiment periods than following low-sentiment periods. For example, the significant OIS-return relation is observed in three out of five SCORE quintiles following high sentiment, but in one SCORE quintile - the highest quintile - following low sentiment. Put differently, OIS has significant predictability as a whole when investor sentiment is high, while it can exhibit the predictive power only among stocks that are difficult to short when sentiment is low.

<Insert Figure 2>

For further investigation, we compare the predictive power of OIS for high-sentiment periods to that for low-sentiment periods over a longer horizon. Figure 2 shows that average return differences between the highest and lowest OIS quintile for a given SCORE quintile, where the line is for the highest SCORE and the dashed line is for the lowest SCORE. Panel A pertains to high-sentiment periods, and Panel B pertains to low-sentiment periods. Notably, we find that even among stocks with the highest SCORE, the predictive power of OIS lasts over six month following high sentiment, while it does not persist after one month following low sentiment. It is apparently in favor of previous studies that relates stock mispricing to the predictability of OIS. Moreover, it provides evidence that overpricing is more prevalent than underpricing. We infer that underpricing is less likely during low-sentiment periods, and hence, the predictability of OIS weakens in those periods.

<Insert Table 7>

The Fama-MacBeth regression for individual firms also provides supportive evidence. We conduct the regression of excess returns on OIS and interaction dummies, OIS×SCORE_H and OIS×SCORE_H as well as several control variables, where SCORE_H (SCORE_L) is set to one for stocks in the highest (lowest) SCORE tercile. Table 7 presents the time-series averages of the regressions coefficients. Consistent with our earlier findings, the regression coefficient on OIS is more negative and significant following high sentiment. In the full specification, the coefficient on OIS is 1.48 with t-statistics of 2.87 following high sentiment, but it is 0.38 with t-statistics of 0.76 following low sentiment (Columns 6 and 9).

Our primary of interest is the regression coefficient on OIS×SCORE_H and OIS×SCORE_L. We find that the coefficient estimates are also consistent with our earlier findings. Column 3 shows that the average coefficient on OIS is 3.27 in the highest SCORE quintile, while it is -0.28 in the lowest SCORE quintile. Column 6, which pertains to high-sentiment periods, also presents the similar results, which indicates that the positive OIS-return relation is stronger among stocks with the highest SCORE. On the other hand, in low-sentiment periods, we find little evidence that OIS has the predicative power for stock returns even in the highest SCORE. The regression coefficient on OIS×SCORE_H is 1.44 in the highest SCORE quintile for low-sentiment periods, which is almost 50% smaller than the coefficient for high-sentiment periods.

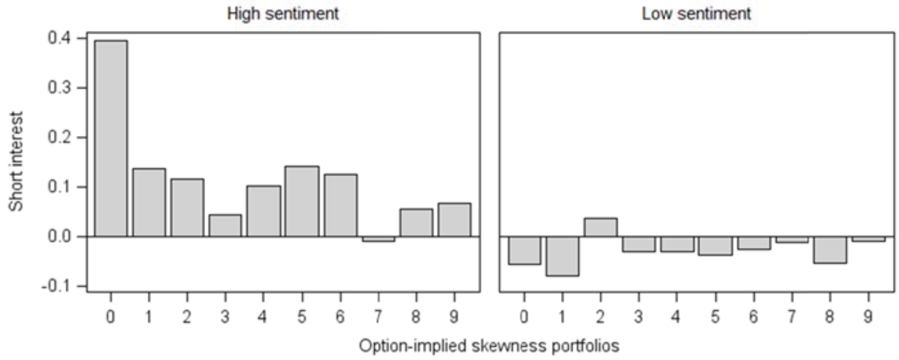
In this subsection, we offer evidence in support of the literature that regards the positive OIS-return relation as evidence of market segmentation between equities and options. If it takes time information observable in the options market to get incorporated into stock prices, and it allows OIS to have predictability for stock returns, the predictability would be stronger where the incorporation is more limited.

4 Conclusion

We reinvestigate the source of the predictability of option-implied skewness (OIS), which documented in previous literature. If the predictability stems from a delayed response of stock price to new information that are currently observed in the options market, OIS would exhibit stronger relation with future stock returns when it takes more time the information to get incorporated into stocks price. Inspired by the literature that examines the effect of shorting costs and investor sentiment on stock mispricing, we verify whether OIS-return relation varies with shorting costs and investor sentiment. In particular, we hypothesize that the predictive power of OIS is stronger when mispricing is more likely.

Our empirical findings support our hypothesis. First, we find that the OIS-return relation is stronger among stocks with high shorting costs, where we measure the shorting costs based on changes in breadth of ownership and price impacts for down market. Second, we observe that the predictability of OIS is more prominent and persistent when investor sentiment is higher. Collectively, we provide evidence that the predictability of OIS in the cross-section is related to the mispricing of underlying stocks, and both shorting costs and investor sentiment play a role as in allowing the mispricing by deferring stock prices from incorporating the information embedded in options.

A. Change in short interest in month t-1



B. Change in short interest in month t

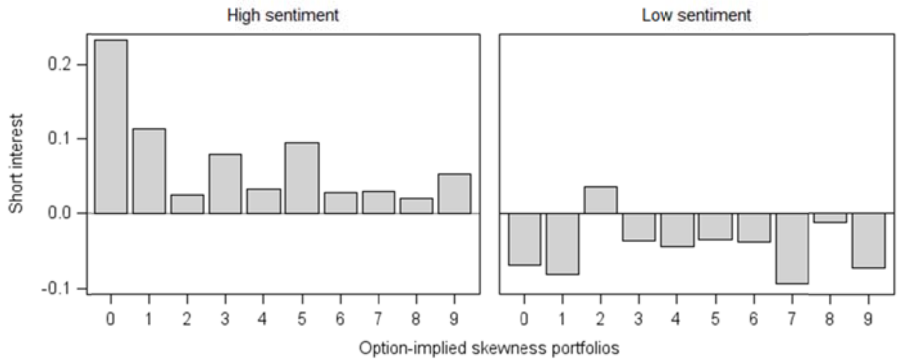


Figure 1 Change in short interest around portfolio formation

This figure present averages of changes in short interest each OIS decile portfolio. Panel A depicts changes in short interest in the month prior to the portfolio formation month t, and Panel B illustrates those in the following month t+1. A high- (low-) sentiment month as the one in which the Baker and Wurgler (2006)'s sentiment index values in the previous month is above (below) the sample median. Our sample consists of all firms listed on NYSE, AMEX, and NASDAQ during the period of 1996 through 2010.

A. High sentiment

B. Low sentiment

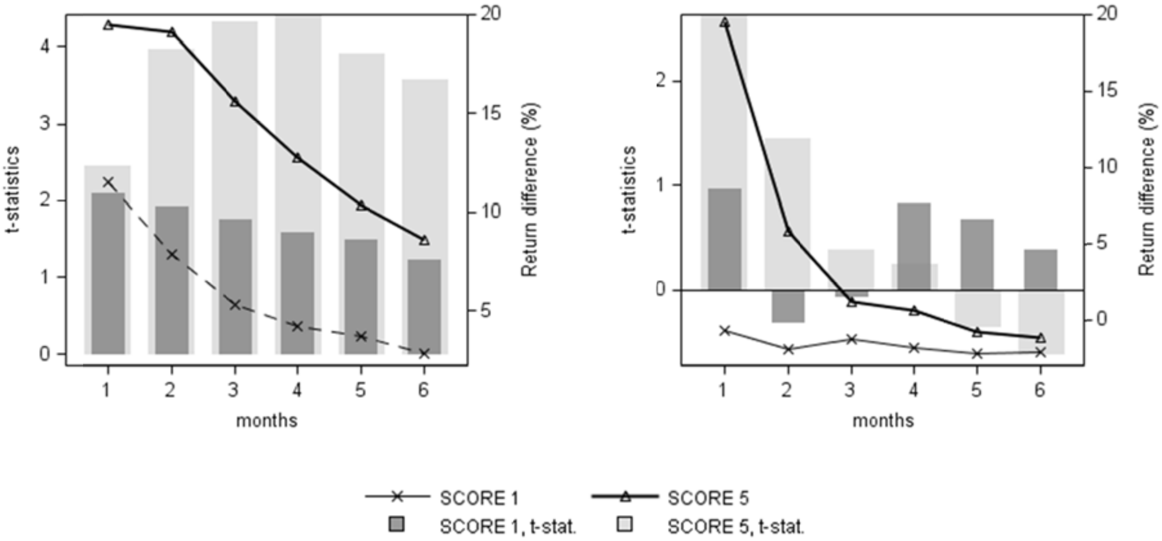


Figure 2 Returns on double-sorted portfolios based on OIS and SCORE over longer periods

This figure presents that average return differences between the highest and lowest OIS quintile for a given SCORE quintile, where the line is for the highest SCORE and the dash is for the lowest SCORE. SCORE is defined as the average of the ranks for DBREADTH and AMIDOWN, where DBREADTH is the ratio of the number of institutions that hold a long position in the stock to the total number of institutions, and AMIDOWN is the half-Amihud measure for down days as the Amihud (2002) measure that is calculated using only data from negative return days. Panel A pertains to high-sentiment periods, and Panel B pertains to low-sentiment periods. A high- (low-) sentiment month as the one in which the Baker and Wurgler (2006)'s sentiment index values in the previous month is above (below) the sample median. Our sample consists of all firms listed on NYSE, AMEX, and NASDAQ during the period of 1996 through 2010.

Table 1 Characteristics and returns on portfolios sorted by option-implied skewness

This table presents average firm characteristics and monthly returns on equal-weighted quintile portfolios sorted by OIS as of the last day of the previous month. SIZE is the logarithm of the firm's market capitalization, and BM is the ratio of the book value of the firm's equity to the market value of equity. MOM is the momentum variable for each stock is defined as the cumulative return on the stock over the previous 6 months starting one month ago. TURN is the logarithm of the firm's share turnover, measured as the trading volume divided by the number of shares outstanding. HS is the return skewness calculated using the previous month's daily stock returns. AD is the standard deviation of all outstanding current fiscal year earnings forecasts scaled by the absolute value of the mean forecast. IO is the fraction of institutional ownership computed by summing the stock holdings of all reporting institutions for each stock in each quarter. AMIHUD is the Amihud (2002) illiquidity measure. AMIDOWN is the half-Amihud measure for down days as the Amihud measure that is calculated using only data from negative return days. DBREADTH is the ratio of the number of institutions that hold a long position in the stock to the total number of institutions in the sample for that quarter. Risk-adjusted returns are those from the time-series regression of the portfolio returns on the three Fama-French (1993) factors. Our sample consists of all firms listed on NYSE, AMEX, and NASDAQ during the period of 1996 through 2010. All returns are percent per month and all t-statistics given in parentheses are adjusted based on Newy-West (1987).

	OIS 1 (low)	2	3	4	OIS 5 (high)	5-1
OIS	-0.49	-0.26	-0.15	-0.07	0.04	
SIZE	22,735	14,728	9,968	7,062	5,640	
BM	0.32	0.33	0.34	0.35	0.36	
MOM (%)	18.77	17.42	17.74	17.24	17.91	
TURN (%)	0.45	0.55	0.69	0.74	1.15	
HS	0.22	0.21	0.21	0.22	0.22	
AD	0.13	11.79	12.49	12.18	14.58	
IO (%)	70.03	69.66	69.31	69.07	66.09	
AMIHUD	1.37	1.68	2.33	3.03	3.73	
AMIDOWN	1.25	1.86	2.55	3.33	4.07	
DBREADTH (%)	0.32	0.25	0.24	0.24	0.22	
Excess return	0.21	0.58	0.99	0.86	1.23	1.02
	(0.39)	(1.04)	(1.79)	(1.46)	(2.08)	(4.40)
Risk-adjusted return	-0.30	0.02	0.42	0.27	0.60	0.90
	(-1.81)	(0.13)	(2.74)	(1.53)	(3.19)	(3.98)

Table 2 The predictability of OIS over longer periods

This table presents cumulative holding period returns over the next 12 months on equal-weighted quintile portfolios sorted by OIS as of the last day of the previous month. Each portfolio returns are annualized for the sake of comparison. Panel A pertains to monthly returns in excess of the risk-free rate, and Panel B pertains to characteristics-adjusted returns suggest by Daniel et al. (1997). Our sample consists of all firms listed on NYSE, AMEX, and NASDAQ during the period of 1996 through 2010. All returns are percent per month and all t-statistics given in parentheses are adjusted based on Newy-West (1987).

k months	OIS 1 (low)	2	3	4	OIS 5 (high)	5-1	
Panel A. Excess return							
1	6.21	10.50	15.40	13.93	18.46	12.26	(4.41)
2	6.03	9.64	12.36	11.47	14.99	8.95	(4.64)
3	6.13	9.38	11.17	10.45	12.83	6.70	(4.59)
4	5.48	8.92	9.53	9.79	10.92	5.44	(4.47)
5	5.23	8.80	9.33	9.47	9.76	4.53	(4.24)
6	5.04	8.43	8.93	9.08	9.15	4.11	(4.32)
7	5.19	8.30	8.93	8.65	8.80	3.61	(4.09)
8	5.36	8.04	8.59	8.06	8.25	2.89	(3.47)
9	5.42	7.73	8.09	7.66	7.90	2.49	(3.12)
10	5.22	7.45	7.91	7.27	7.53	2.31	(3.07)
11	5.29	7.32	7.68	7.10	7.40	2.11	(2.94)
12	5.19	7.29	7.41	6.90	7.27	2.08	(3.00)
Panel B. Characteristics-adjusted return							
1	-3.03	1.50	5.94	3.73	8.14	11.17	(4.78)
2	-3.29	0.42	2.66	1.14	4.39	7.68	(4.59)
3	-3.16	0.02	1.39	0.13	2.32	5.48	(4.41)
4	-3.95	-0.60	-0.32	-0.61	0.24	4.20	(3.95)
5	-4.49	-1.06	-0.79	-1.22	-1.28	3.22	(3.46)
6	-4.75	-1.52	-1.36	-1.71	-2.00	2.75	(3.32)
7	-4.63	-1.67	-1.30	-2.02	-2.29	2.34	(3.02)
8	-4.47	-1.94	-1.64	-2.58	-2.82	1.65	(2.25)
9	-4.39	-2.22	-2.12	-2.90	-3.06	1.33	(1.89)
10	-4.48	-2.38	-2.15	-3.15	-3.28	1.21	(1.79)
11	-4.37	-2.46	-2.33	-3.20	-3.28	1.08	(1.69)
12	-4.44	-2.44	-2.52	-3.36	-3.34	1.10	(1.76)

Table 3 Returns on double-sorted portfolios based on OIS and shorting costs

This table presents monthly returns on double-sorted portfolios based on OIS and three measures for shorting costs. We sort stocks first into quintiles by our shorting cost measure and then form five portfolios within each quintile by OIS. Panel A (B) [C] presents the subsequent months' average excess returns as well as risk adjusted returns on DBREADTH (AMIDOWN) [SCORE]-OIS portfolios. AMIDOWN is the half-Amihud measure for down days as the Amihud (2002) measure that is calculated using only data from negative return days. DBREADTH is the ratio of the number of institutions that hold a long position in the stock to the total number of institutions in the sample for that quarter. SCORE is defined as the average of the ranks for DBREADTH and AMIDOWN. Risk-adjusted returns are those from the time-series regression of the portfolio returns on the three Fama-French (1993) factors. Our sample consists of all firms listed on NYSE, AMEX, and NASDAQ during the period of 1996 through 2010. All returns are percent per month and all t-statistics given in parentheses are adjusted based on Newy-West (1987).

	Excess return						Risk-adjusted return					
	OIS 1 (low)	2	3	4	OIS 5 (high)	5-1	OIS 1 (low)	2	3	4	OIS 5 (high)	5-1
Panel A. Change in breadth (DBREADTH)												
1	-0.44	0.27	0.64	0.79	1.12	1.55	-1.05	-0.33	0.02	0.18	0.43	1.48
	(-0.70)	(0.41)	(0.96)	(1.24)	(1.52)	(3.98)	(-3.25)	(-0.95)	(0.05)	(0.55)	(1.00)	(3.78)
2	0.28	0.54	0.97	1.08	1.27	0.99	-0.37	-0.09	0.31	0.38	0.58	0.95
	(0.47)	(0.91)	(1.46)	(1.54)	(1.80)	(2.65)	(-1.40)	(-0.37)	(1.13)	(1.27)	(1.73)	(2.49)
3	0.42	0.58	1.38	1.03	1.31	0.89	-0.16	0.00	0.68	0.34	0.63	0.79
	(0.72)	(0.95)	(2.28)	(1.65)	(2.03)	(2.46)	(-0.77)	(-0.01)	(3.42)	(1.31)	(2.23)	(2.22)
4	0.36	0.51	1.36	0.63	1.24	0.88	-0.18	-0.04	0.77	0.03	0.55	0.74
	(0.62)	(0.90)	(2.39)	(1.05)	(1.97)	(2.60)	(-0.77)	(-0.19)	(3.04)	(0.12)	(2.10)	(2.34)
5	0.66	0.75	0.98	1.13	1.49	0.83	0.22	0.28	0.46	0.58	0.93	0.72
	(1.06)	(1.24)	(1.67)	(1.87)	(2.44)	(2.44)	(0.70)	(0.93)	(1.55)	(1.92)	(2.86)	(2.16)
5-1	1.09	0.47	0.35	0.34	0.37		1.27	0.62	0.44	0.40	0.50	
	(2.15)	(0.89)	(0.69)	(0.69)	(0.62)		(2.66)	(1.17)	(0.92)	(0.83)	(0.88)	
Panel B. Down-half-Amihud (AMIDOWN)												
1	0.29	0.27	0.60	0.70	0.68	0.39	-0.07	-0.12	0.23	0.27	0.26	0.34
	(0.56)	(0.55)	(1.32)	(1.58)	(1.70)	(1.26)	(-0.35)	(-0.76)	(1.44)	(1.61)	(1.50)	(1.18)
2	0.45	0.77	0.88	1.08	0.77	0.32	-0.11	0.24	0.36	0.54	0.23	0.34
	(0.77)	(1.41)	(1.84)	(2.37)	(1.68)	(0.84)	(-0.41)	(1.06)	(1.82)	(2.65)	(1.03)	(1.01)
3	0.54	0.42	0.79	0.61	0.82	0.28	-0.13	-0.26	0.18	-0.03	0.18	0.31
	(0.80)	(0.66)	(1.37)	(1.02)	(1.50)	(0.80)	(-0.52)	(-1.03)	(0.75)	(-0.11)	(0.77)	(0.92)
4	-0.20	0.60	1.10	1.05	0.86	1.07	-0.90	-0.20	0.41	0.38	0.20	1.10
	(-0.29)	(0.82)	(1.56)	(1.47)	(1.34)	(3.25)	(-3.30)	(-0.75)	(1.39)	(1.26)	(0.77)	(3.38)
5	0.93	1.14	1.11	1.59	2.32	1.39	0.13	0.44	0.33	0.83	1.55	1.41
	(1.14)	(1.50)	(1.35)	(1.92)	(2.78)	(3.05)	(0.37)	(1.35)	(0.95)	(2.29)	(4.09)	(3.04)
5-1	0.65	0.87	0.51	0.89	1.64		0.21	0.57	0.10	0.56	1.28	
	(1.20)	(1.89)	(0.92)	(1.53)	(2.63)		(0.53)	(1.64)	(0.25)	(1.39)	(2.98)	
Panel C. SCORE												
1	0.46	0.66	0.94	1.20	1.04	0.59	0.07	0.22	0.51	0.73	0.57	0.50
	(0.83)	(1.22)	(1.81)	(2.44)	(2.22)	(1.86)	(0.28)	(0.81)	(1.93)	(3.07)	(2.14)	(1.72)
2	0.45	0.50	0.65	0.67	0.90	0.45	-0.01	0.05	0.08	0.13	0.32	0.34
	(0.79)	(0.91)	(1.22)	(1.31)	(1.63)	(1.31)	(-0.06)	(0.24)	(0.34)	(0.62)	(1.24)	(1.01)
3	0.12	0.36	1.14	0.87	1.01	0.89	-0.51	-0.20	0.52	0.25	0.36	0.87
	(0.20)	(0.64)	(2.02)	(1.52)	(1.77)	(2.68)	(-2.08)	(-0.85)	(2.38)	(1.01)	(1.67)	(2.67)
4	0.26	0.64	0.95	0.64	1.17	0.91	-0.42	-0.10	0.23	-0.05	0.44	0.87
	(0.38)	(0.95)	(1.43)	(0.95)	(1.76)	(2.41)	(-1.33)	(-0.39)	(0.79)	(-0.16)	(1.52)	(2.25)
5	0.19	0.81	1.30	1.40	1.85	1.65	-0.61	0.04	0.56	0.69	1.11	1.73
	(0.24)	(1.04)	(1.58)	(1.81)	(2.28)	(3.64)	(-1.57)	(0.12)	(1.46)	(1.84)	(2.63)	(3.73)

5-1	-0.26 (-0.46)	0.15 (0.27)	0.36 (0.61)	0.21 (0.37)	0.80 (1.26)		-0.68 (-1.35)	-0.18 (-0.38)	0.04 (0.09)	-0.04 (-0.08)	0.54 (1.00)

Table 4 Fama-MacBeth regressions: shorting costs

This table reports the time-series averages of the coefficients from the Fama-MacBeth (1973) cross-section of excess stock returns on OIS and other variables of interest. The independent variables are OIS, OIS×D_DBREADTH, and OIS×D_AMIDOWN, where D_DBREADTH (D_AMIDOWN) is set to one for stocks of which DBREADTH (AMIDOWN) above (below) the median value for the sample, or zero otherwise. AMIDOWN is the half-Amihud measure for down days as the Amihud (2002) measure that is calculated using only data from negative return days. DBREADTH is the ratio of the number of institutions that hold a long position in the stock to the total number of institutions in the sample for that quarter. Control variables are firm size (SIZE), book-to-market ratio (BM), past returns (MOM), turnover (TURN), historical skewness (HS), analyst disagreement (AD), and institutional ownership (IO). Our sample consists of all firms listed on NYSE, AMEX, and NASDAQ during the period of 1996 through 2010. All t-statistics given in parentheses are adjusted based on Newy-West (1987).

	[1]	[2]	[3]	[4]	[5]	[6]
Intercept	1.46	2.96	7.52	4.93	8.37	8.56
	(2.60)	(1.22)	(3.37)	(2.42)	(3.64)	(3.74)
OIS	1.82	1.33	0.79	0.60	0.14	-0.02
	(4.81)	(3.11)	(2.34)	(1.51)	(0.33)	(-0.04)
OIS×D_DBREATH	.	.	.	0.41	.	0.24
	.	.	.	(1.14)	.	(0.65)
OIS×D_ AMIDOWN	.	.	.	.	1.92	1.95
	.	.	.	.	(2.94)	(2.93)
DBREATH	.	.	2.96	-1.82	.	0.06
	.	.	(0.36)	(-0.21)	.	(0.01)
AMIDOWN	.	.	-0.82	.	-0.76	-0.77
	.	.	(-4.04)	.	(-3.66)	(-3.75)
SIZE	.	-0.12	-0.95	-0.16	-0.95	-0.97
	.	(-0.90)	(-3.94)	(-1.37)	(-3.89)	(-4.02)
BM	.	0.42	0.42	0.56	0.40	0.42
	.	(0.89)	(1.33)	(1.74)	(1.26)	(1.33)
MOM	.	.	0.46	0.42	0.46	0.44
	.	.	(0.88)	(0.82)	(0.86)	(0.84)
TURN	.	.	-0.91	-0.46	-0.90	-0.92
	.	.	(-4.43)	(-2.80)	(-4.32)	(-4.48)
HS	.	.	0.05	0.04	0.05	0.06
	.	.	(0.85)	(0.68)	(0.84)	(0.90)
AD	.	.	-0.04	-0.03	-0.04	-0.03
	.	.	(-0.20)	(-0.15)	(-0.17)	(-0.14)
IO	.	.	0.04	0.27	0.07	0.09
	.	.	(0.08)	(0.47)	(0.12)	(0.16)

Table 5 The predictability of OIS between high- and low-sentiment periods

Panel A reports average excess returns and risk-adjusted returns for each OIS quintile portfolio. The risk-adjusted returns in high- and low-sentiment periods are estimates of a_H and a_L in the regression,

$$r_{i,t} = a_H d_{H,t} + a_L d_{L,t} + bMKT_t + sSMB_t + hHML_t + \epsilon_{i,t}$$

where $d_{H,t}$ and $d_{L,t}$ are dummy variables indicating high- and low-sentiment periods, and $r_{i,t}$ the excess return in month t on each OIS portfolio. A high- (low-) sentiment month as the one in which the Baker and Wurgler (2006)'s sentiment index values in the previous month is above (below) the sample median. Panel B reports the time-series averages of the regression coefficients for each sentiment period, respectively. AMIDOWN is the half-Amihud measure for down days as the Amihud (2002) measure that is calculated using only data from negative return days. DBREADTH is the ratio of the number of institutions that hold a long position in the stock to the total number of institutions in the sample for that quarter. Control variables are firm size (SIZE), book-to-market ratio (BM), past returns (MOM), turnover (TURN), historical skewness (HS), analyst disagreement (AD), and institutional ownership (IO). A high- (low-) sentiment month as the one in which the Baker and Wurgler (2006)'s sentiment index values in the previous month is above (below) the sample median. Our sample consists of all firms listed on NYSE, AMEX, and NASDAQ during the period of 1996 through 2010. All t-statistics given in parentheses are adjusted based on Newy-West (1987).

Panel A. Portfolio sorts

	Excess return						Factor-adjusted return					
	1 Low	2	3	4	5 High	5-1	1 Low	2	3	4	5 High	5-1
High sentiment	-0.08	0.28	0.18	0.60	0.64	0.72	-0.09	0.28	0.22	0.67	0.69	0.78
	(-0.10)	(0.35)	(0.19)	(0.60)	(0.65)	(1.91)	(-0.50)	(1.34)	(0.91)	(2.29)	(2.44)	(2.92)
Low sentiment	1.16	1.26	1.10	1.50	1.55	0.39	0.10	0.12	-0.19	0.11	0.15	0.05
	(1.84)	(1.96)	(1.60)	(2.01)	(2.04)	(1.46)	(0.66)	(0.73)	(-0.99)	(0.53)	(0.63)	(0.21)

Panel B. Fama-MacBeth regressions

	High sentiment			Low sentiment		
	[1]	[2]	[3]	[1]	[2]	[3]
Intercept	0.81	-0.57	7.56	2.11	6.54	7.49
	(0.95)	(-0.14)	(2.03)	(2.90)	(2.78)	(3.03)
OIS	2.37	2.16	1.25	1.28	0.48	0.31
	(3.95)	(2.95)	(2.44)	(2.78)	(1.16)	(0.73)
DBREATH	.	.	2.04	.	.	3.89
	.	.	(0.18)	.	.	(0.33)
AMIDOWN	.	.	-1.23	.	.	-0.41
	.	.	(-3.95)	.	.	(-1.59)
SIZE	.	0.09	-1.21	.	-0.33	-0.68
	.	(0.37)	(-3.23)	.	(-2.65)	(-2.28)
BM	.	0.18	0.08	.	0.66	0.76
	.	(0.23)	(0.19)	.	(1.32)	(1.71)
MOM	.	.	1.50	.	.	-0.60
	.	.	(2.73)	.	.	(-0.68)
TURN	.	.	-1.47	.	.	-0.34
	.	.	(-4.29)	.	.	(-1.63)
HS	.	.	-0.02	.	.	0.13
	.	.	(-0.20)	.	.	(1.61)
AD	.	.	-0.01	.	.	-0.08
	.	.	(-0.02)	.	.	(-0.27)
IO	.	.	0.57			-0.48
	.	.	(0.58)			(-0.82)

Table 6 Returns on double-sorted portfolios based on OIS and SCORE

Panel A (B) reports average excess returns and risk-adjusted returns on double-sorted SCORE-OIS portfolios following high- (low-) sentiment months. The risk-adjusted returns in high- and low-sentiment periods are estimates of a_H and a_L in the regression,

$$r_{i,t} = a_H d_{H,t} + a_L d_{L,t} + bMKT_t + sSMB_t + hHML_t + \epsilon_{i,t}$$

where $d_{H,t}$ and $d_{L,t}$ are dummy variables indicating high- and low-sentiment periods, and $r_{i,t}$ the excess return in month t on each OIS portfolio. A high- (low-) sentiment month as the one in which the Baker and Wurgler (2006)'s sentiment index values in the previous month is above (below) the sample median. Our sample consists of all firms listed on NYSE, AMEX, and NASDAQ during the period of 1996 through 2010. All t-statistics given in parentheses are adjusted based on Newy-West (1987).

	Excess return						Risk-adjusted return					
	OIS 1 (low)	2	3	4	OIS 5 (high)	5-1	OIS 1 (low)	2	3	4	OIS 5 (high)	5-1
Panel A. High sentiment												
SCORE 1	-0.28	0.25	0.46	0.92	0.88	1.16	-0.06	0.39	0.57	0.94	0.83	0.90
	(-0.32)	(0.28)	(0.56)	(1.18)	(1.24)	(2.34)	(-0.17)	(0.83)	(1.33)	(2.32)	(2.01)	(2.20)
2	0.08	-0.17	0.14	0.36	0.63	0.55	0.25	0.01	0.09	0.36	0.61	0.37
	(0.09)	(-0.19)	(0.17)	(0.45)	(0.74)	(0.96)	(0.66)	(0.05)	(0.27)	(1.04)	(1.38)	(0.64)
3	-0.66	-0.67	0.66	0.62	0.71	1.37	-0.72	-0.67	0.62	0.58	0.67	1.39
	(-0.71)	(-0.81)	(0.76)	(0.70)	(0.80)	(2.59)	(-1.73)	(-1.84)	(1.73)	(1.58)	(2.14)	(2.70)
4	-0.52	0.05	0.24	0.31	0.49	1.02	-0.53	0.02	0.23	0.35	0.42	0.95
	(-0.49)	(0.04)	(0.23)	(0.27)	(0.47)	(1.68)	(-0.96)	(0.05)	(0.52)	(0.74)	(0.96)	(1.56)
SCORE 5	-0.63	0.09	0.93	1.06	1.06	1.70	-0.56	0.19	1.12	1.21	1.18	1.74
	(-0.48)	(0.07)	(0.67)	(0.85)	(0.83)	(2.54)	(-0.80)	(0.31)	(1.70)	(1.86)	(1.73)	(2.52)
Panel B. Low sentiment												
SCORE 1	1.20	1.07	1.42	1.48	1.21	0.01	0.21	0.06	0.45	0.51	0.31	0.11
	(1.84)	(1.77)	(2.28)	(2.45)	(1.95)	(0.01)	(0.63)	(0.18)	(1.43)	(1.71)	(0.90)	(0.27)
2	0.83	1.17	1.16	0.99	1.17	0.35	-0.28	0.08	0.06	-0.09	0.03	0.31
	(1.21)	(1.80)	(1.74)	(1.56)	(1.65)	(0.92)	(-0.86)	(0.31)	(0.21)	(-0.34)	(0.10)	(0.79)
3	0.91	1.42	1.63	1.11	1.32	0.41	-0.30	0.27	0.43	-0.09	0.06	0.36
	(1.28)	(1.86)	(2.26)	(1.53)	(1.82)	(1.03)	(-1.14)	(0.94)	(1.55)	(-0.27)	(0.19)	(0.89)
4	1.05	1.25	1.67	0.97	1.86	0.81	-0.32	-0.23	0.23	-0.44	0.47	0.78
	(1.23)	(1.50)	(2.03)	(1.36)	(2.28)	(1.76)	(-0.91)	(-0.67)	(0.61)	(-1.26)	(1.22)	(1.68)
SCORE 5	1.03	1.54	1.66	1.75	2.64	1.61	-0.67	-0.11	-0.02	0.16	1.05	1.72
	(1.08)	(1.80)	(1.91)	(1.89)	(2.64)	(2.60)	(-1.77)	(-0.29)	(-0.04)	(0.41)	(1.97)	(2.84)

Table 7 Fama-MacBeth regressions: SCORE and sentiment

This table reports the time-series averages of the coefficients from the Fama-MacBeth (1973) cross-section of excess stock returns on OIS and other variables of interest, for each sentiment periods. The independent variables are OIS, OIS×SCORE_H, and OIS×SCORE_H, where SCORE_H (SCORE_L) is a dummy for the highest (lowest) tercile of SCORE. SCORE is defined as the average of the ranks for DBREADTH and AMIDOWN. AMIDOWN is the half-Amihud measure for down days as the Amihud (2002) measure that is calculated using only data from negative return days. DBREADTH is the ratio of the number of institutions that hold a long position in the stock to the total number of institutions in the sample for that quarter. Control variables are firm size (SIZE), book-to-market ratio (BM), past returns (MOM), turnover (TURN), historical skewness (HS), analyst disagreement (AD), and institutional ownership (IO). A high- (low-) sentiment month as the one in which the Baker and Wurgler (2006)'s sentiment index values in the previous month is above (below) the sample median. Our sample consists of all firms listed on NYSE, AMEX, and NASDAQ during the period of 1996 through 2010. Our sample consists of all firms listed on NYSE, AMEX, and NASDAQ during the period of 1996 through 2010. All t-statistics given in parentheses are adjusted based on Newy-West (1987).

	Whole sample			High sentiment			Low sentiment		
	[1]	[2]	[3]	[1]	[2]	[3]	[1]	[2]	[3]
Intercept	1.33	7.36	7.10	1.29	6.08	5.94	1.37	8.66	8.28
	(2.79)	(3.42)	(3.32)	(1.72)	(1.80)	(1.79)	(2.31)	(3.23)	(3.06)
OIS	1.69	0.79	0.93	2.44	1.25	1.48	0.92	0.32	0.38
	(4.49)	(2.36)	(2.59)	(4.04)	(2.46)	(2.87)	(2.13)	(0.75)	(0.76)
OIS*SCORE_H	.	.	1.34	.	.	1.62	.	.	1.06
	.	.	(1.61)	.	.	(1.21)	.	.	(1.07)
OIS*SCORE_L	.	.	-1.11	.	.	-1.08	.	.	-1.14
	.	.	(-2.42)	.	.	(-1.57)	.	.	(-1.87)
SCORE	0.02	-0.07	-0.03	-0.09	-0.09	-0.06	0.12	-0.04	0.01
	(0.26)	(-1.56)	(-0.52)	(-0.94)	(-1.59)	(-1.02)	(1.70)	(-0.68)	(0.14)
SIZE	.	-0.26	-0.27	.	-0.13	-0.14	.	-0.39	-0.39
	.	(-2.22)	(-2.27)	.	(-0.68)	(-0.74)	.	(-2.95)	(-2.91)
BM	.	0.59	0.58	.	0.35	0.34	.	0.82	0.82
	.	(1.80)	(1.78)	.	(0.74)	(0.71)	.	(1.85)	(1.87)
MOM	.	0.27	0.26	.	1.25	1.23	.	-0.73	-0.72
	.	(0.52)	(0.50)	.	(2.26)	(2.23)	.	(-0.84)	(-0.83)
TURN	.	-0.51	-0.50	.	-0.82	-0.82	.	-0.19	-0.19
	.	(-3.03)	(-3.00)	.	(-2.92)	(-2.91)	.	(-1.09)	(-1.05)
HS	.	0.04	0.04	.	-0.05	-0.06	.	0.14	0.13
	.	(0.69)	(0.62)	.	(-0.58)	(-0.60)	.	(1.86)	(1.80)
AD	.	-0.03	-0.04	.	0.03	0.03	.	-0.09	-0.11
	.	(-0.13)	(-0.17)	.	(0.09)	(0.10)	.	(-0.30)	(-0.36)
IO	·	0.16	0.21	·	0.72	0.78	·	-0.41	-0.36
	.	(0.27)	(0.37)	.	(0.72)	(0.79)	.	(-0.68)	(-0.61)

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