Informed trading in options market and stock return predictability

Abstract

Prior research has highlighted the importance of two distinct types of informed trading in options market: trading on price direction of underlying stocks and trading on their uncertainty. Surprisingly, however, there are no studies considering them in a unified framework. This paper attempts to fill the gap. We predict that when both the *directional* and *volatility information* can motivate options trading, the return predictability of options volume hinges on the shape of the volatility smirk. Consistent with the prediction, we find that the negative relationship between options volume and future stock returns is concentrated in stocks exhibiting steep volatility smirks.

Keywords: Options, Trading volume, Volatility smirk, Information

JEL classification: G11, G12, G13, G14

1. Introduction

Extant literature in Finance has highlighted the role of options markets as a venue for information-based trading. Options markets attract informed traders by mitigating short-sale constraints in stock market and providing a higher leverage (Black (1975); Diamond and Verrecchia (1987)). Moreover, options markets are uniquely suited to investors with information about future volatility (Back (1993); Ni, Pan, and Poteshman (2008)). Consequently, options markets contain valuable information about the underlying security.[1] Although two distinct types of information, particularly information about future stock prices (hereafter *directional information*) and information about future stock volatility (hereafter *volatility information*), are often considered for the reasons why investors choose to trade options, previous studies have accorded them separate treatment.

This paper fills the gap by theoretically and empirically investigating the differing effects of directional and volatility informed trading in a unified framework. We theoretically show that the relation between options trade and future stock price varies with the shape of the volatility smirk, depending on which of the directional or volatility information prevails as a motive for options trading. Following Roll, Schwartz, and Subrahmanyam (2010), we use the ratio of total options volume to the underlying stock volume (O/S) to measure informed trades in options markets. Consistent with the theoretical prediction, we find significant differences in the return predictive power of O/S across stocks exhibiting different shapes of the volatility smirk. At the end of each week, we sort firms based on O/S and the steepness of the smirks. Then we consider a strategy of buying stocks with low O/S and shorting stocks with high O/S. For stocks exhibiting steep smirks, the strategy provides an average risk-adjusted hedge return of 0.40% in the week following the formation date (23.1% annualized). For stocks exhibiting less pronounced smirks, the strategy's profits are indistinguishable from zero.

[1] Many studies on the options-stock market linkage have examined numerous variables regarding options price and volume. Options price-related variables include implied stock prices (Chakravarty, Gulen, and Mayhew, 2004; Manaster and Rendleman, 1982); differences in implied volatilities between call and put options (Bali and Hovakimian, 2009; Cremers and Weinbaum, 2010); slope of implied volatility smirk (Xing, Zhang, and Zhao, 2010); change in options implied volatilities (An, Ang, Bali, and Cakici, 2014), to name a few. Options volume-related variables include the residual call options volume (Anthony, 1988); signed options volume (Easley, O'Hara, and Srinivas, 1998); call volume imbalance (Cao, Chen, and Griffin, 2005); put to call volume ratio (Pan and Poteshman, 2006); and options to stock volume ratio (Johnson and So, 2012).

We argue that the cross-sectional variation of the O/S-return relation with the shape of the volatility smirk is driven by the difference in the relative significance of directional versus volatility informed trading in options markets. For example, investors with negative information about stock prices cause net buying pressure for out-of-the-money (OTM) puts but net selling pressure for at-the-money (ATM) calls, leading to the higher implied volatility for OTM puts than that of ATM calls.[2] In addition, as the negative news motivating options trades is impounded into the stock price, low stock returns will be followed. However, investors with positive information about stock volatility cause net buying pressure for both OTM puts and ATM calls, leading to relatively flat implied volatility curve. In addition, volatility informed trades in options markets do not predict future stock price to the extent that volatility information is not correlated with directional information. This example shows that directional informed trades in options generate steep volatility smirks and portend future stock returns, while volatility informed trades neither generate volatility smirks nor predict stock returns.

We formally explore the differing implications of directional and volatility informed trading using a model that allows for the asymmetric information on both stock prices and volatility among investors who can trade in the options and stock markets. Easley, O'Hara, and Srinivas (1998) construct a multimarket model wherein directional informed traders choose to transact in the options and/or stock markets. We extend this model to accommodate volatility informed traders in addition to directional informed traders. Our extended model provides a framework for examining how the options market statistics and their information contents vary with which of the directional or volatility information prevails as a motive for options trading. Using this model, we illustrate that the difference in the relative concentration of directional versus volatility informed traders gives rise to the variation in the shapes of the volatility smirk and the degree to which options trades predict the stock returns.

Our article is closely related to Johnson and So (2012), who present evidence that stocks with high O/S have low subsequent returns. A short sale restriction in the stock market makes it costly to trade stocks on bad news, causing traders to use options more frequently for bad news than for good

[2] Options' expensiveness, represented by the shape of options implied volatility curve, is often explained by demand imbalance across options (Bollen and Whaley (2004); Garleanu, Pedersen, and Poteshman (2009)).

news. Accordingly, Johnson and So (2012) argue that high O/S reflects the prevalence of traders with negative information about the equity value, thereby predicting low future equity value. Unlike Johnson and So (2012), we recognize volatility information as an important options trading motive in addition to negative directional information.[3] Since an agent with information about future volatility has no choice but to trade in options markets, the demand for volatility trading would increase the volume in options markets relative to the stock market. We show that for stocks whose options trading is mainly motivated by directional information, high O/S is a strong negative predictor for future prices, as in Johnson and So (2012). However, for stocks whose options trading is mainly motivated by volatility information, high O/S is no longer a predictor for future prices. Our analysis highlights the importance of distinguishing between two distinct options trading motives in understanding the O/S-return relation and demonstrates the more general nature of this relation.

The rest of the paper is organized as follows. Section 2 provides our extension of the Easley, O'Hara, and Srinivas (1998) model and shows that the relative significance of directional versus volatility informed trading in options market causes the return predictability of options volume to vary with the shape of the volatility smirk. Section 3 describes the data and Section 4 presents the empirical results that options volume interacts with the volatility smirk in predicting the cross-section of stock returns. Section 5 concludes.

2. The model

Easley, O'Hara, and Srinivas (1998) developed a model of multimarket trading, in which traders choose to transact in the options and/or stock markets when they are informed about future stock price. In this section, we extend the multimarket model to include information asymmetry on future stock volatility and the short-sale cost of stock.

[3] The volatility information trading in options markets has been well documented in the volatility forecasting literature (see, e.g., Blair, Poon, and Taylor, 2001; Busch, Christensen, and Nielsen, 2011; Christensen and Prabhala, 1998; Jiang and Tian, 2005; Taylor, Yadav, and Zhang, 2010).

A key feature of our model is that the two types of informed traders - directional and volatility informed traders - differ in their choice of where and what to trade. First, regarding where to trade, the volatility informed have no choice but to trade in the options market. The directional informed, who are susceptible to short-sale costs in the stock market, can choose to trade in options more frequently for bad news than for good news. Second, regarding what to trade, the volatility informed trade call and put options in the same direction, thereby exerting net buying pressure of the same sign on call and put options. The directional informed, on the other hand, trade calls and puts in the opposite direction, thus exerting net demand pressure of the opposite sign on calls and puts. The different behaviors of the two types of traders result in differing predictions about both relative options trading volume and the price structure of options.

There are three tradable assets in the model: a stock, a call option with exercise price K_c, and a put option with exercise price K_p. We focus on European options with a single expiration date *J*. The underlying stock liquidates for $\tilde{S}$ at some future time *T*, before the options expire at time J. The value of $\tilde{S}$ is unknown prior to time *T*, but it is common knowledge that $\tilde{S} \in \{S_L, S_H\}$, with $S_H > S_L$. The volatility of the stock returns for the remaining life of the options has a value at time *T* given by the random variable $\tilde{\sigma}$, where $\tilde{\sigma} \in \{\sigma_L, \sigma_H\}$, with $\sigma_H > \sigma_L$. The call and put options values at time *T*, denoted by $\tilde{C}$ and $\tilde{P}$ respectively, are given by functions of the stock price $\tilde{S}$ and the volatility $\tilde{\sigma}$ at time *T*: $\tilde{C} = C(\tilde{S}, \tilde{\sigma})$ and $\tilde{P} = P(\tilde{S}, \tilde{\sigma})$.

We define two types of information events: a signal Ψ_S about the future stock price and a signal Ψ_σ about the future stock volatility. We assume that information events occur before the start of trade and the values of the two signals are independently determined. Both types of signals, Ψ_S and Ψ_σ, are equally likely to take on one of two values, L and H. The stock liquidates for S_L if $\Psi_S = L$ or S_H if $\Psi_S = H$. Similarly, the value of the future volatility is σ_L if $\Psi_\sigma = L$ or σ_H if $\Psi_\sigma = H$. This probabilistic structure of information is common knowledge, but only some traders know of the value of the signal. The fraction α of the universe of traders is informed and fraction $1 - \alpha$ is uninformed. Informed traders are assumed to observe only one type of signal. Of the informed traders, the fraction

$1 - \delta$ know the value of Ψ_S, but not Ψ_σ. The remaining fraction δ know the value of Ψ_σ, but not Ψ_S. Here, we refer to the former as "directional informed traders" and the latter as "volatility informed traders."

Figure 1 illustrates the three time points in the model. At the initial time point 0, trades in the stock and options markets occur. As in Easley, O'Hara, and Srinivas (1998), a trade is assumed to occur at a fixed size such that a trade consists of a single round lot of γ shares of stock or a single options contract controlling θ shares of stock. Also, traders can execute only one trade at a time (i.e., they cannot execute multiple trades simultaneously). In addition, traders must pay a lending fee to a third party when shorting the stock, as assumed in Johnson and So (2012). For simplicity, we assume that the short-sale cost reduces a short-seller's net payoff by $\rho > 0$. At some time T before the options mature, the reality is known and the information asymmetry is resolved. There are four possible states: $\{S_H, \sigma_H\}$, $\{S_H, \sigma_L\}$, $\{S_L, \sigma_H\}$, and $\{S_L, \sigma_L\}$.

[Figure 1 about here]

There are four types of market participants: market makers, directional informed traders, volatility informed traders, and uninformed traders. Market makers in each market are competitive, setting the bid and ask prices so that conditional on an order their expected profit is zero. We denote by b_s and a_s the bid and ask prices for the stock; b_c and a_c the bid and ask prices for the call option; and b_p and a_p the bid and ask prices for the put option. Market makers cannot distinguish whether a specific buy or sell order is from an informed trader or an uninformed trader.

Informed traders choose the trade that results in the highest expected profit given their information. Unlike directional informed traders, who can trade in either the stock or options markets, volatility informed traders can use only options contracts to take advantage of their information. Specifically, a directional informed trader who knows that $\tilde{S} = S_H$ could buy the stock, buy the call, or sell the put. Then the expected profit is:

$$\pi_H^d = \begin{cases} \gamma(-a_s + S_H) & \text{if buy the stock,} \\ \theta\left(-a_c + E\left[\tilde{C}\middle|\tilde{S} = S_H\right]\right) & \text{if buy the call,} \\ \theta\left(b_p - E[\tilde{P}|\tilde{S} = S_H\ ]\right) & \text{if sell the put.} \end{cases} \tag{1}$$

A directional informed trader who knows that $\tilde{S} = S_L$ could sell the stock, sell the call, or buy the put. The expected profit is:

$$\pi_L^d = \begin{cases} \gamma(b_s - S_L)(1-\rho) & \text{if sell the stock,} \\ \theta\left(b_c - E\left[\tilde{C}\middle|\tilde{S} = S_L\ \right]\right) & \text{if sell the call,} \\ \theta\left(-a_p + E[\tilde{P}|\tilde{S} = S_L]\right) & \text{if buy the put.} \end{cases} \tag{2}$$

A volatility informed trader who knows that $\tilde{\sigma} = \sigma_H$ could buy the call or the put. Then the expected profit is:

$$\pi_H^v = \begin{cases} \theta\left(-a_c + E\left[\tilde{C}\middle|\tilde{\sigma} = \sigma_H\right]\right) & \text{if buy the call,} \\ \theta\left(-a_p + E[\tilde{P}|\tilde{\sigma} = \sigma_H]\right) & \text{if buy the put.} \end{cases} \tag{3}$$

A volatility informed trader who knows that $\tilde{\sigma} = \sigma_L$ could sell the call or the put. Then the expected profit is:

$$\pi_L^v = \begin{cases} \theta\left(b_c - E\left[\tilde{C}\middle|\tilde{\sigma} = \sigma_L\ \right]\right) & \text{if sell the call,} \\ \theta\left(b_p - E[\tilde{P}|\tilde{\sigma} = \sigma_L\ ]\right) & \text{if sell the put.} \end{cases} \tag{4}$$

Figure 2 summarizes the structure of information and the decisions of informed traders. We denote by η_{dS} the fraction of directional informed traders who choose to trade in the stock market, and by η_{dC} the fraction of directional informed traders who choose to trade call options. The subscript *d* indicates the value of the signal Ψ_S that traders receive and takes on one of two values, *H* and *L*. The fraction of volatility informed traders who choose to trade call options are denoted by ζ_v, where *v* indicates the value of the signal Ψ_σ that traders receive and takes on one of two values, *H* and *L*. The exact values of $\{\eta_{HS}, \eta_{HC}, \eta_{LS}, \eta_{LC}, \zeta_H, \zeta_L\}$ are determined in the equilibrium.

Uninformed traders do not select a trade to maximize their profit, but are instead exogenously allocated to specific trades. As is standard in microstructure models, the uninformed are liquidity providers (or noise traders) who trade for reasons not included in the model, for example, the need to hedge, or a false conviction that they can beat the market. We assume that the fraction of uninformed traders who buy stock, sell stock, buy calls, sell calls, buy puts, and sell puts are q_1, q_2, q_3, q_4, q_5, and q_6, respectively, where $\sum_{i=1}^{6} q_i = 1$.

[Figure 2 about here]

2.1. Equilibrium

Given our setting, two conditions must be met for the stock and option markets to constitute equilibrium. First, because market makers in each are competitive and risk-neutral, a zero profit condition applies, such that the bid and ask prices the market makers set equal the expected values of the securities given their beliefs about the decisions of informed traders. Second, informed traders' decisions on where and what to trade are optimal and as conjectured by the market makers.

Like Easley, O'Hara, and Srinivas (1998), two types of equilibria can occur: a separating equilibrium and a pooling equilibrium. A separating equilibrium occurs when a certain type of informed traders transact in only one market, separated from other types of traders. For example, if the leverage effect of options is not large enough, all directional informed traders will choose to trade only in the stock market. On the other hand, a pooling equilibrium occurs when one type of informed trader is willing to transact in several different venues, together with other types of traders. Which type of equilibria will occur depends on parameters such as the liquidity of the market and options leverage, discussed in Appendix A. We focus on pooling equilibria throughout.

The bid and ask prices for each asset $\{a_s, b_s, a_c, b_c, a_p, b_p\}$ and the fraction of informed traders in each market $\{\eta_{HS}, \eta_{HC}, \eta_{LS}, \eta_{LC}, \zeta_H, \zeta_L\}$ are the 12 equilibrium parameters. They are determined to satisfy 12 equations, which ensure that the market maker's expected profit is zero for each trade and that informed traders are indifferent between possible trades at equilibrium. These equations are presented in Appendix B.

2.2. How do the information content of options trading volume and the volatility smirk vary with the concentration of directional versus volatility informed traders?

We are interested in how different types of informed traders affect the information content of trading volumes and the price structure of options. Examining the two extreme cases provides insight into the differing impacts of directional versus volatility informed traders. In the first case, all informed traders are assumed to be directional informed ($\delta = 0$). This case corresponds to the Johnson and So (2012) model illustrating the effect of a short-sale cost on directional informed traders' choices. We assume throughout the existence of a short-sale cost as in Johnson and So (2012). In the second case, all informed traders are assumed to be volatility informed ($\delta = 1$). The following propositions describe the mean equity values conditional on a trader's choice of trading venue and the options prices in equilibrium for the two cases. The proofs are provided in Appendix C.

PROPOSITION 1: *When all informed traders are directional informed ($\delta = 0$), the mean stock value conditional on an options trade is less than that conditional on a stock trade ($E\left[\tilde{S}\middle|option\ trade\right] < E\left[\tilde{S}\middle|stock\ trade\right]$). In addition, the difference in prices between an OTM put and an ATM call is larger than the difference in the unconditional expected values between them.*

PROPOSITION 2: *When all informed traders are volatility informed ($\delta = 1$), the mean stock value conditional on an options trade is the same as that conditional on a stock trade ($E\left[\tilde{S}\middle|option\ trade\right] = E\left[\tilde{S}\middle|stock\ trade\right]$). In addition, the difference in prices between an OTM put and an ATM call equals the difference in the unconditional expected values between them.*

To translate the propositions into empirical predictions, we follow Johnson and So (2012) and use relative trading volumes in the stock and options markets as an empirical construct for traders' choices between the two markets. Moreover, the price difference between an OTM put and an ATM call is represented by the slope of the implied volatility curve. This leads to the following empirical predictions.

EMPIRICAL PREDICTIONS: *When directional informed traders dominate the options market, a high ratio of options volume to stock volume predicts low future stock prices and the options volatility curve has a steeper slope. On the other hand, when volatility informed traders dominate the options market, the options-to-stock-volume ratio is not related to future stock prices and the options volatility curve is flat.*

Taken together, our model suggests that the return predictability of the relative options volume and the shape of volatility smirks vary with the relative concentrations of directional versus volatility informed traders in the markets. Thus, the shape of the volatility smirk identifies when the relative options volume has information about future stock returns. In particular, a high options-to-stock-volume ratio predicts negative future stock returns when the volatility smirk is steep, but not when the volatility smirk is flat.

3. Data

Our sample period is from January 1996 to December 2012. The options data are from the Ivy OptionMetrics database, which provides end-of-day bid and ask quotes, open interests, and volumes on all exchange-listed options on U.S. equities. It also computes their implied volatilities and greeks using Cox, Ross, and Rubinstein's (1979) binomial tree model. We obtain return data for the stocks that underlie the options from the Center for Research in Security Prices (CRSP). General accounting data and earnings forecast data come from Compustat and the Institutional Brokers' Estimate System (IBES), respectively.

We apply a series of data filters to minimize the impact of recoding errors and illiquidity. First, following Xing, Zhang, and Zhao (2010), options with implied volatilities less than 3% and more than 200% are discarded. Second, we eliminate all observations for which the underlying stock has zero trading volume or is priced less than a dollar. Third, we require options contracts to have positive open interest, non-missing volume data, and a price (i.e., the midpoint of bid and ask quotes) of at least $0.125. In addition, we also exclude options with less than 5 trading days and more than 60 trading days to expiration.[4] Finally, since some of our analyses involve measuring a historical average of relative options volume, we require each observation in the sample to have a history of six months of weekly options and stock volumes.

We begin by measuring two different aspects of options markets: traders' preference for options markets over the underlying stock market as a trading venue and the structure of options prices. As an empirical construct for the relative merit of trading in the options market, we employ two alternative measures. The first is the ratio of options trading volume to underlying stock volume, $\mathrm{O/S}$, which 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:

$$O/S_{i,w} = \frac{OPVOL_{i,w}}{STVOL_{i,w}}, \tag{5}$$

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 round lots of 100.[5] The second measure is the deviation of O/S from its historical average, $\Delta\mathrm{O/S}$, calculated as follows:

$$\Delta O/S_{i,w} = O/S_{i,w} - \overline{O/S_{i}}, \tag{6}$$

[4] Following the literature, we exclude options with about a week or less to expiration. Options with less than 60 days to expiration are often grouped in the short-term options category and investigated in aggregate (see, e.g., Bakshi, Kapadia, and Madan, 2003; Xing, Zhang, and Zhao, 2010). Our reported results are based on options with short-term maturities. The results are qualitatively unchanged if we include options with longer maturities.

[5] This accounts for the fact that each options contract is for 100 shares of the underlying stock.

where $\overline{O/S_i}$ is the average $O/S_{i,w}$ for stock i over the past six-month (4 to 28 week) period. This second measure controls for time-invariant differences between firms with high and low O/S that are unrelated to informed trading.

The structure of options prices is often represented by the slope of the implied volatility curve (Rubinstein, 1994). To estimate the slope of the implied volatility curve, we follow Xing, Zhang, and Zhao (2010). We therefore compute $SKEW_{i,w}$ as the difference between the implied volatilities of an OTM put and an ATM call, denoted by $IV_{i,w}^{OTMP}$ and $IV_{i,w}^{ATMC}$, respectively:

$$SKEW_{i,w} = IV_{i,w}^{OTMP} - IV_{i,w}^{ATMC}. \tag{7}$$

A put option is defined as OTM when the moneyness (defined as the strike price divided by the closing underlying stock price) is lower than 0.95, and a call option is defined as ATM when the moneyness is between 0.95 and 1.05. For each stock and day we select an OTM put and an ATM call whose moneyness is closest to one to determine a single SKEW observation for each stock per day. We compute the weekly SKEW by taking the week's average daily SKEW.

The full sample for this study consists of the intersection of all US firms with non-missing O/S, ΔO/S, and SKEW measures and available stock return observations. We restrict the sample to firm-weeks with a minimum of 25 call and 25 put options contracts to address problems with illiquid options markets. The total number of firm-weeks is 672,209, corresponding to 826 weeks and approximately 1,652 unique firms per year. There are 9,669 firm-weeks in 1996, when the sample begins, and 44,681 in 2012, when the sample ends.[6] The maximum number of firm-weeks, 51,954, is recorded in 2008.

Panel A of Table 1 presents the descriptive statistics of $O/S_{i,w}$ and $SKEW_{i,w}$ for each year of the sample. We first compute the mean and quartiles of these options variables over the cross section for each week and then report the time series averages of the summary statistics. The sample mean of O/S is 6.93%, which indicates that stock trading volumes in round lots are roughly 14 times higher than

[6] The requirement for six months of prior options trading volumes for each observation results in far fewer firm-week observations in 1996.

options volumes. The mean O/S is greater than the median O/S throughout the sample period, indicating a high concentration of relative options volume among a small subset of firms. The sample mean of SKEW is 6.25%, indicating that the implied volatilities of OTM puts are on average higher than those of ATM calls by roughly 6%. Also, the mean SKEW is slightly greater than the median SKEW during our sample period.

[Table 1 about here]

The last column of Panel A of Table 1 shows the time series average of the weekly cross-sectional correlations between O/S and SKEW. The correlation is not strong throughout the sample period, with the mean of 1.86%. The low correlation between O/S and SKEW implies that they hold somewhat independent information. This broadly supports the view that a high options-to-stock-volume ratio signifies more than a high concentration of negatively informed directional traders in options markets, which presumably results in steep volatility skew.

Panel B of Table 1 reports the summary statistics of other firm characteristics. Firms in our sample are large and have low book-to-market ratios relative to an average firm in the CRSP. The average market capitalization (SIZE) of our sample firms is $11.92 billion, which is far larger than the average firm size of $2.05 billion for all CRSP firms. The average book-to-market (BM) ratio of our sample firms is 0.46, which is lower than 0.72 in the CRSP universe. This is not surprising given that firms with traded options tend to be large relative to firms without traded options (Mayhew and Mihov, 2004). In addition, our initial data requirement of non-missing SKEW measures and the weekly trading volume of 25 calls and 25 puts further skews our sample toward large firms. Our sample firms also tend to have performed well in the past: the average cumulative stock return over the past six months (MOMENT) is 13.36% for our sample, whereas it is 5.65% for the average CRSP firm. The Amihud (2002) illiquidity measure (AMIHUD) is computed as the daily ratio of absolute return to the dollar volume of the stock, averaged over the previous month. The average value of AMIHUD (multiplied by 10^7) is 0.022 for our sample, far less than the 16.63 for all CRSP firms, implying that our sample firms are much more liquid. Correspondingly, our sample firms also tend to be less volatile. Historical volatility of stock returns (HVOL) is measured over the previous month using daily stock returns. The average value of HVOL is 56% for our sample, and 65% for all CRSP firms.

Each week, we rank all eligible stocks independently on the basis of SKEW and O/S. We break the stocks into three SKEW groups based on the breakpoints for the bottom 30% (flat), middle 40%, and top 30% (steep) of the ranked values of SKEW. The stocks are also assigned to one of 10 portfolios based on O/S. The intersections resulting from the two independent rankings give rise to 30 SKEW- and O/S-sorted portfolios. We have an average of 814 firms per week, leaving an average of roughly 30 firms in each of the SKEW and O/S portfolios.

Panel B of Table 1 also reports the average firm characteristics for these SKEW and O/S portfolios, as well as for the full sample. Rows correspond to the SKEW portfolios, with S3 representing the portfolio of stocks with the steepest implied volatility smirk. The stock with the flattest smirk (S1) has an average slope of 1.06%, the stock with a medium smirk (S2) has an average slope of 5.22%, and the stock with the steepest smirk (S3) has an average slope of 12.82%. Columns correspond to the O/S deciles, with V10 representing the highest O/S portfolio. O/S increases exponentially from 0.57% to 27.58% as one proceeds from V1 to V10. We report descriptive characteristics only for two extreme and two intermediate O/S portfolios for simplicity of presentation. Looking across each row, we see that high and low O/S portfolios do not differ significantly in terms of their SKEW values. Looking down each column, we see that O/S values are of similar magnitudes. This is consistent with the low correlation between SKEW and O/S shown in Panel A.

While O/S shows little variation across SKEW portfolios, levels of both options and equity volumes decrease monotonically as one proceeds from the flattest-smirked stocks (S1) to the steepest-smirked stocks (S3). For instance, the average options trading volume for S1 stocks is 13,619 contracts per week, and that of S3 stocks is 7,195. The declining pattern is also shown in the number of call and put contracts traded weekly, denoted by VLC and VLP, respectively. Equity volume in round lots, denoted by STVOL, decreases from 144,588 in S1 to 100,723 in S3.

Extreme SKEW firms tend to be smaller compared to the medium-smirked portfolio. The average market capitalization of the stocks first increases from $11.99 billion in S1 to $15.57 billion in S2, and subsequently decreases to $6.97 billion in S3. For book-to-market ratios, the steepest-smirked portfolio tends to have somewhat larger values, but the difference from the medium-smirked portfolio is small. Past stock market performance tends to be lower for firms with steeper volatility smirks: the average values of MOMENT decrease monotonically from 14.49% in S1 to 11.26% in S3.

Extreme SKEW firms tend to be less liquid and more volatile than the medium SKEW firms. The Amihud (2002) illiquidity measure (multiplied by 10^7) is 0.021 and 0.032 for the S1 and S3 stocks, respectively, while it is 0.014 for the S2 stocks. The historical volatility of stock returns is 55.23% and 61.77% for the S1and S3 stocks, respectively, with the latter showing a larger discrepancy from the 52.55% value for the S2 stocks.

Unlike asymmetric patterns across the SKEW portfolios, firm characteristics exhibit monotonic variation across O/S deciles. As reported by Johnson and So (2012), high O/S firms tend to be larger and have lower book-to-market ratios and higher return momentum. In addition, their stock markets tend to be more volatile, evident from the HVOL values. In the analysis, we take these heterogeneities of firm characteristics across various SKEW and O/S portfolios into account.

4. Empirical Results

Our primary goal is to examine how the return predictability of relative option volume varies with the shape of the volatility smirk. The analysis is based on portfolio sorts and cross-sectional regressions. In Subsection 4.1, we examine returns for portfolios sorted on the relative options volume and the slope of the volatility smirk. In Subsection 4.2, we use Fama and MacBeth (1973) regressions to investigate the interaction between options volume and volatility smirk in predicting equity returns. In Subsection 4.3, we examine the effect of volatility smirks on the persistence of the return predictability by options volume. In Subsection 4.4, we provide the results of the robustness check. Finally, in Subsection 4.5, we analyze the interaction between the options volume and volatility smirks prior to earnings announcements.

4.1. Portfolio approach

In this subsection, we examine returns to portfolios formed based on a two-way sort: one based on the volatility smirks (SKEW) and the second based on the relative options volume (i.e., O/S or ΔO/S). In particular, every five trading days, we form 3 × 10 independently sorted SKEW and O/S (ΔO/S) portfolios. We skip one trading day between the portfolio formation and holding periods to avoid problems caused by nonsynchronous closing times of the stock and options markets.[7] We hold the portfolios for five consecutive trading days.[8] Each portfolio return is calculated as the equally-weighted average return of its constituent stocks.

To adjust for systematic risk, we calculate the portfolios' abnormal returns using the capital asset pricing model (CAPM), Fama and French's (1993) three-factor model, and Carhart's (1997) four-factor model. The abnormal return is the constant α in three variants of the following factor model regression:

$$R_w^p = \alpha + \beta' F_w + \epsilon_w, \tag{8}$$

where R_w^p is an excess return over the risk-free rate to a portfolio for week w and F_w is a vector of the weekly risk factors.[9] The risk factors include excess market returns, a book-to-market factor (HML_w), a size factor (SMB_w), or a momentum factor (UMD_w), depending on the factor model of interest.

Panel A of Table 2 presents the excess returns and estimated results of the factor models for various SKEW and O/S portfolios, as well as for long-short portfolios. We first examine the variation

[7] The equity options market closes at 4:02 PM EST while the underlying equity market closes at 4 PM EST. As pointed out by Battalio and Schultz (2006), such nonsynchronicity can result in options prices which contain information not yet reflected in the underlying equity prices.
[8] As in Johnson and So (2012), when there are no trading holidays, we measure the options statistics (O/S and SKEW) over the period from Monday through Friday of a given calendar week, skip the Friday close-to-Monday close return, and compute a weekly return from the close of markets on Monday to the close of markets on the following Monday (the Monday close-to-Monday close return).
[9] We compute weekly risk factors consistent with our return measurement interval, following the method described on Kenneth French's Web site.

of returns across O/S deciles for all firms in the sample. Looking across the rows labeled "All" in Subpanel A.1, we observe that portfolio returns decrease with O/S. In the four-factor regression, for example, we find that firms in the lowest O/S decile earn, on average, a 2.9 basis points (bps) alpha while firms in the highest O/S decile earn a -12.0 bps alpha. The strategy of buying stocks in the lowest O/S decile and shorting stocks in the highest O/S decile, V1-V10, yields a four-factor alpha of 14.9 (t-statistic = 2.90) bps per week (8% annualized). The result is similar in magnitude and statistical significance for the CAPM and three-factor models. These results confirm the negative cross-sectional relation between O/S and future returns documented by Johnson and So (2012).[10]

[Table 2 about here]

Because we are interested in the varying return predictability of O/S across stocks with different volatility smirk shapes, we next examine the O/S long-short strategy (V1-V10) implemented within flattest-smirked (S1), medium-smirked (S2), and steepest-smirked (S3) stocks. The results show that the impact of the options volatility smirk is striking. Only among the steepest-smirked (S3) stocks do returns to portfolios decrease monotonically with O/S. The O/S long-short strategy is not profitable among the flattest- and medium-smirked stocks, but highly profitable among the steepest-smirked stocks. For instance, the four-factor alphas of the O/S long-short strategy are 10.8 (t-statistic = 1.37), 0.2 (t-statistic = 0.03), and 39.7 (t-statistic = 4.90) bps per week in the flattest-, medium-, and steepest-smirked stocks, respectively. Adjusting for risk using other factor models again makes little difference in the results, as is evident from the CAPM and three-factor alphas.

In Table 2, we also ensure that our results are consistent with Xing, Zhang, and Zhao's (2010) findings that stocks with the steepest volatility smirks in their traded options underperform stocks with

[10] The magnitude of the returns of the O/S portfolio strategy in our sample is lower than that reported in Johnson and So (2012). This difference is due to the difference in the samples. First and foremost, unlike Johnson and So (2012), we require that each observation has non-missing SKEW measures. This restriction reduces the sample size by 20% and the profitability of the O/S portfolio strategy. When we perform the analysis without the restriction of the available SKEW variable, for example, the four-factor alpha of the O/S decile-based strategy is 23.1 (t-statistic = 4.59) bps per week. Another, but minor, difference is that the options variables in our sample are computed from options expiring within 60 trading days, while Johnson and So (2012) use options expiring within 35 trading days.

flatter smirks. Looking down the columns labeled "All" in Subpanel A.1, we observe that returns to portfolios decrease with SKEW. For instance, in the four-factor regression, we find that the portfolio of stocks in the flattest-smirked group have a 4 bps alpha in the following week while the portfolio of stocks in the steepest-smirked group have a -14.5 bps alpha. The strategy of a long position in stocks with low SKEW and a short position in stocks with high SKEW, S1-S3, yields a four-factor alpha of 18.5 (t-statistic = 5.03) bps per week (10% annualized).

In addition, we observe that the profitability of the SKEW long-short strategy (S1-S3) is in general most pronounced among the highest O/S firms. This indicates that the predictive power of the options volatility skew is strongest for firms whose options markets attract more trading volume relative to stock markets, consistent with the notion that informed traders are more active in high volume markets (Admati and Pfleiderer, 1988; Kyle, 1985).

Subpanel A.2 of Table 2 presents the factor loadings (the estimates of β in Eq. (8)) in the four-factor model.[11] We observe that the loading on the market factor increases with O/S, indicating that high O/S firms have more market exposure. High O/S firms also tend to have a large negative loading on the HML factor and a high loading on the UMD factor compared to low O/S firms. This is consistent with the firm characteristics shown in Panel B of Table 1: high O/S firms tend to be winners with low book-to-market ratios. On the other hand, compared to low SKEW firms, high SKEW firms tend to have high loadings on the SMB and HML factors and a large negative loading on the UMD factor, confirming that high SKEW firms are relatively small and losing.

Next, we turn to the results for portfolios based on SKEW and $\Delta O/S$. By replacing O/S with $\Delta O/S$, we mitigate the concern that static firm characteristics which are systematically related to O/S but not captured by the four-factor risk adjustment might generate the abnormal returns. Panel B of Table 2 shows that the $\Delta O/S$-based portfolio strategy is also profitable. As shown in the rows labeled "All" in Subpanel B.1, returns to portfolios decrease with $\Delta O/S$. The strategy of buying stocks in the lowest $\Delta O/S$ decile and shorting stocks in the highest $\Delta O/S$ decile, V1-V10, yields a four-factor alpha

[11] To save space, the factor loadings in the CAPM and three-factor models are not reported.

of 15.0 (t-statistic = 3.00) bps per week (8% annualized), suggesting that compensation for a static form of risk is not driving the returns on the O/S-based portfolios shown in Panel A.

Remarkably, the $\Delta O/S$ long-short strategy earns a positive abnormal return only among the steepest-smirked (S3) stocks. For instance, the four-factor alphas of the $\Delta O/S$ long-short strategy are 10.1 (t-statistic = 1.25), 3.8 (t-statistic = 0.56), and 31.2 (t-statistic = 3.54) bps per week in flattest-, medium-, and steepest-smirked stocks, respectively. Overall, the alphas from the ΔO/S long-short strategies implemented for S3 stocks are lower relative to the O/S long-short strategy but remain economically and statistically significant for all factor models. As expected, the factor loadings of the ΔO/S long-short strategy decrease in magnitude compared with those of the O/S long-short strategy.

Collectively, the results from the double-sorted portfolios based on options volume and volatility smirk pinpoint the segment of stocks driving the return predictability of relative options volumes. Specifically, the portfolio strategies based on the relative options volume are profitable for stocks with the steepest volatility smirks, but not for stocks with less pronounced volatility smirks. These are consistent with our proposition that the options volume provides information about directional price changes only when directional informed traders initiate more trades in options markets as opposed to volatility informed traders, which might be captured by the steep volatility smirk.

4.2. Fama-MacBeth regressions

In this subsection, we use cross-sectional regression analysis to scrutinize how options volumes interact with volatility smirks in predicting future stock returns. Based on the theoretical background, we propose that high options volumes driven by directional informed traders accompanies steep volatility smirks, while volumes driven by volatility informed traders coincides with flat smirks. If so, the degree of the return predictability of the options volumes should increase as the options volumes accompany a steeper volatility smirk.

Table 3 reports Fama-MacBeth coefficient estimates and t-statistics from the regressions of the firm's equity returns on the options market statistics of interest and other control variables.[12] In particular, each week we run the variants of the following cross-sectional regressions:

$$RET_{i,w} = a_w + b_w SKEW_{i,w-1} + c_w Z_{i,w-1} + d_w\left(Z_{i,w-1} \times SKEW_{i,w-1}\right) + e'_w \Theta_{i,w-1} + \epsilon_{i,w}, \tag{9}$$

where $RET_{i,w}$ is the return on stock *i* for week w, $SKEW_{i,w-1}$ the volatility skew measure observed for options on stock *i* at week $w-1$, $Z_{i,w-1}$ the relative options volume measure of interest, and $\Theta_{i,w-1}$ a vector of control variables. We use O/S as the relative options volume measure in Panel A and $\Delta O/S$ in Panel B. The control variables are chosen based on Johnson and So's (2012) analysis. As before, we skip one trading day between observing options variables and stock return measurements.

[Table 3 about here]

We first examine the return predictability of the volatility skew and relative options volumes separately. Column 1 of Panel A provides the results of regressing the equity return on the volatility skew (and other control variables). The SKEW coefficients have a significantly negative value of -1.309, indicating that, ceteris paribus, firms in the top 30% skew group underperform firms in the bottom 30% skew group by a weekly average of 0.15% (1.309 × (12.82 - 1.06) / 100).[13] Regarding the O/S measure, we consider three raw and transformed variables in the regressions: the decile rank of O/S (in columns 2 through 4), O/S itself (in columns 5 through 7), and the logarithm of O/S (in columns 8 through 10).[14] In column 2, the coefficient on the deciles of O/S is -0.011, with a significant t-statistic of -1.99. This implies that firms in the highest O/S decile underperform firms in the lowest O/S decile by a weekly average of 0.10% (0.011 × 9). Consistently, the coefficients on O/S in column

[12] The coefficient estimates shown in the table are the time-series averages of weekly estimates. Standard errors are computed in the usual Fama-MacBeth fashion from the time-series standard deviation of coefficient estimates, adjusted for autocorrelation using Newey and West's (1987) method.

[13] The average values of SKEW measured in the top and bottom 30% SKEW groups are 12.82% and 1.06%, respectively, as shown in Panel B of Table 1.

[14] From Panel A of Table 1, the distribution of O/S is positively skewed. Using a logarithm is the natural way to address this.

5 and the logarithm of O/S in column 8 are significantly negative, corroborating the negative relation between the options-to-stock-volume ratio and future returns.[15] Overall, we find that the magnitudes of the return differences between the firms in the extreme groups of SKEW or O/S implied in the estimates are somewhat reduced compared to those in the portfolio approach. This may be because we control for numerous firm characteristics with the cross-sectional regression.

Next, we regress future returns on the volatility skew and relative options volume together. Comparing columns 2 and 3, columns 5 and 6, or columns 8 and 9, we find that including the volatility skew in the regression does not significantly affect the coefficient on the options volume measure, indicating that the predictive ability of relative options volumes is not subsumed by volatility skew.

The most important observation in Panel A of Table 3 is that the coefficients on the options volume variables become insignificant in the presence of the interaction term with SKEW, while the coefficients on the interaction term are significantly negative (shown in columns 4, 7, and 10). These results suggest that the negative relationship between O/S and future equity returns is pronounced only when the options market exhibits a steeper volatility skew. For instance, in column 4, the coefficient on the deciles of O/S is 0.003, with a t-statistic of 0.42, while the coefficient on the interaction term (Decile $(O/S) \times SKEW$) is -0.195, with a t-statistic of -3.26. These coefficients imply that for firms in the bottom 30% skew group, the difference in future returns between the highest and lowest O/S decile is 0.01% ((0.003 - 0.195 × 1.06 / 100) × 9) per week, while it is -0.20% ((0.003 - 0.195 × 12.82 / 100) × 9) per week for firms in the top 30% skew group.[16] We also find similar results from the regressions using O/S and the logarithm of O/S (reported in columns 7 and 10).[17]

[15] The average values of O/S in the highest and lowest O/S deciles are 27.58% and 0.57%, respectively, as shown in Panel B of Table 1. Thus, the coefficient on O/S in column 5, -0.393, indicates that the firms in the highest O/S decile underperform firms in the lowest O/S decile by a weekly average of 0.11% (0.393 × (27.58 - 0.57)/100). Additionally, the coefficient on the logarithm of O/S in column 8 is -0.031, indicating that the highest O/S decile firms underperform the lowest decile firms by a weekly average of 0.12% (0.031 × (ln(27.58) - ln(0.57))).

[16] The average values of SKEW measure in the bottom and top 30% SKEW groups are 1.06% and 12.82%, respectively, as shown in Panel B of Table 1.

[17] In column 7, the coefficients on O/S and its interaction term with SKEW are 0.021 (t-statistic = 0.08) and -4.875 (t-statistic = -2.15), respectively. These coefficients imply that the difference in future returns between the highest and lowest O/S decile firms is -0.01% ((0.021 - 4.875 × 1.06 / 100) × (27.58 - 0.57) / 100) per week for firms in the S1 group, while it is -0.16% ((0.021 - 4.875 × 12.82 / 100) × (27.58 - 0.57) / 100) per week for firms in the S3 group. In column 10, the coefficients on the logarithm of O/S and its interaction term with SKEW are 0.007 (t-statistic = 0.36) and -0.504 (t-statistic = -3.36), respectively. These coefficients imply that the difference in future returns between the highest and lowest O/S decile firms is 0.01% ((0.007 - 0.504 × 1.06 / 100) × (ln(27.58) - ln(0.57))) per week for firms in the S1 group, while it is -0.22% ((0.007 - 0.504 × 12.82 / 100) × (ln(27.58) - ln(0.57))) per week for firms in the S3 group.

In Panel B of Table 3, we repeat the regressions in Panel A but replace O/S with $\Delta O/S$ and consider two alternative $\Delta O/S$-based variables in the regressions: deciles of $\Delta O/S$ (in columns 2 through 4) and $\Delta O/S$ itself (in columns 5 through 7). As in Panel A, we find strong evidence that before introducing the interaction term with the volatility skew, the options volume variable (the deciles of $\Delta O/S$ or $\Delta O/S$ itself) has a negative and statistically significant coefficient. When including the interaction term, however, the coefficients on the options volume variables become insignificant. Most notably, the coefficients on the interaction term are negative and statistically significant, suggesting that abnormally high levels of O/S can predict negative future returns only for stocks with steep volatility smirks.

In Table 4, we use the alternative specifications to examine the differing levels of predictability by the relative options volume across stocks with the flat versus steep volatility smirks. We introduce dummy variables for the three SKEW groups:

$$RET_{i,w} = a_w + b_{1w}SKEW\ 1st\ Dum_{i,w-1} + b_{2w}SKEW\ 3rd\ Dum_{i,w-1} + c_w Z_{i,w-1} + d_{1w}\left(Z_{i,w-1} \times SKEW\ 1st\ Dum_{i,w-1}\right) + d_{2w}\left(Z_{i,w-1} \times SKEW\ 3rd\ Dum_{i,w-1}\right) + e'_w \Theta_{i,w-1} + \epsilon_{i,w}, \quad (10)$$

where $SKEW$ 1st $Dum_{i,w-1}$ ($SKEW$ 3rd $Dum_{i,w-1}$) is a dummy variable that takes the value of one if stock i's SKEW value belongs to the bottom (top) 30% of all ranked values of SKEW at week $w-1$ and zero otherwise.

[Table 4 about here]

Panels A and B of Table 4 present the results for O/S- and $\Delta O/S$-based variables as the options volume measure, respectively. Regardless of the choice of options volume variable, we find that the coefficients on both the options volume variable and its interaction term with *SKEW 1st Dum* are insignificant. By contrast, the coefficient on the interaction term with *SKEW 3rd Dum* is negative and highly significant. These results indicate that a high options-to-stock-volume ratio is predictive of negative future returns for stocks with the steepest volatility smirks, but not for the flattest- and medium-smirked stocks.

Overall, the regression-based evidence is consistent with our portfolio-based findings in the previous section. Across all specifications, we find that a high options-to-stock-volume ratio accompanied by steep volatility smirks is a significant negative predictor of future equity returns, while that accompanied by the flat volatility smirks has no predictive power for directional price changes.

4.3. How long does the predictability last?

The previous sections demonstrate that the return predictability of relative options volumes differs across stocks with different volatility smirks. In this subsection, we examine the persistence of the differing predictability using two approaches: first, we investigate long-term returns of the O/S ($\Delta O/S$)-based portfolio strategies by groups of stocks with different volatility smirks; second, we investigate whether relative options volumes interacting with volatility skew has predictive power for n-week-ahead stock returns using cross-sectional regressions.

Figure 3 shows for each SKEW group, S1 to S3, the four-factor alphas of the O/S long-short strategies over a twelve week period after portfolio formation. The top graph represents weekly alphas and their 95% confidence interval. The bottom graph presents the cumulative alphas. The top graph shows that for the steepest smirked (S3) stocks, the lower bound of the 95% confidence interval is above zero up to six weeks, indicating that the profitability of the O/S strategy persists for six weeks. By contrast, for stocks with less pronounced smirks (S1 and S2), the alphas are statistically indistinguishable from zero for the entire time horizon (except the second week, where alpha is significantly positive for S1 stocks). The bottom graph shows the striking differences in the persistence of return predictability among SKEW groups. Over the twelve weeks, the four-factor alphas of the O/S long-short strategy total more than 2% for the S3 stocks, while the cumulative 12-week alphas are less than 0.7% for the S1 and S2 stocks.

[Figure 3 about here]

Figure 4 repeats the analysis of Figure 3, but with the $\Delta O/S$ long-short strategies. Again, among the S1 and S2 stocks, the lower bound of the 95% confidence interval is below zero for all twelve weeks. Only among the S3 stocks is the lower bound of the 95% confidence interval above zero but only for one week ahead. The bottom graph shows that the cumulative 12-week alpha is less than 0.25% for the S1 and S2 stocks, but reaches 1% for the S3 stocks. The return predictability associated with $\Delta O/S$ is relatively week and short-lived compared to O/S.

[Figure 4 about here]

Table 5 reports Fama-MacBeth regression results where we repeat the analysis in Table 3 (column 4), but with one- to twelve-week-ahead returns as the dependent variable. We use deciles of O/S and $\Delta O/S$ as the relative options volume measure in Panels A and B, respectively. All control variables specified in Table 3 are included in the estimation, though not reported in the table. The main coefficients of interest in Panels A and B are those on deciles of relative options volume and its interaction term with volatility skew. We observe that the coefficients on the decile variable itself are insignificant across all horizons, but with significantly negative coefficients on the interaction term up to four weeks (one week) in Panel A (Panel B). The regression-based evidence is broadly consistent with the results shown in Figures 3 and 4. In particular, the return predictability of relative options volume, to a lesser or greater extent depending on which measure of O/S or $\Delta O/S$ in use, exists and persists only among the steep-smirked stocks.

[Table 5 about here]

4.4. Robustness

Table 6 presents several robustness checks on our results with the portfolio approach. In Subpanel A.1, we repeat the analysis in Panel A of Table 2 for two sub-periods: The first covers 1996 to 2003, and the second covers 2004 to 2012. Subpanel A.1 demonstrates the striking impact of volatility smirks on the return predictability of O/S. In the first sub-period, the overall profitability of the O/S long-short strategy disappears. Partitioning the firms on the basis of volatility smirks, however, shows that the O/S strategy delivers large profits among stocks exhibiting steep smirks. For example, the O/S strategy implemented for all firms generates an insignificant three-factor alpha of 10.7 (t-statistic = 1.17) bps per week between 1996 and 2003, but when implemented within the steepest smirked stocks (S3) it earns a significant alpha of 46.3 (t-statistic = 3.26) bps per week. Likewise, results in the second sub-period show that the O/S strategy is profitable only among the S3 stocks. Comparison across the two sub-samples suggests that the profitability of the O/S strategy among the S3 stocks decreases in the 2004-2012 period.

[Table 6 about here]

Our portfolio results so far are based on three skew portfolios and ten options volume portfolios (3 × 10). Subpanel A.2 of Table 6 shows that our results are not specific to this partitioning. In particular, we report results using five skew and five options volume portfolios (5 × 5). Generally, the difference in returns between the lowest and highest O/S quintile portfolios would be lower relative to the difference between extreme O/S decile portfolios. In fact, Subpanel A.2 shows that the three-factor alpha of the O/S quintile strategy is 9.8 bps per week, lower than the corresponding value of the O/S decile strategy (14.0 bps per week) shown in Table 2. Of particular interest is the variation in returns to O/S quintile strategies across SKEW quintiles. The rightmost column in Subpanel A.2 shows that the three-factor alpha of the O/S quintile strategy is significantly positive only for the steepest smirked stocks (S5).

We also provide robustness checks on results using $\Delta O/S$ in Panel B of Table 6. Subpanel B.1 shows that in both sub-samples 1996-2003 and 2004-2012, the $\Delta O/S$ decile strategy is only profitable among the steepest smirked stocks, with higher profitability in the earlier period. Using five-by-five double sorted portfolios on $\Delta O/S$ and SKEW, Subpanel B.2 again shows that the return predictability of $\Delta O/S$ exists only when accompanied by steep smirks.

4.5. Options trading volume, volatility smirk, and earnings surprises

In this subsection, we examine whether options volume interacting with volatility smirks foreshadows future earnings news. If high options volume accompanied by steep volatility smirks is indeed driven by directional informed traders, then its informativeness should be pronounced around the release of significant firm-specific information such as earnings announcements.[18]

Table 7 contains a series of Fama-MacBeth regressions, where we regress the upcoming earnings surprise on volatility smirks, deciles of relative options volume, and their interaction term, separately and together. We use four measures to capture the news released at earnings announcements. The first earnings surprise measure, SURPRISE1, is the difference between the firm's actual quarterly earnings per share (EPS) and the analysts' consensus forecast on EPS, divided by the beginning-of-quarter stock price. The second measure, SURPRISE2, is the difference between actual EPS and analysts' EPS forecasts, scaled by the standard deviation of this difference over the previous eight quarters. The third measure, SUE1, is the standardized unexpected earnings defined as the seasonally adjusted EPS (i.e., the current quarter EPS minus the EPS in the same quarter of the previous fiscal year), divided by

[18] Informed traders' activity increases around information events. Amin and Lee (1997) document the abnormally high trading volume in options markets prior to earnings announcements and its role in the dissemination of earnings news. Consistently, Roll, Schwartz, and Subrahmanyam (2010) show that options volume relative to stock volume increases substantially around earnings announcements. Additionally, Atilgan (2014) reports that the return predictability of the difference between put and call volatilities is much stronger during earnings announcements than in normal times.

the beginning-of-quarter stock price. The final measure, SUE2, is the seasonally adjusted EPS divided by its standard deviation over the previous eight quarters.

[Table 7 about here]

In Table 7, the first two columns for each earnings surprise measure present the results of future earnings surprise regressions on SKEW and deciles of O/S, respectively. The coefficient estimates are broadly consistent with the findings in prior studies.[19] In separate regressions, both the volatility smirk and relative options volume are shown to be strong negative predictors of future earnings news.

Of primary interest in Table 7 is the interaction effect between options volume and volatility smirks, shown in the last column for each earnings surprise measure. Notably, the coefficients on the interaction term between the deciles of O/S and SKEW are negative and statistically significant for all earnings surprise measures. In addition, both the magnitude and statistical significance of the coefficients on O/S are greatly reduced in the presence of the interaction term, compared to those from the regressions without the interaction term. Taken together, the results in Table 7 indicate that a high options-to-stock-volume ratio accompanied by steep volatility smirks possesses a greater predictive power for negative earning news than when it is not accompanied by steep smirks.

5. Conclusion

Both directional and volatility information about stock price have been known to drive trading in options market. Numerous studies have investigated the informational link between options market and stock market, but they typically focused only on one type of informed trading. In this paper, we extend the prior research by considering the distinct types of informed trading in a unified framework. By doing so, we shed light on the question about how the relative significance of directional versus

[19] Xing, Zhang, and Zhao (2010) find that firms with steep volatility smirks experience negative earnings shocks in the future. Johnson and So (2012) show that a high options-to-stock-volume ratio predicts negative earnings surprises.

volatility informed trading in options market affects the information flows between options and their underlying stocks markets.

In particular, we extend the Easley, O'Hara, and Srinivas (1998) model by accommodating volatility informed trading in addition to directional informed trading. Our model predicts that options trades motivated by directional information about underlying security prices are negatively linked with future equity prices in the presence of short-sales costs and accompany steep volatility smirk, while there is no such relationship when volatility structure is flat.

We test the theoretical prediction by analyzing the interaction between options volume and volatility smirk in predicting the cross-section of stock returns. The empirical results, based on portfolio sorts and cross-sectional regressions, show that negative relationship between relative options volume and future stock returns documented in Johnson and So (2012) is concentrated in stocks exhibiting a steep volatility smirk. Specifically, when accompanied by the steep smirk, stocks with the lowest options-to-stock-volume ratio outperform stocks with the highest ratio by 0.40% in the subsequent week. However, the return predictability of the options-to-stock-volume ratio disappears for stocks with flat smirk. These results highlight the need to discriminate between the two distinct options trading motives in examining the links between the options and stock markets.

Appendix A. Separating and pooling equilibria

Our approach to calculating the necessary and sufficient conditions for pooling equilibrium is essentially identical to Easley, O'Hara, and Srinivas (1998). That is, we determine the conditions under which the equilibrium will involve $\eta_{HS}, \eta_{HC}, \eta_{LS}, \eta_{LC}, \zeta_H, \zeta_L$<1.

Before investigating, we make a simplifying assumption. To keep the model tractable, we use a Taylor series expansion to approximate the option prices. We first calculate the unconditional expected values of the future stock price and volatility, denoted by $S^*(= (S_H + S_L)/2)$ and $\sigma^*(= (\sigma_H + \sigma_L)/2)$, respectively. Then we define $C^* \equiv C(S^*, \sigma^*)$ and $P^* \equiv P(S^*, \sigma^*)$. Taking a first-order Taylor series expansion of call and put option prices around (S^*, σ^*) yields:

$$C(S_d, \sigma_v) = C^* + (S_d - S^*)\Delta_C + (\sigma_v - \sigma^*)\nabla_C, \quad d = H, L, and\ v = H, L, \tag{11}$$

$$P(S_d, \sigma_v) = P^* + (S_d - S^*)\Delta_P + (\sigma_v - \sigma^*)\nabla_P, \quad d = H, L, \text{and } v = H, L, \tag{12}$$

where Δ is the *delta* of an option (rate of change of the option price with respect to the price of the underlying stock) and ∇ is the *vega* of an option (rate of change of the option price with respect to the volatility of the underlying stock).

Taking advantage of this approximation, the conditional and unconditional expectations of option prices can be calculated simply: $\mathrm{E}[\tilde{C}|\tilde{S} = S_L] = C^* - (S_H - S_L)\Delta_C/2$; $\mathrm{E}[\tilde{C}|\tilde{S} = S_H] = C^* + (S_H - S_L)\Delta_C/2$; $\mathrm{E}[\tilde{C}|\tilde{\sigma} = \sigma_L] = C^* - (S_H - S_L)\nabla_C/2$; $\mathrm{E}[\tilde{C}|\tilde{\sigma} = \sigma_H] = C^* + (S_H - S_L)\nabla_C/2$; $\mathrm{E}[\tilde{C}] = C^*$; $\mathrm{E}[\tilde{P}|\tilde{S} = S_L] = P^* + (S_H - S_L)|\Delta_P|/2$; $\mathrm{E}[\tilde{P}|\tilde{S} = S_H] = P^* - (S_H - S_L)|\Delta_P|/2$; $\mathrm{E}[\tilde{P}|\tilde{\sigma} = \sigma_L] = P^* - (S_H - S_L)\nabla_P/2$; $\mathrm{E}[\tilde{P}|\tilde{\sigma} = \sigma_H] = P^* + (S_H - S_L)\nabla_P/2$; $\mathrm{E}[\tilde{P}] = P^*$.

Now we determine the pooling equilibrium conditions for two extreme cases: one where $\delta = 0$ and the other where $\delta = 1$. We provide the calculations for the case where $\delta = 0$ and traders are informed that $\tilde{S} = S_L$. Suppose η_{LS}=1, then we find conditions where the informed trader's profit from trading the options exceeds the profit from trading the stock. Given η_{LS}=1, the expected profit from selling the stock is

$$\gamma(1-\rho)\frac{(S_H-S_L)}{2}\frac{2(1-\alpha)q_2}{\alpha+2(1-\alpha)q_2}. \tag{13}$$

The expected profit from selling the call (if η_{LS}=1) is

$$\theta\frac{(S_H-S_L)\Delta_C}{2}, \tag{14}$$

and the expected profit from buying the put (if η_{LS}=1) is

$$\theta\frac{(S_H-S_L)|\Delta_P|}{2}. \tag{15}$$

These profit conditions dictate that some S_L-informed traders will use options (i.e., η_{LS}<1) if

$$\frac{\theta}{\gamma}>\frac{(1-\rho)}{\max\{\Delta_C,|\Delta_P|\}}\cdot\frac{2(1-\alpha)q_2}{\alpha+2(1-\alpha)q_2}. \tag{16}$$

Similarly, suppose η_{LC}=1. The expected profit from selling the stock (if η_{LC}=1) is

$$\gamma(1-\rho)\frac{(S_H-S_L)}{2}. \tag{17}$$

The expected profit from selling the call (if η_{LC}=1) is

$$\theta\frac{(S_H-S_L)\Delta_C}{2}\frac{2(1-\alpha)q_4}{\alpha+2(1-\alpha)q_4}, \tag{18}$$

and the expected profit from buying the put (if η_{LC}=1) is

$$\theta\frac{(S_H-S_L)|\Delta_P|}{2}. \tag{19}$$

These profit conditions dictate that some S_L-informed traders will sell the stock or buy the put (i.e., η_{LC}<1) if

$$\frac{\theta}{\gamma}<\frac{(1-\rho)}{\Delta_C}\cdot\frac{\alpha+2(1-\alpha)q_4}{2(1-\alpha)q_4}\ or\ \frac{\Delta_C}{|\Delta_P|}<\frac{\alpha+2(1-\alpha)q_4}{2(1-\alpha)q_4}. \tag{20}$$

Similarly, suppose $1-\eta_{LS}-\eta_{LC}$=1. The expected profit from selling the stock (if η_{LS}=η_{LC}=0) is

$$\gamma(1-\rho)\frac{(S_H-S_L)}{2} \tag{21}$$

The expected profit from selling the call (if η_{LS}=η_{LC}=0) is

$$\theta\frac{(S_H - S_L)\Delta_C}{2}, \tag{22}$$

and the expected profit from buying the put (if η_{LS}=η_{LC}=0) is

$$\theta\frac{(S_H - S_L)|\Delta_P|}{2}\frac{2(1-\alpha)q_5}{\alpha + 2(1-\alpha)q_5}. \tag{23}$$

These profit conditions dictate that some S_L-informed traders will sell the stock or sell the call (i.e., $1 - \eta_{LS} - \eta_{LC}$<1) if

$$\frac{\theta}{\gamma} < \frac{(1-\rho)}{|\Delta_P|}\cdot\frac{\alpha + 2(1-\alpha)q_5}{2(1-\alpha)q_5} \; or \; \frac{2(1-\alpha)q_5}{\alpha + 2(1-\alpha)q_5} < \frac{\Delta_C}{|\Delta_P|}. \tag{24}$$

A similar logic applies to the S_H-informed traders, resulting in the following conditions. Given that $\delta = 0$, some S_H-informed traders will use options (i.e., η_{HS}<1) if

$$\frac{\theta}{\gamma} > \frac{1}{\max\{\Delta_C, |\Delta_P|\}}\cdot\frac{2(1-\alpha)q_1}{\alpha + 2(1-\alpha)q_1}, \tag{25}$$

and they will buy the stock or sell the put (i.e., η_{HC}<1) if

$$\frac{\theta}{\gamma} < \frac{1}{\Delta_C}\cdot\frac{\alpha + 2(1-\alpha)q_3}{2(1-\alpha)q_3} \; or \; \frac{\Delta_C}{|\Delta_P|} < \frac{\alpha + 2(1-\alpha)q_3}{2(1-\alpha)q_3}, \tag{26}$$

and they will buy the stock or buy the call (i.e., $1 - \eta_{HS} - \eta_{HC}$<1) if

$$\frac{\theta}{\gamma} < \frac{1}{|\Delta_P|}\cdot\frac{\alpha + 2(1-\alpha)q_6}{2(1-\alpha)q_6} \; or \; \frac{2(1-\alpha)q_6}{\alpha + 2(1-\alpha)q_6} < \frac{\Delta_C}{|\Delta_P|}. \tag{27}$$

Similarly, we draw the following equilibrium conditions for the case where $\delta = 1$. Some σ_L-informed traders will use call options and others will use put options ($\text{i.e.}, 0 < \zeta_L < 1$) if

$$\frac{2(1-\alpha)q_6}{\alpha + 2(1-\alpha)q_6} < \frac{\nabla_C}{\nabla_P} < \frac{\alpha + 2(1-\alpha)q_4}{2(1-\alpha)q_4}. \tag{28}$$

Some σ_H-informed traders will use call options and others will use put options ($\text{i.e.}, 0 < \zeta_H < 1$) if

$$\frac{2(1-\alpha)q_5}{\alpha+2(1-\alpha)q_5} < \frac{\nabla_C}{\nabla_P} < \frac{\alpha+2(1-\alpha)q_3}{2(1-\alpha)q_3}. \tag{29}$$

Appendix B. Simultaneous equations

The full set of simultaneous equations that characterize the pooling equilibrium are as follows:

$$b_S = \frac{\alpha(1-\delta)\frac{1}{2}\eta_{LS}S_L + (1-\alpha)q_2\frac{1}{2}(S_H+S_L)}{\alpha(1-\delta)\frac{1}{2}\eta_{LS} + (1-\alpha)q_2}, \tag{30}$$

$$a_S = \frac{\alpha(1-\delta)\frac{1}{2}\eta_{HS}S_H + (1-\alpha)q_1\frac{1}{2}(S_H+S_L)}{\alpha(1-\delta)\frac{1}{2}\eta_{HS} + (1-\alpha)q_1}, \tag{31}$$

$$b_C = \frac{\alpha(1-\delta)\frac{1}{2}\eta_{LC}E\left[\tilde{C}|\tilde{S}=S_L\right] + \alpha\delta\frac{1}{2}\zeta_L E\left[\tilde{C}|\tilde{\sigma}=\sigma_L\right] + (1-\alpha)q_4 E\left[\tilde{C}\right]}{\alpha(1-\delta)\frac{1}{2}\eta_{LC} + \alpha\delta\frac{1}{2}\zeta_L + (1-\alpha)q_4}, \tag{32}$$

$$a_C = \frac{\alpha(1-\delta)\frac{1}{2}\eta_{HC}E\left[\tilde{C}|\tilde{S}=S_H\right] + \alpha\delta\frac{1}{2}\zeta_H E\left[\tilde{C}|\tilde{\sigma}=\sigma_H\right] + (1-\alpha)q_3 E\left[\tilde{C}\right]}{\alpha(1-\delta)\frac{1}{2}\eta_{HC} + \alpha\delta\frac{1}{2}\zeta_H + (1-\alpha)q_3}, \tag{33}$$

$$b_P = \frac{\alpha(1-\delta)\frac{1}{2}(1-\eta_{HS}-\eta_{HC})E\left[\tilde{P}|\tilde{S}=S_H\right] + \alpha\delta\frac{1}{2}(1-\zeta_L)E[\tilde{P}|\tilde{\sigma}=\sigma_L] + (1-\alpha)q_6 E[\tilde{P}]}{\alpha(1-\delta)\frac{1}{2}(1-\eta_{HS}-\eta_{HC}) + \alpha\delta\frac{1}{2}(1-\zeta_L) + (1-\alpha)q_6}, \tag{34}$$

$$a_P = \frac{\alpha(1-\delta)\frac{1}{2}(1-\eta_{LS}-\eta_{LC})E\left[\tilde{P}|\tilde{S}=S_L\right] + \alpha\delta\frac{1}{2}(1-\zeta_H)E[\tilde{P}|\tilde{\sigma}=\sigma_H] + (1-\alpha)q_5 E[\tilde{P}]}{\alpha(1-\delta)\frac{1}{2}(1-\eta_{LS}-\eta_{LC}) + \alpha\delta\frac{1}{2}(1-\zeta_H) + (1-\alpha)q_5}, \tag{35}$$

$$\gamma(-a_s+S_H) = \theta\left(-a_c + E\left[\tilde{C}|\tilde{S}=S_H\right]\right), \tag{36}$$

$$\gamma(-a_s+S_H) = \theta\left(b_p - E[\tilde{P}|\tilde{S}=S_H]\right), \tag{37}$$

$$\gamma(b_s-S_L)(1-\rho) = \theta\left(b_c - E\left[\tilde{C}|\tilde{S}=S_L\right]\right), \tag{38}$$

$$\gamma(b_s - S_L)(1-\rho) = \theta\left(-a_p + E[\tilde{P}|\tilde{S} = S_L]\right), \tag{39}$$

$$\theta\left(-a_c + E[\tilde{C}|\tilde{\sigma} = \sigma_H]\right) = \theta\left(-a_p + E[\tilde{P}|\tilde{\sigma} = \sigma_H]\right), \tag{40}$$

$$\theta\left(b_c - E[\tilde{C}|\tilde{\sigma} = \sigma_L]\right) = \theta\left(b_p - E[\tilde{P}|\tilde{\sigma} = \sigma_L]\right). \tag{41}$$

Eqs. (30) - (35) are the zero profit conditions for the market maker. Eq. (30) (Eq. (31)), for example, ensures that the bid (ask) price for a stock is exactly its expected value given that a trader wants to sell (buy) it to the market maker. Eqs. (36) - (41) ensure that informed traders are indifferent among possible trades: Eqs. (36) and (37) ensure that directional informed traders who know that $\tilde{S} = S_H$ are indifferent between buying stocks, buying calls, and shorting puts; Eqs. (38) and (39) ensure that directional informed traders who know that $\tilde{S} = S_L$ are indifferent between shorting stocks, shorting calls, and buying puts; Eq. (40) ensures that volatility informed traders who know that $\tilde{\sigma} = \sigma_H$ are indifferent between buying calls and buying puts; Eq. (41) ensures that volatility informed traders who know that $\tilde{\sigma} = \sigma_L$ are indifferent between shorting calls and shorting puts.

To obtain a closed form solution for simultaneous equations, we use a Taylor series approximation of the option prices given in Eqs. (11) and (12). Then Eqs. (30) - (41) can be rewritten as follows:

$$b_S = S^* - \frac{(S_H - S_L)}{2} \frac{\alpha(1-\delta)\eta_{LS}}{\alpha(1-\delta)\eta_{LS} + 2(1-\alpha)q_2}, \tag{42}$$

$$a_S = S^* + \frac{(S_H - S_L)}{2} \frac{\alpha(1-\delta)\eta_{HS}}{\alpha(1-\delta)\eta_{HS} + 2(1-\alpha)q_1}, \tag{43}$$

$$b_C = C^* - \frac{(S_H - S_L)\Delta_C}{2} \frac{\alpha(1-\delta)\eta_{LC} + \alpha\delta\zeta_L \frac{(\sigma_H - \sigma_L)\nabla_C}{(S_H - S_L)\Delta_C}}{\alpha(1-\delta)\eta_{LC} + \alpha\delta\zeta_L + 2(1-\alpha)q_4}, \tag{44}$$

$$a_C = C^* + \frac{(S_H - S_L)\Delta_C}{2} \frac{\alpha(1-\delta)\eta_{HC} + \alpha\delta\zeta_H \frac{(\sigma_H - \sigma_L)\nabla_C}{(S_H - S_L)\Delta_C}}{\alpha(1-\delta)\eta_{HC} + \alpha\delta\zeta_H + 2(1-\alpha)q_3}, \tag{45}$$

$$b_P = P^* - \frac{(S_H - S_L)(-\Delta_P)}{2} \frac{\alpha(1-\delta)(1-\eta_{HS}-\eta_{HC}) + \alpha\delta(1-\zeta_L)\frac{(\sigma_H - \sigma_L)\nabla_P}{(S_H - S_L)(-\Delta_P)}}{\alpha(1-\delta)(1-\eta_{HS}-\eta_{HC}) + \alpha\delta(1-\zeta_L) + 2(1-\alpha)q_6}, \tag{46}$$

$$a_P = P^* + \frac{(S_H - S_L)(-\Delta_P)}{2} \frac{\alpha(1-\delta)(1-\eta_{LS}-\eta_{LC}) + \alpha\delta(1-\zeta_H)\frac{(\sigma_H - \sigma_L)\nabla_P}{(S_H - S_L)(-\Delta_P)}}{\alpha(1-\delta)(1-\eta_{LS}-\eta_{LC}) + \alpha\delta(1-\zeta_H) + 2(1-\alpha)q_5}, \tag{47}$$

$$\gamma \frac{(S_H - S_L)}{2} \frac{2(1-\alpha)q_1}{\alpha(1-\delta)\eta_{HS} + 2(1-\alpha)q_1} = \theta \frac{(S_H - S_L)\Delta_C}{2} \frac{\alpha\delta\zeta_H\left(1 - \frac{(\sigma_H - \sigma_L)\nabla_C}{(S_H - S_L)\Delta_C}\right) + 2(1-\alpha)q_3}{\alpha(1-\delta)\eta_{HC} + \alpha\delta\zeta_H + 2(1-\alpha)q_3}, \tag{48}$$

$$\gamma \frac{(S_H - S_L)}{2} \frac{2(1-\alpha)q_1}{\alpha(1-\delta)\eta_{HS} + 2(1-\alpha)q_1} = \theta \frac{(S_H - S_L)(-\Delta_P)}{2} \frac{\alpha\delta(1-\zeta_L)\left(1 - \frac{(\sigma_H - \sigma_L)\nabla_P}{(S_H - S_L)(-\Delta_P)}\right) + 2(1-\alpha)q_6}{\alpha(1-\delta)(1-\eta_{HS}-\eta_{HC}) + \alpha\delta(1-\zeta_L) + 2(1-\alpha)q_6}, \tag{49}$$

$$\gamma(1-\rho) \frac{(S_H - S_L)}{2} \frac{2(1-\alpha)q_2}{\alpha(1-\delta)\eta_{LS} + 2(1-\alpha)q_2} = \theta \frac{(S_H - S_L)\Delta_C}{2} \frac{\alpha\delta\zeta_L\left(1 - \frac{(\sigma_H - \sigma_L)\nabla_C}{(S_H - S_L)\Delta_C}\right) + 2(1-\alpha)q_4}{\alpha(1-\delta)\eta_{LO} + \alpha\delta\zeta_L + 2(1-\alpha)q_4}, \tag{50}$$

$$\begin{aligned}\gamma(1-\rho) \frac{(S_H - S_L)}{2} &\frac{2(1-\alpha)q_2}{\alpha(1-\delta)\eta_{LS} + 2(1-\alpha)q_2} \\ &= \theta \frac{(S_H - S_L)(-\Delta_P)}{2} \frac{\alpha\delta(1-\zeta_H)\left(1 - \frac{(\sigma_H - \sigma_L)\nabla_P}{(S_H - S_L)(-\Delta_P)}\right) + 2(1-\alpha)q_5}{\alpha(1-\delta)(1-\eta_{LS}-\eta_{LC}) + \alpha\delta(1-\zeta_H) + 2(1-\alpha)q_5},\end{aligned} \tag{51}$$

$$\begin{aligned}&\theta\left(-\frac{(S_H - S_L)\Delta_C}{2} \frac{\alpha(1-\delta)\eta_{HC} + \alpha\delta\zeta_H\frac{(\sigma_H - \sigma_L)\nabla_C}{(S_H - S_L)\Delta_C}}{\alpha(1-\delta)\eta_{HC} + \alpha\delta\zeta_H + 2(1-\alpha)q_3} + \frac{(\sigma_H - \sigma_L)\nabla_C}{2}\right) \\ &\quad = \theta\left(-\frac{(S_H - S_L)(-\Delta_P)}{2} \frac{\alpha(1-\delta)(1-\eta_{LS}-\eta_{LC}) + \alpha\delta(1-\zeta_H)\frac{(\sigma_H - \sigma_L)\nabla_P}{(S_H - S_L)(-\Delta_P)}}{\alpha(1-\delta)(1-\eta_{LS}-\eta_{LC}) + \alpha\delta(1-\zeta_H) + 2(1-\alpha)q_5} + \frac{(\sigma_H - \sigma_L)\nabla_P}{2}\right),\end{aligned} \tag{52}$$

$$\begin{aligned}&\theta\left(-\frac{(S_H - S_L)\Delta_C}{2} \frac{\alpha(1-\delta)\eta_{LC} + \alpha\delta\zeta_L\frac{(\sigma_H - \sigma_L)\nabla_C}{(S_H - S_L)\Delta_C}}{\alpha(1-\delta)\eta_{LC} + \alpha\delta\zeta_L + 2(1-\alpha)q_4} + \frac{(\sigma_H - \sigma_L)\nabla_C}{2}\right) \\ &\quad = \theta\left(-\frac{(S_H - S_L)(-\Delta_P)}{2} \frac{\alpha(1-\delta)(1-\eta_{HS}-\eta_{HC}) + \alpha\delta(1-\zeta_L)\frac{(\sigma_H - \sigma_L)\nabla_P}{(S_H - S_L)(-\Delta_P)}}{\alpha(1-\delta)(1-\eta_{HS}-\eta_{HC}) + \alpha\delta(1-\zeta_L) + 2(1-\alpha)q_6} + \frac{(\sigma_H - \sigma_L)\nabla_P}{2}\right).\end{aligned} \tag{53}$$

Eqs. (42) - (47) show that, as is usually the case in a world of asymmetric information, the bid-ask spread develops around the unconditional expected value of the asset. Notice that the bid-ask spread depends on the range of possible future values of the asset and the expected presence of informed traders in the market.

Appendix C. Proofs of propositions

We restrict our attention throughout to an out-of-the-money (OTM) put option and an at-the-money (ATM) call option to avoid difficulties connected with varying exercise prices. Then, the deltas and vegas of the options satisfy $\Delta_C > |\Delta_P|$ and $\nabla_C > \nabla_P$. Also, we assume that uninformed demand satisfies $q_1 = q_2 = q_3 = q_4 = q_5 = q_6 (\equiv q)$ for simplicity because our goal is to examine the impacts of directional and volatility informed traders. This simplifies the pooling equilibrium conditions as follows:

Given $\delta = 0$, $0 < \eta_{HS}, \eta_{HC}, \eta_{LS}, \eta_{LC} < 1$ if

$$\frac{1}{\Delta_C} \cdot \frac{2(1-\alpha)q}{\alpha + 2(1-\alpha)q} < \frac{\theta}{\gamma} < \frac{1-\rho}{\Delta_C} \cdot \frac{\alpha + 2(1-\alpha)q}{2(1-\alpha)q}, \tag{54}$$

and

$$\frac{\Delta_C}{|\Delta_P|} < \frac{\alpha + 2(1-\alpha)q}{2(1-\alpha)q}. \tag{55}$$

Given $\delta = 1$, $0 < \zeta_H, \zeta_L < 1$ if

$$\frac{\nabla_C}{\nabla_P} < \frac{\alpha + 2(1-\alpha)q}{2(1-\alpha)q}. \tag{56}$$

We assume that the exogenous parameters are chosen so that there exists a set of parameters satisfying Eqs. (54) and (55) or Eq. (56) for a pooling equilibrium.

PROPOSITION 1: *When all informed traders are directional informed ($\delta = 0$), in a pooling equilibrium, $E[\tilde{S} | option\ trade] < E[\tilde{S} | stock\ trade]$ and $P_0 - C_0 > P^* - C^*$, where P_0 and C_0 are the midpoints of the bid and ask quotes for the put and call options, respectively .*

Proof. In the case where $\delta = 0$, the parameters ζ_H and ζ_L are rendered meaningless and Eqs. (42) - (51) characterize the equilibrium. We first compute $\eta_{HS}, \eta_{HC}, \eta_{LS}$, and η_{LC} to satisfy Eqs. (48) - (51) simultaneously:

$$\eta_{HS} = \frac{\alpha\gamma - 2(1-\alpha)q\{\theta(|\Delta_C| + |\Delta_P|) - 2\gamma\}}{\alpha\{\gamma + \theta(|\Delta_C| + |\Delta_P|)\}}, \tag{57}$$

$$\eta_{HC} = \frac{\alpha(1-\eta_{HS})|\Delta_C| + 2(1-\alpha)q(|\Delta_C| - |\Delta_P|)}{\alpha(|\Delta_C| + |\Delta_P|)}, \tag{58}$$

$$\eta_{LS} = \frac{\alpha\gamma(1-\rho) - 2(1-\alpha)q\{\theta(|\Delta_C| + |\Delta_P|) - 2\gamma(1-\rho)\}}{\alpha\{\gamma(1-\rho) + \theta(|\Delta_C| + |\Delta_P|)\}}, \tag{59}$$

$$\eta_{LC} = \frac{\alpha(1-\eta_{LS})|\Delta_C| + 2(1-\alpha)q(|\Delta_C| - |\Delta_P|)}{\alpha(|\Delta_C| + |\Delta_P|)}. \tag{60}$$

We then calculate the expected stock values conditional on the stock and option trades. The calculation of these conditional expectations follows from a standard application of Bayes' Rule, and results in the following expressions:

$$\mathrm{E}[\tilde{S}|\text{stock trade}] = S^* + \frac{S_H - S_L}{2}\frac{\alpha(\eta_{HS} - \eta_{LS})}{4(1-\alpha)q + \alpha(\eta_{HS} + \eta_{LS})}, \tag{61}$$

$$\mathrm{E}[\tilde{S}|\text{option trade}] = S^* - \frac{S_H - S_L}{2}\frac{\alpha(\eta_{HS} - \eta_{LS})}{8(1-\alpha)q + 2\alpha - \alpha(\eta_{HS} + \eta_{LS})}. \tag{62}$$

Substituting Eqs. (57) and (59) into Eqs. (61) and (62), we obtain:

$$\begin{aligned} &\mathrm{E}[\tilde{S}|\text{stock trade}] - \mathrm{E}[\tilde{S}|\text{option trade}] \\ &\quad = \frac{S_H - S_L}{2}\cdot\frac{\rho}{\{\alpha + 6(1-\alpha)q\}}\cdot\frac{\{\theta(|\Delta_C| + |\Delta_P|) + \gamma\}\{\theta(|\Delta_C| + |\Delta_P|) + \gamma(1-\rho)\}}{\left\{\theta(|\Delta_C| + |\Delta_P|) + \gamma\left(1 - \frac{\rho}{2}\right)\right\}\{\theta(|\Delta_C| + |\Delta_P|)\rho + 2(1-\rho)(\theta(|\Delta_C| + |\Delta_P|) + \gamma)\}}, \end{aligned} \tag{63}$$

which is greater than zero when $\rho > 0$.

The put and call option prices, calculated as the midpoints of the equilibrium bid and ask quotes, are as follows:

$$P_0 = \frac{a_P + b_P}{2} = P^* + \frac{(S_H - S_L)|\Delta_P|}{4}\left\{-\frac{2(1-\alpha)q}{\alpha(1-\eta_{LS}-\eta_{LC}) + 2(1-\alpha)q} + \frac{2(1-\alpha)q}{\alpha(1-\eta_{HS}-\eta_{HC}) + 2(1-\alpha)q}\right\}, \tag{64}$$

$$C_0 = \frac{a_C + b_C}{2} = C^* + \frac{(S_H - S_L)\Delta_C}{4}\left\{-\frac{2(1-\alpha)q}{\alpha\eta_{HC} + 2(1-\alpha)q} + \frac{2(1-\alpha)\mathrm{q}}{\alpha\eta_{LC} + 2(1-\alpha)\mathrm{q}}\right\}. \tag{65}$$

Substituting Eqs. (57) - (60) into Eqs. (64) and (65) yields:

$$P_0 - C_0 = P^* - C^* + (S_H - S_L)\frac{\gamma\rho(1-\alpha)q}{\theta\{\alpha + 6(1-\alpha)q\}}, \tag{66}$$

which is greater than $P^* - C^*$ when $\rho > 0$. This says that the difference in prices between the OTM put and ATM call is larger than the difference between their unconditional expected values. ■

PROPOSITION 2: *When all informed traders are volatility informed ($\delta = 1$), in a pooling equilibrium,* $E[\tilde{S}|option\ trade] = E[\tilde{S}|stock\ trade]$ *and* $P_0 - C_0 = P^* - C^*$.

Proof. In the case where $\delta = 1$, the parameters $\eta_{HS}, \eta_{HC}, \eta_{LS}$, and η_{LC} are rendered meaningless and Eqs. (42) - (47), (52), and (53) characterize the equilibrium. We first compute ζ_H and ζ_L to satisfy Eqs. (52) and (53) simultaneously:

$$\zeta_H = \zeta_L = \frac{\alpha\nabla_C + 2(1-\alpha)q(\nabla_C - \nabla_P)}{\alpha(\nabla_C + \nabla_P)}. \tag{67}$$

As in the proof of Proposition 1, we next calculate the conditional expected values of the stock. The calculation shows that the expected stock values conditional on the stock and option trades have the same value, namely, $E[\tilde{S}|option\ trade] = E[\tilde{S}|stock\ trade] = S^*$. This is expected since the difference in mean equity values conditional on the trading venues is caused by the short-sale cost in the stock market, which is only relevant when informed traders use equity.

The put and call option prices are calculated as follows:

$$P_0 = P^* + \frac{(\sigma_H - \sigma_L)\nabla_P}{4}\left\{-\frac{2(1-\alpha)q}{\alpha(1-\zeta_H) + 2(1-\alpha)q} + \frac{2(1-\alpha)q}{\alpha(1-\zeta_L) + 2(1-\alpha)q}\right\}, \tag{68}$$

$$C_0 = C^* + \frac{(\sigma_H - \sigma_L)\nabla_C}{4}\left\{-\frac{2(1-\alpha)q}{\alpha\zeta_H + 2(1-\alpha)q} + \frac{2(1-\alpha)q}{\alpha\zeta_L + 2(1-\alpha)q}\right\}. \tag{69}$$

Substituting Eq. (67) into Eqs. (68) and (69) yields:

$$P_0 - C_0 = P^* - C^*. \tag{70}$$

This says that the difference in prices between the OTM put and ATM call is the same as the difference between their unconditional expected values. ■

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Table 1. Descriptive statistics

Panel A reports sample size information and descriptive statistics for $O/S_{i,w}$ and $SKEW_{i,w}$ for each year of the sample, as well as for the full sample. FIRMS represents the number of unique firms contained in the sample per year. $O/S_{i,w}$ represents the ratio of option volume to stock volume of firm i in week w. $SKEW_{i,w}$ represents the difference between the implied volatilities of an OTM put and an ATM call. We first compute the cross-sectional mean and quartiles of O/S and SKEW for each week, and then report the time series average of these weekly summary statistics. CORR is the time series average of the cross-sectional correlations between O/S and SKEW. Panel B reports the average firm characteristics for portfolios formed on the basis of SKEW and O/S. At the end of each week we sort all available stocks into terciles (S1 to S3) based on SKEW. The extreme terciles contain 30% of the sample, while the middle tercile contains 40% of the sample. Stocks in S1 have the lowest SKEW, while stocks in S3 have the highest SKEW. We then independently sort these same stocks into deciles (V1 to V10) based on O/S, with V10 representing the highest O/S portfolio. The reported values are the time series average of the cross-sectional mean characteristics. FIRMS is the average number of unique firms contained in each portfolio in each week. OPVOL represents the total option contract volume traded in a given week. VLC (VLP) represents the total call (put) contract volume traded in a given week. STVOL represents the total stock volume traded in a given week (in units of 100 shares). SIZE is the market capitalization (in billions of dollars). BM is the book to market ratio. SIZE and BM are measured at the end of June prior to week w. MOMENT represents cumulative stock return over the prior six months (percent). AMIHUD is the average of daily Amihud (2002) illiquidity ratios over the previous month (multiplied by 10^7). The daily Amihud illiquidity is computed as the absolute return per dollar of daily trading volume. HVOL represents the historical volatility of stock returns measured over the previous month using daily stock returns (in percent).

Panel A: Sample size and descriptive statistics of O/S and SKEW by year

			O/S(%)				SKEW(%)				CORR
Year	FIRMS	Firm-weeks	MEAN	P25	MEDIAN	P75	MEAN	P25	MEDIAN	P75	(%)
1996	1,057	9,669	7.150	2.312	4.470	8.727	5.332	1.411	4.166	8.101	5.302
1997	1,633	31,120	6.856	2.163	4.265	8.349	5.561	1.294	4.243	8.298	2.845
1998	1,828	34,061	6.049	1.919	3.823	7.388	6.106	1.580	4.658	8.959	4.739
1999	1,853	37,034	5.796	1.867	3.793	7.493	4.928	1.061	3.621	7.170	1.896
2000	1,840	41,887	5.431	1.890	3.743	6.933	4.429	0.720	3.277	6.772	0.409
2001	1,607	36,836	4.641	1.507	3.048	5.812	6.659	3.244	5.708	8.967	8.515
2002	1,524	33,469	4.592	1.364	2.941	5.840	8.576	5.009	7.515	10.805	4.366
2003	1,467	33,169	5.890	1.566	3.533	7.324	7.545	4.471	6.380	9.203	-0.691
2004	1,598	36,912	6.991	1.854	4.232	8.833	5.856	3.349	4.901	7.186	1.821
2005	1,619	38,734	7.990	1.977	4.548	9.768	5.828	3.042	4.631	6.920	4.100
2006	1,711	45,743	8.813	2.293	5.325	11.264	5.296	2.801	4.365	6.573	1.543
2007	1,848	50,778	8.706	2.110	4.995	10.689	5.504	2.734	4.527	6.971	6.244
2008	1,818	51,954	6.978	1.565	3.780	8.415	7.991	4.070	6.528	10.121	5.914
2009	1,683	47,325	7.489	1.827	4.270	9.045	7.890	4.767	6.918	9.836	-7.163
2010	1,718	48,325	7.790	1.766	4.177	9.123	6.023	3.664	5.229	7.323	-2.322
2011	1,703	50,512	8.229	1.701	4.290	9.829	6.154	3.520	5.101	7.200	1.095
2012	1,580	44,681	8.556	1.747	4.362	10.021	5.954	3.440	4.949	6.971	-4.682
All		672,209	6.932	1.832	4.081	8.516	6.246	3.008	5.135	8.080	1.861

Panel B: Sample size and firm characteristics by 30 portfolios (3-by-10) based on SKEW and O/S

	All	V1 (Low)	V4	V7	V10 (High)	All	V1	V4	V7	V10
	FIRMS					O/S(%)				
All	814	81	81	82	81	6.93	0.57	2.60	6.30	27.58
S1 (Flat)	245	23	24	25	26	7.27	0.57	2.60	6.31	27.60
S2	326	30	32	34	31	6.79	0.57	2.60	6.30	26.09
S3 (Steep)	244	28	25	22	24	6.77	0.57	2.60	6.29	29.15
	SKEW(%)					OPVOL				
All	6.25	6.67	6.20	5.99	6.63	10,872	377	2,494	10,921	41,997
S1	1.06	0.98	0.99	1.12	1.09	13,619	409	2,844	12,412	49,192
S2	5.22	5.24	5.22	5.21	5.19	11,562	384	2,588	11,769	44,187
S3	12.82	13.41	12.52	12.40	14.17	7,195	358	2,100	7,493	27,153
	VLC					VLP				
All	6,552	235	1,567	6,702	25,051	4,320	142	927	4,220	16,946
S1	8,503	257	1,842	7,853	30,678	5,117	152	1,002	4,559	18,514
S2	6,918	239	1,600	7,126	26,213	4,644	145	987	4,643	17,974
S3	4,107	223	1,305	4,487	14,985	3,088	135	795	3,006	12,168
	STVOL					SIZE (billions of dollars)				
All	129,608	73,171	97,428	171,177	157,659	11.92	5.57	7.60	15.17	19.59
S1	144,588	77,595	107,998	189,110	168,285	11.99	5.70	7.66	15.65	17.86
S2	139,981	74,391	100,801	184,116	178,117	15.57	6.61	9.78	18.96	26.56
S3	100,723	70,877	85,427	124,413	105,946	6.97	4.30	4.86	8.45	10.16
	BM					MOMENT (%)				
All	0.46	0.53	0.47	0.44	0.41	13.36	8.54	12.16	13.57	19.84
S1	0.45	0.52	0.47	0.44	0.41	14.49	7.93	13.06	14.96	22.40
S2	0.45	0.52	0.46	0.43	0.40	14.09	8.38	12.31	14.52	21.00
S3	0.49	0.55	0.49	0.46	0.44	11.26	9.14	10.83	11.16	15.66
	AMIHUD (x10^7)					HVOL(%)				
All	0.022	0.017	0.023	0.022	0.024	56.12	48.81	55.95	58.00	59.30
S1	0.021	0.016	0.023	0.022	0.024	55.23	48.01	54.76	57.12	58.16
S2	0.014	0.013	0.017	0.015	0.013	52.55	45.59	52.25	54.67	55.47
S3	0.032	0.022	0.032	0.034	0.041	61.77	53.17	61.77	64.25	65.68

Table 2. Returns and factor loadings for portfolios based on volatility smirk and options volume

Panel A presents the excess returns and estimated results of the factor models for various SKEW and O/S portfolios. SKEW represents the difference between the implied volatilities of an OTM put and an ATM call. O/S represents the ratio of option volume to stock volume. Portfolios are formed based on an independent sort by the three SKEW and ten O/S groups, as in Panel B of Table 1. The SKEW and O/S portfolios numbered "one" have the lowest SKEW and O/S, respectively. To compute portfolio returns, we skip one trading day after portfolio formation, and compute the equally-weighted return of all firms in each portfolio over the following five trading days. Subpanel A.1 reports the average weekly excess return over the risk-free rate and intercepts from the time-series factor regression of the weekly excess return on three sets of contemporaneous risk factors: excess market return (MKTRF); three Fama-French factors (MKTRF, SMB, and HML); and the three Fama-French and momentum factors (UMD). Subpanel A.2 reports the factor loadings in the four-factor model. Panel B reports the analogous results for $\Delta O/S$ replacing O/S, where $\Delta O/S$ equals the deviation of O/S from its historical average over the previous six months. All returns are shown as percentages and t-statistics are in parentheses (bold if significant at the 5% level).

Panel A: 3×10 Portfolios independently sorted on SKEW and O/S

	All	V1 (Low)	V4	V7	V10 (High)	V1-V10	All	V1	V4	V7	V10	V1-V10
Subpanel A.1: Portfolio returns												
	Excess return (%)						CAPM alpha (%)					
All	0.104	0.149	0.138	0.117	0.024	0.125	-0.004	0.054	0.032	0.005	-0.086	**0.140**
	(0.85)	(1.37)	(1.12)	(0.90)	(0.19)	(1.87)	(-0.09)	(1.40)	(0.68)	(0.10)	(-1.52)	**(2.15)**
S1 (Flat)	0.174	0.188	**0.294**	0.217	0.120	0.068	0.069	0.094	**0.189**	0.108	0.015	0.079
	(1.43)	(1.68)	**(2.23)**	(1.58)	(0.87)	(0.75)	(1.46)	(1.94)	**(2.74)**	(1.48)	(0.19)	(0.88)
S2	0.122	0.126	0.117	0.123	0.143	-0.016	0.018	0.034	0.014	0.013	0.033	0.001
	(1.05)	(1.17)	(0.97)	(0.95)	(1.08)	(-0.21)	(0.51)	(0.77)	(0.28)	(0.24)	(0.54)	(0.01)
S3 (Steep)	0.008	0.134	0.006	-0.005	-0.238	**0.371**	**-0.106**	0.035	-0.105	-0.123	**-0.350**	**0.386**
	(0.06)	(1.12)	(0.04)	(-0.03)	(-1.64)	**(4.10)**	**(-2.15)**	(0.62)	(-1.51)	(-1.56)	**(-4.33)**	**(4.31)**
S1-S3	**0.167**	0.055	**0.288**	**0.222**	**0.358**		**0.174**	0.058	**0.294**	**0.231**	**0.365**	
	(3.91)	(0.92)	**(3.67)**	**(2.60)**	**(4.03)**		**(4.16)**	(0.97)	**(3.75)**	**(2.71)**	**(4.11)**	
	Three-factor alpha (%)						Four-factor alpha (%)					
All	-0.037	0.023	-0.004	-0.019	**-0.117**	**0.140**	-0.033	0.029	0.002	-0.013	**-0.120**	**0.149**
	(-1.49)	(0.68)	(-0.12)	(-0.48)	**(-2.78)**	**(2.66)**	(-1.36)	(0.88)	(0.06)	(-0.33)	**(-2.85)**	**(2.90)**
S1	0.040	0.070	**0.159**	0.092	-0.023	0.093	0.040	0.076	**0.162**	0.092	-0.032	0.108
	(1.21)	(1.50)	**(2.63)**	(1.49)	(-0.36)	(1.16)	(1.22)	(1.65)	**(2.69)**	(1.49)	(-0.49)	(1.37)
S2	-0.005	0.009	-0.013	-0.007	0.016	-0.007	-0.003	0.013	-0.007	-0.002	0.011	0.002
	(-0.20)	(0.21)	(-0.28)	(-0.15)	(0.31)	(-0.11)	(-0.14)	(0.31)	(-0.17)	(-0.04)	(0.22)	(0.03)
S3	**-0.156**	-0.006	**-0.160**	**-0.166**	**-0.400**	**0.395**	**-0.145**	0.003	**-0.149**	**-0.151**	**-0.394**	**0.397**
	(-4.38)	(-0.11)	**(-2.68)**	**(-2.39)**	**(-5.72)**	**(4.87)**	**(-4.43)**	(0.06)	**(-2.57)**	**(-2.26)**	**(-5.66)**	**(4.90)**
S1-S3	**0.195**	0.076	**0.319**	**0.258**	**0.377**		**0.185**	0.073	**0.311**	**0.243**	**0.362**	
	(5.00)	(1.29)	**(4.14)**	**(3.09)**	**(4.27)**		**(5.03)**	(1.24)	**(4.07)**	**(2.99)**	**(4.20)**	
Subpanel A.2: Factor loadings in the four-factor model												
	MKTRF beta						SMB beta					
All	**1.181**	**1.063**	**1.159**	**1.217**	**1.234**	**-0.171**	**0.529**	**0.265**	**0.551**	**0.513**	**0.586**	**-0.322**
	(120.93)	**(78.88)**	**(80.48)**	**(77.18)**	**(72.75)**	**(-8.21)**	**(32.61)**	**(11.82)**	**(23.05)**	**(19.60)**	**(20.81)**	**(-9.31)**
S1	**1.172**	**1.059**	**1.156**	**1.216**	**1.210**	**-0.151**	**0.540**	**0.238**	**0.546**	**0.479**	**0.685**	**-0.447**
	(88.68)	**(56.90)**	**(47.44)**	**(48.70)**	**(46.28)**	**(-4.74)**	**(24.61)**	**(7.70)**	**(13.47)**	**(11.54)**	**(15.78)**	**(-8.46)**
S2	**1.163**	**1.039**	**1.137**	**1.204**	**1.246**	**-0.206**	**0.418**	**0.204**	**0.423**	**0.434**	**0.432**	**-0.228**
	(117.87)	**(61.92)**	**(64.45)**	**(65.76)**	**(60.54)**	**(-7.81)**	**(25.47)**	**(7.33)**	**(14.43)**	**(14.25)**	**(12.64)**	**(-5.18)**
S3	**1.214**	**1.089**	**1.191**	**1.238**	**1.216**	**-0.127**	**0.667**	**0.342**	**0.715**	**0.691**	**0.753**	**-0.411**
	(91.73)	**(53.19)**	**(50.80)**	**(45.84)**	**(43.24)**	**(-3.88)**	**(30.33)**	**(10.06)**	**(18.37)**	**(15.41)**	**(16.11)**	**(-7.54)**
S1-S3	**-0.042**	-0.030	-0.034	-0.022	-0.006		**-0.126**	**-0.104**	**-0.170**	**-0.212**	-0.068	
	(-2.80)	(-1.25)	(-1.11)	(-0.65)	(-0.18)		**(-5.12)**	**(-2.63)**	**(-3.31)**	**(-3.89)**	(-1.17)	
	HML beta						UMD beta					
All	**-0.138**	**0.250**	**-0.109**	**-0.319**	**-0.257**	**0.507**	**-0.062**	**-0.097**	**-0.100**	**-0.099**	**0.040**	**-0.137**
	(-8.36)	**(10.98)**	**(-4.47)**	**(-11.98)**	**(-8.97)**	**(14.43)**	**(-6.06)**	**(-6.90)**	**(-6.67)**	**(-6.07)**	**(2.29)**	**(-6.34)**
S1	**-0.233**	**0.128**	**-0.228**	**-0.442**	**-0.247**	**0.376**	-0.007	**-0.093**	**-0.053**	0.004	**0.134**	**-0.227**
	(-10.42)	**(4.08)**	**(-5.52)**	**(-10.48)**	**(-5.60)**	**(6.99)**	(-0.48)	**(-4.80)**	**(-2.08)**	(0.14)	**(4.94)**	**(-6.87)**
S2	**-0.173**	**0.236**	**-0.111**	**-0.290**	**-0.317**	**0.553**	**-0.024**	**-0.066**	**-0.079**	**-0.078**	**0.075**	**-0.142**
	(-10.38)	**(8.32)**	**(-3.73)**	**(-9.38)**	**(-9.11)**	**(12.38)**	**(-2.35)**	**(-3.80)**	**(-4.30)**	**(-4.08)**	**(3.53)**	**(-5.16)**
S3	0.004	**0.351**	0.029	**-0.214**	**-0.128**	**0.479**	**-0.167**	**-0.136**	**-0.175**	**-0.231**	**-0.098**	-0.037
	(0.18)	**(10.14)**	(0.74)	**(-4.69)**	**(-2.70)**	**(8.64)**	**(-12.12)**	**(-6.38)**	**(-7.19)**	**(-8.23)**	**(-3.36)**	(-1.10)
S1-S3	**-0.237**	**-0.222**	**-0.257**	**-0.228**	**-0.119**		**0.160**	0.043	**0.123**	**0.234**	**0.232**	
	(-9.42)	**(-5.55)**	**(-4.93)**	**(-4.11)**	**(-2.02)**		**(10.36)**	(1.74)	**(3.82)**	**(6.87)**	**(6.41)**	

Panel B: 3×10 Portfolios independently sorted on SKEW and $\Delta O/S$

	All	V1 (Low)	V4	V7	V10 (High)	V1-V10	All	V1	V4	V7	V10	V1-V10
Subpanel B.1: Portfolio alphas												
	Excess return (%)						CAPM alpha (%)					
All	0.104	0.176	0.160	0.081	0.041	**0.136**	-0.004	0.060	0.050	-0.022	-0.063	**0.123**
	(0.85)	(1.29)	(1.27)	(0.68)	(0.33)	**(2.41)**	(-0.09)	(1.08)	(1.12)	(-0.50)	(-1.14)	**(2.25)**
S1 (Flat)	0.174	0.273	**0.319**	0.157	0.179	0.094	0.069	**0.159**	**0.211**	0.058	0.078	0.080
	(1.43)	(1.88)	**(2.42)**	(1.29)	(1.37)	(1.12)	(1.46)	**(2.01)**	**(3.33)**	(0.98)	(1.06)	(0.97)
S2	0.122	0.154	0.134	0.048	0.135	0.019	0.018	0.041	0.030	-0.055	0.034	0.007
	(1.05)	(1.14)	(1.11)	(0.39)	(1.08)	(0.26)	(0.51)	(0.68)	(0.65)	(-1.04)	(0.53)	(0.10)
S3 (Steep)	0.008	0.077	0.033	0.043	-0.216	**0.293**	**-0.106**	-0.043	-0.085	-0.064	**-0.325**	**0.283**
	(0.06)	(0.52)	(0.23)	(0.32)	(-1.52)	**(3.23)**	**(-2.15)**	(-0.56)	(-1.20)	(-0.94)	**(-4.10)**	**(3.14)**
S1-S3	**0.167**	**0.196**	**0.286**	0.114	**0.394**		**0.174**	**0.201**	**0.296**	0.122	**0.403**	
	(3.91)	**(2.24)**	**(3.60)**	(1.50)	**(4.55)**		**(4.16)**	**(2.31)**	**(3.76)**	(1.62)	**(4.68)**	
	Three-factor alpha (%)						Four-factor alpha (%)					
All	-0.037	0.029	0.024	-0.056	**-0.104**	**0.133**	-0.033	0.041	0.032	-0.058	**-0.109**	**0.150**
	(-1.49)	(0.66)	(0.63)	(-1.68)	**(-2.54)**	**(2.44)**	(-1.36)	(1.00)	(0.89)	(-1.72)	**(-2.69)**	**(3.00)**
S1	0.040	0.125	**0.192**	0.034	0.038	0.086	0.040	0.130	**0.199**	0.031	0.029	0.101
	(1.21)	(1.86)	**(3.40)**	(0.64)	(0.61)	(1.04)	(1.22)	(1.95)	**(3.57)**	(0.59)	(0.47)	(1.25)
S2	-0.005	0.022	0.013	-0.083	0.004	0.019	-0.003	0.033	0.018	-0.086	-0.005	0.038
	(-0.20)	(0.42)	(0.30)	(-1.82)	(0.07)	(0.25)	(-0.14)	(0.66)	(0.43)	(-1.90)	(-0.09)	(0.56)
S3	**-0.156**	-0.086	**-0.133**	**-0.118**	**-0.384**	**0.298**	**-0.145**	-0.068	-0.118	-0.115	**-0.380**	**0.312**
	(-4.38)	(-1.25)	**(-2.08)**	**(-1.98)**	**(-5.63)**	**(3.31)**	**(-4.43)**	(-1.05)	(-1.94)	(-1.93)	**(-5.59)**	**(3.54)**
S1-S3	**0.195**	**0.210**	**0.324**	**0.151**	**0.422**		**0.185**	**0.198**	**0.317**	**0.146**	**0.409**	
	(5.00)	**(2.44)**	**(4.24)**	**(2.05)**	**(4.93)**		**(5.03)**	**(2.33)**	**(4.17)**	**(1.99)**	**(4.87)**	
Subpanel B.2: Factor loadings in the four-factor model												
	MKTRF beta						SMB beta					
All	**1.181**	**1.236**	**1.184**	**1.161**	**1.177**	**0.059**	**0.529**	**0.573**	**0.449**	**0.506**	**0.638**	-0.066
	(120.93)	**(74.27)**	**(81.60)**	**(85.54)**	**(71.63)**	**(2.90)**	**(32.61)**	**(20.71)**	**(18.63)**	**(22.44)**	**(23.36)**	(-1.95)
S1	**1.172**	**1.237**	**1.173**	**1.123**	**1.160**	**0.078**	**0.540**	**0.658**	**0.427**	**0.433**	**0.651**	0.007
	(88.68)	**(45.85)**	**(52.05)**	**(52.56)**	**(46.49)**	**(2.38)**	**(24.61)**	**(14.68)**	**(11.40)**	**(12.21)**	**(15.71)**	(0.13)
S2	**1.163**	**1.204**	**1.145**	**1.164**	**1.172**	0.032	**0.418**	**0.451**	**0.322**	**0.451**	**0.516**	-0.065
	(117.87)	**(59.02)**	**(66.91)**	**(63.46)**	**(53.73)**	(1.14)	**(25.47)**	**(13.30)**	**(11.32)**	**(14.80)**	**(14.23)**	(-1.41)
S3	**1.214**	**1.249**	**1.253**	**1.194**	**1.200**	0.049	**0.667**	**0.651**	**0.631**	**0.658**	**0.783**	**-0.132**
	(91.73)	**(47.73)**	**(50.88)**	**(49.76)**	**(43.67)**	(1.36)	**(30.33)**	**(14.98)**	**(15.41)**	**(16.50)**	**(17.15)**	**(-2.23)**
S1-S3	**-0.042**	-0.012	**-0.080**	**-0.071**	-0.041		**-0.126**	0.007	**-0.203**	**-0.224**	**-0.132**	
	(-2.80)	(-0.34)	**(-2.60)**	**(-2.41)**	(-1.20)		**(-5.12)**	(0.12)	**(-3.98)**	**(-4.55)**	**(-2.34)**	
	HML beta						UMD beta					
All	**-0.138**	**-0.280**	**-0.162**	**-0.049**	**-0.098**	**-0.182**	**-0.062**	**-0.188**	**-0.132**	0.019	**0.076**	**-0.265**
	(-8.36)	**(-9.94)**	**(-6.60)**	**(-2.13)**	**(-3.52)**	**(-5.32)**	**(-6.06)**	**(-10.90)**	**(-8.77)**	(1.38)	**(4.46)**	**(-12.60)**
S1	**-0.233**	**-0.337**	**-0.304**	**-0.154**	**-0.139**	**-0.198**	-0.007	**-0.086**	**-0.108**	0.039	**0.144**	**-0.229**
	(-10.42)	**(-7.39)**	**(-7.99)**	**(-4.27)**	**(-3.31)**	**(-3.58)**	(-0.48)	**(-3.05)**	**(-4.61)**	(1.77)	**(5.55)**	**(-6.77)**
S2	**-0.173**	**-0.351**	**-0.151**	**-0.096**	**-0.143**	**-0.207**	**-0.024**	**-0.172**	**-0.082**	**0.050**	**0.136**	**-0.308**
	(-10.38)	**(-10.17)**	**(-5.20)**	**(-3.08)**	**(-3.88)**	**(-4.42)**	**(-2.35)**	**(-8.13)**	**(-4.64)**	**(2.62)**	**(5.99)**	**(-10.67)**
S3	0.004	**-0.154**	-0.001	**0.122**	0.026	**-0.180**	**-0.167**	**-0.280**	**-0.226**	-0.044	-0.055	**-0.224**
	(0.18)	**(-3.48)**	(-0.03)	**(3.00)**	(0.56)	**(-2.99)**	**(-12.12)**	**(-10.29)**	**(-8.84)**	(-1.77)	(-1.94)	**(-6.06)**
S1-S3	**-0.237**	**-0.183**	**-0.303**	**-0.276**	**-0.166**		**0.160**	**0.194**	**0.118**	**0.083**	**0.199**	
	(-9.42)	**(-3.16)**	**(-5.84)**	**(-5.49)**	**(-2.89)**		**(10.36)**	**(5.45)**	**(3.71)**	**(2.71)**	**(5.65)**	

Table 3. Fama-MacBeth regressions

Panel A presents the results from a series of Fama-MacBeth regressions. Each week w, we run the variants of the following cross-sectional regressions of the firm's stock return:

$$RET_{i,w} = a_w + b_w SKEW_{i,w-1} + c_w Z_{i,w-1} + +d_w(Z_{i,w-1} \times SKEW_{i,w-1}) + e'_w \Theta_{i,w-1} + \epsilon_{i,w}.$$

$RET_{i,w}$ is the stock i's return measured over a week w after skipping a trading day following the observation of $SKEW_{i,w-1}$ and $O/S_{i,w-1}$. $SKEW_{i,w-1}$ is volatility skew observed for options on stock i at week $w-1$ and $O/S_{i,w-1}$ is the option to stock volume ratio. $Z_{i,w-1}$ is an O/S-based variable, taking on deciles of $O/S_{i,w-1}$, $O/S_{i,w-1}$itself, or the logarithm of $O/S_{i,w-1}$. Decile portfolios on the basis of $O/S_{i,w-1}$ are formed at the end of week $w-1$, with the highest values located in the 10th decile. $\Theta_{i,w-1}$ is a vector of the following control variables: AMIHUD is the average of daily Amihud (2002) illiquidity ratios over the previous month (multiplied by 10^7); BM represents the firm's book to market ratio; Ln(SIZE) is the log of the firm's market capitalization in millions of dollars; RET_{w-1} is the firm's stock return in the portfolio formation week; MOMENT represents cumulative stock return over the prior six months; HVOL is the historical volatility of stock returns measured over the previous month using daily stock returns. Panel B repeats this analysis using $\Delta O/S$ instead of O/S, where $\Delta O/S$ represents the deviation of O/S from its historical average over the prior six months. $Z_{i,w-1}$ takes on deciles of $\Delta O/S_{i,w-1}$ or $\Delta O/S_{i,w-1}$itself in Panel B. Standard errors are computed across weekly coefficient estimates, following Fama and MacBeth (1973). The resulting t-statistics are shown in parentheses. The notations ***, **, and * indicate that the coefficient is significant at the 1%, 5%, and 10% level, respectively. All returns are shown as percentages. The last row provides the average adjusted R^2 from the weekly regressions.

Panel A: Using O/S to measure options volume

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Intercept	0.454**	0.356*	0.459**	0.406**	0.343*	0.448**	0.444**	0.343*	0.448**	0.427**
	(2.25)	(1.79)	(2.30)	(2.04)	(1.71)	(2.22)	(2.22)	(1.71)	(2.23)	(2.14)
SKEW	-1.309***		-1.306***	-0.283		-1.289***	-0.980***		-1.302***	-0.690***
	(-5.57)		(-5.58)	(-0.83)		(-5.47)	(-3.91)		(-5.54)	(-2.59)
Decile (O/S)		-0.011**	-0.010*	0.003						
		(-1.99)	(-1.82)	(0.42)						
Decile (O/S) × SKEW				-0.195***						
				(-3.26)						
O/S					-0.393**	-0.324*	0.021			
					(-2.00)	(-1.65)	(0.08)			
O/S × SKEW							-4.875**			
							(-2.15)			
Ln (O/S)								-0.031**	-0.029*	0.007
								(-1.97)	(-1.80)	(0.36)
Ln (O/S) × SKEW										-0.504***
										(-3.36)
AMIHUD	-0.270	-0.640	-0.228	-0.215	-0.648	-0.240	-0.223	-0.630	-0.218	-0.210
	(-0.54)	(-1.30)	(-0.45)	(-0.42)	(-1.33)	(-0.48)	(-0.44)	(-1.28)	(-0.43)	(-0.41)
BM	0.008	-0.005	0.000	0.001	-0.003	0.002	0.001	-0.005	0.000	0.001
	(0.13)	(-0.07)	(0.01)	(0.02)	(-0.04)	(0.04)	(0.02)	(-0.08)	(0.00)	(0.01)
Ln(SIZE)	-0.020	-0.011	-0.015	-0.017	-0.013	-0.017	-0.019	-0.011	-0.016	-0.018
	(-1.10)	(-0.56)	(-0.81)	(-0.90)	(-0.69)	(-0.94)	(-1.02)	(-0.59)	(-0.83)	(-0.94)
$WRET_{t-1}$	-0.016***	-0.016***	-0.016***	-0.016***	-0.016***	-0.016***	-0.016***	-0.016***	-0.016***	-0.016***
	(-4.91)	(-4.80)	(-4.86)	(-4.94)	(-4.82)	(-4.88)	(-4.93)	(-4.81)	(-4.88)	(-4.96)
MOMENT	0.000	0.001	0.000	0.000	0.001	0.000	0.001	0.001	0.000	0.000
	(0.41)	(0.57)	(0.44)	(0.42)	(0.59)	(0.46)	(0.47)	(0.57)	(0.44)	(0.43)
HVOL	-0.156	-0.138	-0.132	-0.137	-0.147	-0.142	-0.149	-0.138	-0.132	-0.140
	(-1.22)	(-1.11)	(-1.06)	(-1.10)	(-1.15)	(-1.11)	(-1.17)	(-1.10)	(-1.06)	(-1.12)
Adj-R^2(%)	7.613	7.614	7.812	7.939	7.615	7.813	8.018	7.612	7.811	7.935

Panel B: Using $\Delta O/S$ as option volume measure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	0.454**	0.396*	0.500**	0.443**	0.361*	0.465**	0.471**
	(2.25)	(1.90)	(2.39)	(2.11)	(1.79)	(2.30)	(2.33)
SKEW	-1.309***		-1.318***	-0.570		-1.307***	-1.270***
	(-5.57)		(-5.62)	(-1.27)		(-5.55)	(-5.33)
Decile (ΔO/S)		-0.008**	-0.007*	0.003			
		(-1.98)	(-1.89)	(0.63)			
Decile(ΔO/S) × SKEW				-0.136**			
				(-2.10)			
ΔO/S					-0.552***	-0.512***	0.123
					(-2.93)	(-2.76)	(0.42)
ΔO/S × SKEW							-7.633**
							(-2.33)
AMIHUD	-0.270	-0.637	-0.227	-0.243	-0.624	-0.219	-0.223
	(-0.54)	(-1.30)	(-0.45)	(-0.48)	(-1.28)	(-0.44)	(-0.44)
BM	0.008	0.003	0.008	0.005	0.003	0.007	0.004
	(0.13)	(0.05)	(0.12)	(0.08)	(0.04)	(0.11)	(0.06)
Ln(SIZE)	-0.020	-0.017	-0.021	-0.021	-0.017	-0.021	-0.022
	(-1.10)	(-0.90)	(-1.13)	(-1.14)	(-0.91)	(-1.14)	(-1.18)
RET_{w-1}	-0.016***	-0.016***	-0.016***	-0.016***	-0.016***	-0.016***	-0.016***
	(-4.91)	(-4.82)	(-4.88)	(-4.89)	(-4.84)	(-4.90)	(-4.91)
MOMENT	0.000	0.001	0.001	0.001	0.001	0.001	0.001
	(0.41)	(0.63)	(0.50)	(0.51)	(0.62)	(0.49)	(0.49)
HVOL	-0.156	-0.167	-0.159	-0.161	-0.165	-0.158	-0.158
	(-1.22)	(-1.31)	(-1.25)	(-1.26)	(-1.29)	(-1.23)	(-1.24)
Adj-R^2(%)	7.613	7.470	7.669	7.823	7.524	7.724	7.956

Table 4. Fama-MacBeth regressions using dummy variables for volatility smirk groups

Panel A presents the results from a series of Fama-MacBeth regressions using dummy variables for skew terciles. Each week w, we run the variants of the following cross-sectional regressions of the firm's stock return:

$$RET_{i,w} = a_w + b_{1w}SKEW\ \text{1st}\ Dum_{i,w-1} + b_{2w}SKEW\ \text{3rd}\ Dum_{i,w-1} + c_w Z_{i,w-1} + d_{1w}\left(Z_{i,w-1} \times SKEW\ \text{1st}\ Dum_{i,w-1}\right) + d_{2w}\left(Z_{i,w-1} \times SKEW\ \text{3rd}\ Dum_{i,w-1}\right) + e'_w \Theta_{i,w-1} + \epsilon_{i,w}\ .$$

$RET_{i,w}$ is the stock i's return measured over a week w as in Table 3. $SKEW$ 1st $Dum_{i,w-1}$ ($SKEW$ 3rd $Dum_{i,w-1}$) is a dummy variable that takes the value of one if the stock i's $SKEW_{i,w-1}$ belongs to the bottom (top) 30% of all ranked values of $SKEW_{i,w-1}$ and zero otherwise. $SKEW_{i,w-1}$ is the difference between the implied volatilities of an OTM put and an ATM call on stock i at week $w-1$. $Z_{i,w-1}$ is an O/S-based variable, taking on deciles of $O/S_{i,w-1}$, $O/S_{i,w-1}$itself, or the logarithm of $O/S_{i,w-1}$, where $O/S_{i,w-1}$ is the option to stock volume ratio. Decile portfolios of O/S are formed independently from the three SKEW groups as in Panel B of Table 1. $\Theta_{i,w-1}$ is a vector of the control variables which are defined in Table 3. Panel B repeats this analysis using $\Delta O/S$ instead of O/S, where $\Delta O/S$ represents the deviation of O/S from its historical average over the prior six months. $Z_{i,w-1}$ takes on deciles of $\Delta O/S_{i,w-1}$ or $\Delta O/S_{i,w-1}$itself in Panel B. Standard errors are computed across weekly coefficient estimates, following Fama and MacBeth (1973). The resulting t-statistics are shown in parentheses. The notations ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. All returns are shown as percentages. The last row provides the average adjusted R^2 from the weekly regressions.

Panel A: Using O/S as option volume measure

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.186*	0.373*	0.179	0.397*	0.181*	0.383*
	(1.79)	(1.87)	(1.63)	(1.96)	(1.74)	(1.91)
SKEW 1st Dum	0.102***	0.096***	0.073**	0.071**	0.088***	0.078***
	(2.62)	(2.60)	(2.26)	(2.54)	(2.89)	(2.89)
SKEW 3rd Dum	0.047	0.058	-0.057	-0.041	-0.008	0.007
	(0.90)	(1.29)	(-1.44)	(-1.45)	(-0.19)	(0.22)
Decile (O/S)	-0.002	0.001				
	(-0.22)	(0.12)				
Decile (O/S) × (SKEW 1st Dum)	-0.009	-0.009				
	(-1.21)	(-1.30)				
Decile (O/S) × (SKEW 3rd Dum)	-0.031***	-0.030***				
	(-3.48)	(-3.33)				
O/S			-0.026	0.064		
			(-0.08)	(0.22)		
O/S × (SKEW 1st Dum)			-0.348	-0.468		
			(-0.90)	(-1.30)		
O/S × (SKEW 3rd Dum)			-0.848**	-0.966**		
			(-2.20)	(-2.56)		
Ln (O/S)					-0.004	0.004
					(-0.17)	(0.20)
Ln (O/S)× (SKEW 1st Dum)					-0.025	-0.023
					(-1.30)	(-1.28)
Ln (O/S)× (SKEW 3rd Dum)					-0.083***	-0.086***
					(-3.56)	(-3.60)
AMIHUD		-0.552		-0.564		-0.539
		(-1.11)		(-1.14)		(-1.08)
BM		-0.004		-0.004		-0.005
		(-0.07)		(-0.06)		(-0.08)
Ln(SIZE)		-0.019		-0.021		-0.020
		(-1.00)		(-1.11)		(-1.04)
RET_{w-1}		-0.016***		-0.016***		-0.016***
		(-4.89)		(-4.93)		(-4.91)
MOMENT		0.000		0.001		0.000
		(0.46)		(0.48)		(0.46)
HVOL		-0.136		-0.141		-0.136
		(-1.10)		(-1.12)		(-1.10)
Adj-R^2(%)	0.814	7.795	0.832	7.891	0.809	7.786

Panel B: Using $\Delta O/S$ to measure options volume

	(1)	(2)	(3)	(4)
Intercept	0.173	0.404*	0.179	0.422**
	(1.40)	(1.90)	(1.57)	(2.07)
SKEW 1st Dum	0.086*	0.083**	0.054*	0.048**
	(1.83)	(2.00)	(1.87)	(2.18)
SKEW 3rd Dum	0.015	0.022	-0.104***	-0.094***
	(0.29)	(0.49)	(-2.69)	(-3.23)
Decile (ΔO/S)	0.000	0.002		
	(0.06)	(0.33)		
Decile (ΔO/S) × (SKEW 1st Dum)	-0.006	-0.006		
	(-0.85)	(-0.98)		
Decile (ΔO/S) × (SKEW 3rd Dum)	-0.024***	-0.023***		
	(-3.24)	(-3.16)		
ΔO/S			-0.042	0.160
			(-0.14)	(0.55)
ΔO/S × (SKEW 1st Dum)			-0.221	-0.437
			(-0.49)	(-1.09)
ΔO/S × (SKEW 3rd Dum)			-1.381***	-1.472***
			(-3.02)	(-3.29)
AMIHUD		-0.561		-0.546
		(-1.13)		(-1.10)
BM		0.002		0.000
		(0.03)		(-0.00)
Ln(SIZE)		-0.022		-0.023
		(-1.20)		(-1.25)
RET_{w-1}		-0.016***		-0.016***
		(-4.87)		(-4.89)
MOMENT		0.001		0.001
		(0.54)		(0.54)
HVOL		-0.159		-0.157
		(-1.25)		(-1.23)
		0.2119		0.2189
Adj-R^2(%)	0.688	7.651	0.774	7.813

Table 5. How long does the predictability last?

Panel A presents the estimates from Fama-MacBeth regression. Each week w, we run the following cross-sectional regressions of the firm's n-week-ahead weekly stock return:

$$RET_{i,w+n} = a_w + b_w SKEW_{i,w} + c_w Decile(O/S_{i,w}) + +d_w\big(Decile(O/S_{i,w}) \times SKEW_{i,w}\big) + e_w'\Theta_{i,w} + \epsilon_{i,w+n},$$

$RET_{i,w+n}$ is the stock i's return measured over the n^{th} week after the observation of $SKEW_{i,w}$ and $O/S_{i,w}$, where n ranges from 1 to 12. $SKEW_{i,w}$ is the difference between the implied volatilities of an OTM put and an ATM call on stock i observed at week w and $O/S_{i,w}$ is the option to stock volume ratio. Decile portfolios based on O/S are formed at the end of each week, with the highest values located in the 10^{th} decile. $\Theta_{i,w-1}$ is a vector of the control variables defined in Table 3. Panel B repeats this analysis using $\Delta O/S$ instead of O/S, where $\Delta O/S$ represents the deviation of O/S from its historical average over the prior six months. Coefficients on the control variables are estimated but not reported. Standard errors are computed across weekly coefficient estimates, following Fama and MacBeth (1973). The resulting t-statistics are shown in parentheses. The notations ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. All returns are shown as percentages. The last row provides the average adjusted R^2 from the weekly regressions.

Panel A: Using O/S to measure option volume

	n^{th} Week											
	1	2	3	4	5	6	7	8	9	10	11	12
Intercept	0.406**	0.467**	0.436**	0.352*	0.393*	0.395**	0.334	0.252	0.280	0.241	0.385*	0.177
	(2.04)	(2.34)	(2.22)	(1.79)	(1.89)	(1.97)	(1.62)	(1.23)	(1.48)	(1.26)	(1.93)	(0.87)
SKEW	-0.283	0.114	0.076	0.112	-0.342	-0.326	0.048	-0.169	0.224	0.792**	0.243	0.326
	(-0.83)	(0.37)	(0.20)	(0.32)	(-1.04)	(-0.97)	(0.13)	(-0.45)	(0.63)	(2.16)	(0.66)	(0.89)
Decile (O/S)	0.003	-0.005	-0.006	0.000	-0.004	-0.006	-0.003	-0.006	-0.002	0.006	0.002	0.004
	(0.42)	(-0.83)	(-0.74)	(0.03)	(-0.57)	(-0.82)	(-0.41)	(-0.86)	(-0.30)	(0.86)	(0.26)	(0.56)
Decile (O/S) × SKEW	-0.195***	-0.144**	-0.150**	-0.147**	-0.085	-0.085	-0.112*	-0.067	-0.150**	-0.237***	-0.172***	-0.195***
	(-3.26)	(-2.58)	(-2.23)	(-2.24)	(-1.40)	(-1.37)	(-1.77)	(-1.10)	(-2.36)	(-3.75)	(-2.67)	(-3.11)
Adj-R^2 (%)	7.939	7.759	7.563	7.659	7.398	7.286	7.217	7.228	7.057	7.000	6.948	6.909

Panel B: Using $\Delta O/S$ as option volume measure

	n^{th} Week											
	1	2	3	4	5	6	7	8	9	10	11	12
Intercept	0.443**	0.539***	0.469**	0.408**	0.440**	0.450**	0.382*	0.290	0.348*	0.259	0.408*	0.170
	(2.11)	(2.59)	(2.25)	(1.97)	(2.06)	(2.14)	(1.76)	(1.34)	(1.73)	(1.28)	(1.94)	(0.80)
SKEW	-0.570	-0.362	-0.332	-0.296	-0.615	-0.793	-0.278	-0.684	-0.583	0.483	0.188	-0.146
	(-1.27)	(-0.89)	(-0.67)	(-0.69)	(-1.37)	(-1.65)	(-0.56)	(-1.27)	(-1.20)	(0.91)	(0.39)	(-0.30)
Decile (ΔO/S)	0.003	-0.006	-0.003	-0.005	-0.004	-0.007	-0.004	-0.004	-0.007	0.008	0.004	0.008
	(0.63)	(-0.95)	(-0.64)	(-1.04)	(-0.88)	(-1.41)	(-0.70)	(-0.62)	(-1.23)	(1.37)	(0.66)	(1.30)
Decile (ΔO/S) × SKEW	-0.136**	-0.058	-0.056	-0.057	-0.035	0.001	-0.038	0.019	-0.003	-0.165**	-0.138**	-0.106
	(-2.10)	(-0.91)	(-0.82)	(-0.96)	(-0.53)	(0.02)	(-0.55)	(0.25)	(-0.04)	(-2.40)	(-2.06)	(-1.58)
Adj-R^2 (%)	7.823	7.620	7.409	7.518	7.302	7.202	7.149	7.178	6.964	6.923	6.873	6.807

Table 6. Returns on portfolios formed on volatility smirk and option volume: Robustness Tests

This table presents several robustness checks on our results with the portfolio approach. In Subpanel A.1, we repeat the analysis in Panel A of Table 2 for two sub-periods: the first spans 1996 to 2003, and the second covers 2004 to 2012. In Subpanel A.2, we repeat the analysis in Panel A of Table 2 using an independent sort by the five SKEW and five O/S groups. Panel B repeats this analysis using $\Delta O/S$ instead of O/S. The reported values are alphas from Fama-French's (1993) three-factor model. All alphas are shown as percentages and t-statistics are in parentheses (bold if significant at the 5% level).

Panel A: Using O/S to measure options volume

Subpanel A.1: Subsample Results

	All	V1 (Low)	V4	V7	V10 (High)	V1-V10	All	V1	V4	V7	V10	V1-V10
	Sample period: 1996-2003						Sample period: 2004-2012					
All	-0.078	-0.024	-0.036	-0.045	-0.131	0.107	-0.001	0.037	0.018	0.021	**-0.096**	**0.133**
	(-1.67)	(-0.37)	(-0.51)	(-0.60)	(-1.82)	(1.17)	(-0.05)	(1.33)	(0.57)	(0.61)	**(-2.02)**	**(2.46)**
S1 (Flat)	0.000	0.034	**0.232**	0.133	-0.126	0.159	**0.075**	0.077	0.095	0.087	0.064	0.013
	(0.01)	(0.40)	**(2.03)**	(1.16)	(-1.11)	(1.12)	**(2.24)**	(1.63)	(1.68)	(1.54)	(0.86)	(0.15)
S2	-0.037	-0.116	-0.103	-0.069	0.077	-0.193	0.026	0.076	0.052	0.065	-0.016	0.092
	(-0.80)	(-1.55)	(-1.21)	(-0.81)	(0.90)	(-1.73)	(1.14)	(1.96)	(1.35)	(1.56)	(-0.27)	(1.30)
S3 (Steep)	**-0.211**	0.007	**-0.258**	-0.217	**-0.457**	**0.463**	**-0.114**	-0.038	-0.081	-0.116	**-0.350**	**0.312**
	(-3.17)	(0.07)	**(-2.30)**	(-1.74)	**(-3.82)**	**(3.26)**	**(-3.49)**	(-0.84)	(-1.39)	(-1.64)	**(-4.32)**	**(3.55)**
S1-S3	**0.212**	0.027	**0.490**	**0.350**	**0.331**		**0.190**	0.115	**0.177**	**0.203**	**0.414**	
	(3.17)	(0.26)	**(3.52)**	**(2.32)**	**(2.18)**		**(4.22)**	(1.79)	**(2.17)**	**(2.31)**	**(4.06)**	

Subpanel A.2: 5×5 Portfolios on SKEW and O/S

	All	V1 (Low)	V2	V3	V4	V5 (High)	V1-V5
All	-0.037	-0.004	0.017	-0.034	-0.060	**-0.102**	**0.098**
	(-1.49)	(-0.15)	(0.55)	(-1.02)	(-1.78)	**(-2.83)**	**(2.23)**
S1 (Flat)	0.050	0.060	**0.170**	0.043	0.018	0.001	0.059
	(1.35)	(1.35)	**(3.10)**	(0.74)	(0.30)	(0.02)	(0.82)
S2	0.033	0.000	0.084	0.013	0.053	0.026	-0.026
	(1.15)	(-0.00)	(1.90)	(0.28)	(1.10)	(0.48)	(-0.36)
S3	-0.001	-0.010	-0.009	-0.001	0.004	-0.017	0.007
	(-0.04)	(-0.22)	(-0.19)	(-0.02)	(0.10)	(-0.34)	(0.11)
S4	-0.058	-0.014	0.020	-0.085	-0.102	-0.101	0.087
	(-1.89)	(-0.31)	(0.41)	(-1.73)	(-1.92)	(-1.81)	(1.23)
S5 (Steep)	**-0.207**	-0.057	**-0.161**	**-0.138**	**-0.291**	**-0.421**	**0.364**
	(-5.03)	(-1.09)	**(-2.86)**	**(-2.25)**	**(-4.19)**	**(-6.29)**	**(4.90)**
S1-S5	**0.257**	0.117	**0.331**	**0.181**	**0.309**	**0.423**	
	(5.69)	(1.93)	**(4.85)**	**(2.49)**	**(3.66)**	**(4.82)**	

Panel B: Using $\Delta O/S$ to measure options volume

Subpanel B.1: Subsample Results

	All	V1 (Low)	V4	V7	V10 (High)	V1-V10	All	V1	V4	V7	V10	V1-V10
	Sample period: 1996-2003						Sample period: 2004-2012					
All	-0.078	0.039	-0.013	**-0.140**	-0.130	0.169	-0.001	0.032	0.054	0.011	**-0.087**	**0.119**
	(-1.67)	(0.53)	(-0.18)	**(-2.19)**	(-1.70)	(1.70)	(-0.05)	(0.66)	(1.70)	(0.36)	**(-2.13)**	**(2.13)**
S1 (Flat)	0.000	0.081	0.203	-0.097	0.074	0.007	**0.075**	**0.165**	**0.190**	**0.143**	0.004	0.161
	(0.01)	(0.67)	(1.86)	(-0.96)	(0.65)	(0.05)	**(2.24)**	**(2.42)**	**(3.77)**	**(2.90)**	(0.05)	(1.90)
S2	-0.037	0.039	-0.040	**-0.213**	0.015	0.024	0.026	0.023	0.055	0.030	-0.005	0.027
	(-0.80)	(0.45)	(-0.48)	**(-2.46)**	(0.15)	(0.18)	(1.14)	(0.36)	(1.38)	(0.71)	(-0.09)	(0.35)
S3 (Steep)	**-0.211**	-0.054	-0.192	-0.127	**-0.507**	**0.454**	**-0.114**	-0.106	-0.091	**-0.122**	**-0.284**	**0.178**
	(-3.17)	(-0.44)	(-1.58)	(-1.11)	**(-4.09)**	**(2.73)**	**(-3.49)**	(-1.43)	(-1.58)	**(-2.28)**	**(-4.00)**	**(1.98)**
S1-S3	**0.212**	0.135	**0.395**	0.030	**0.581**		**0.190**	**0.271**	**0.280**	**0.265**	**0.288**	
	(3.17)	(0.86)	**(2.74)**	(0.22)	**(3.80)**		**(4.22)**	**(2.97)**	**(3.78)**	**(3.81)**	**(3.09)**	

Subpanel B.2: 5×5 Portfolios on SKEW and ΔO/S

	All	V1 (Low)	V2	V3	V4	V5 (High)	V1-V5
All	-0.037	-0.014	-0.010	-0.032	-0.036	**-0.092**	0.078
	(-1.49)	(-0.36)	(-0.29)	(-1.11)	(-1.18)	**(-2.77)**	(1.76)
S1 (Flat)	0.050	0.081	0.105	0.023	0.030	0.010	0.071
	(1.35)	(1.27)	(1.77)	(0.46)	(0.58)	(0.17)	(0.94)
S2	0.033	0.032	0.042	0.006	0.064	0.034	-0.002
	(1.15)	(0.65)	(0.91)	(0.13)	(1.37)	(0.67)	(-0.03)
S3	-0.001	-0.022	0.030	-0.040	-0.002	0.024	-0.047
	(-0.04)	(-0.44)	(0.69)	(-0.96)	(-0.05)	(0.49)	(-0.67)
S4	-0.058	-0.036	-0.079	-0.004	-0.057	-0.094	0.058
	(-1.89)	(-0.67)	(-1.68)	(-0.08)	(-1.12)	(-1.80)	(0.84)
S5 (Steep)	**-0.207**	**-0.130**	**-0.128**	**-0.168**	**-0.201**	**-0.395**	**0.265**
	(-5.03)	**(-1.97)**	**(-2.02)**	**(-3.00)**	**(-3.47)**	**(-6.64)**	**(3.51)**
S1-S5	**0.257**	**0.211**	**0.232**	**0.192**	**0.231**	**0.405**	
	(5.69)	**(2.69)**	**(3.10)**	**(2.74)**	**(3.31)**	**(5.16)**	

Table 7. Earnings Surprises

This table contains a series of Fama-MacBeth regressions, where we regress the upcoming earnings surprise on SKEW, deciles of O/S, and their interaction term, separately and together. SKEW is the difference between the implied volatilities of an OTM put and an ATM call. O/S is the ratio of options volume to stock volume. Other explanatory variables considered in Tables 3 through 5 are also included in the estimation. We use four measures to capture the news released at earnings announcements:

$$\text{SURPRISE1} = \frac{EPS_t - \widehat{EPS}_t}{P_{t-1}}, \quad \text{SURPRISE2} = \frac{EPS_t - \widehat{EPS}_t}{STD\{EPS_k - \widehat{EPS}_k\}_{k=t-1}^{t-8}}, \quad \text{SUE1} = \frac{EPS_t - EPS_{t-4}}{P_{t-1}}, \quad \text{SUE2} = \frac{EPS_t - EPS_{t-4}}{STD\{EPS_k - EPS_{k-4}\}_{k=t-1}^{t-8}}$$

where EPS_t is the firm's actual earnings per share (EPS) for quarter t, $\widehat{EPS}_t$ the analyst consensus forecast on EPS for quarter t, EPS_{t-4} EPS for the same quarter of the previous fiscal year, P_{t-1} the beginning-of-quarter stock price, $STD\{x_k\}_{k=t-1}^{t-8}$ the standard deviation of *x* over the prior eight quarters. Standard errors are computed across weekly coefficient estimates, following Fama and MacBeth (1973). The resulting t-statistics are shown in parentheses. The notations ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. All returns are shown as percentages. The last row provides the average adjusted R^2 from the weekly regressions.

	SURPRISE1			SURPRISE2			SUE1			SUE2		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Intercept	-0.122***	-0.144***	-0.131***	-0.068	-0.171*	-0.102	0.280**	0.212*	0.235*	0.482***	0.396***	0.454***
	(-4.94)	(-6.00)	(-5.31)	(-0.73)	(-1.86)	(-1.12)	(2.18)	(1.72)	(1.85)	(4.10)	(3.40)	(3.88)
SKEW	-0.378***		-0.077	-1.637***		-0.465**	-1.293***		-0.376	-1.273***		-0.664***
	(-8.07)		(-1.31)	(-12.15)		(-2.55)	(-5.65)		(-1.45)	(-8.92)		(-3.04)
Decile (O/S)		-0.008***	-0.004***		-0.022***	-0.006*		-0.018***	-0.007**		-0.007*	0.001
		(-11.42)	(-3.82)		(-8.19)	(-1.75)		(-5.23)	(-2.00)		(-1.70)	(0.19)
Decile(O/S) × SKEW			-0.060***			-0.232***			-0.168***			-0.113***
			(-4.88)			(-5.91)			(-3.49)			(-3.14)
AMIHUD	-2.091***	-2.120***	-2.046***	-8.468***	-8.740***	-8.357***	-0.865**	-1.125***	-0.717**	-2.127***	-2.533***	-2.050***
	(-14.50)	(-13.99)	(-14.24)	(-17.15)	(-16.75)	(-16.96)	(-2.45)	(-3.09)	(-1.96)	(-7.02)	(-7.94)	(-6.51)
BM	0.050***	0.042***	0.045***	-0.208***	-0.234***	-0.225***	-0.170**	-0.194***	-0.185*	-0.713***	-0.728***	-0.724***
	(5.28)	(4.22)	(4.66)	(-8.59)	(-9.23)	(-9.04)	(-2.42)	(-2.64)	(-2.58)	(-16.84)	(-16.64)	(-16.73)
Ln(SIZE)	0.016***	0.021***	0.019***	0.101***	0.116***	0.107***	-0.002	0.010	0.006	0.090***	0.097***	0.092***
	(7.75)	(9.88)	(8.89)	(11.14)	(12.08)	(11.34)	(-0.23)	(1.04)	(0.60)	(6.93)	(6.95)	(6.61)
RET_{w-1}	0.002***	0.002***	0.002***	0.012***	0.012***	0.012***	0.010***	0.010***	0.010***	0.012***	0.012***	0.012***
	(8.72)	(8.94)	(9.08)	(13.29)	(13.74)	(13.72)	(7.87)	(8.19)	(8.06)	(11.78)	(11.93)	(11.91)
MOMENT	0.001***	0.001***	0.001***	0.004***	0.004***	0.004***	0.011***	0.011***	0.011***	0.011***	0.011***	0.011***
	(5.60)	(6.43)	(6.00)	(9.77)	(10.34)	(10.00)	(15.78)	(15.91)	(15.72)	(19.32)	(19.27)	(19.22)
HVOL	-0.002	0.006	0.013	-0.156***	-0.137***	-0.112**	-0.291***	-0.279***	-0.240***	-0.775***	-0.775***	-0.756***
	(-0.11)	(0.44)	(0.97)	(-3.55)	(-3.14)	(-2.59)	(-3.26)	(-3.12)	(-2.75)	(-13.45)	(-13.81)	(-13.43)
Adj-R^2(%)	4.138	3.957	4.526	4.706	4.553	4.895	6.244	5.959	6.596	7.373	7.345	7.639

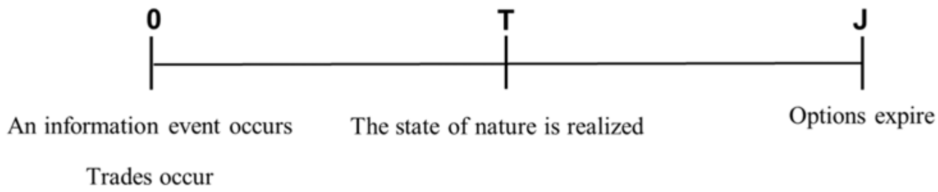


Fig. 1. Time points in the model

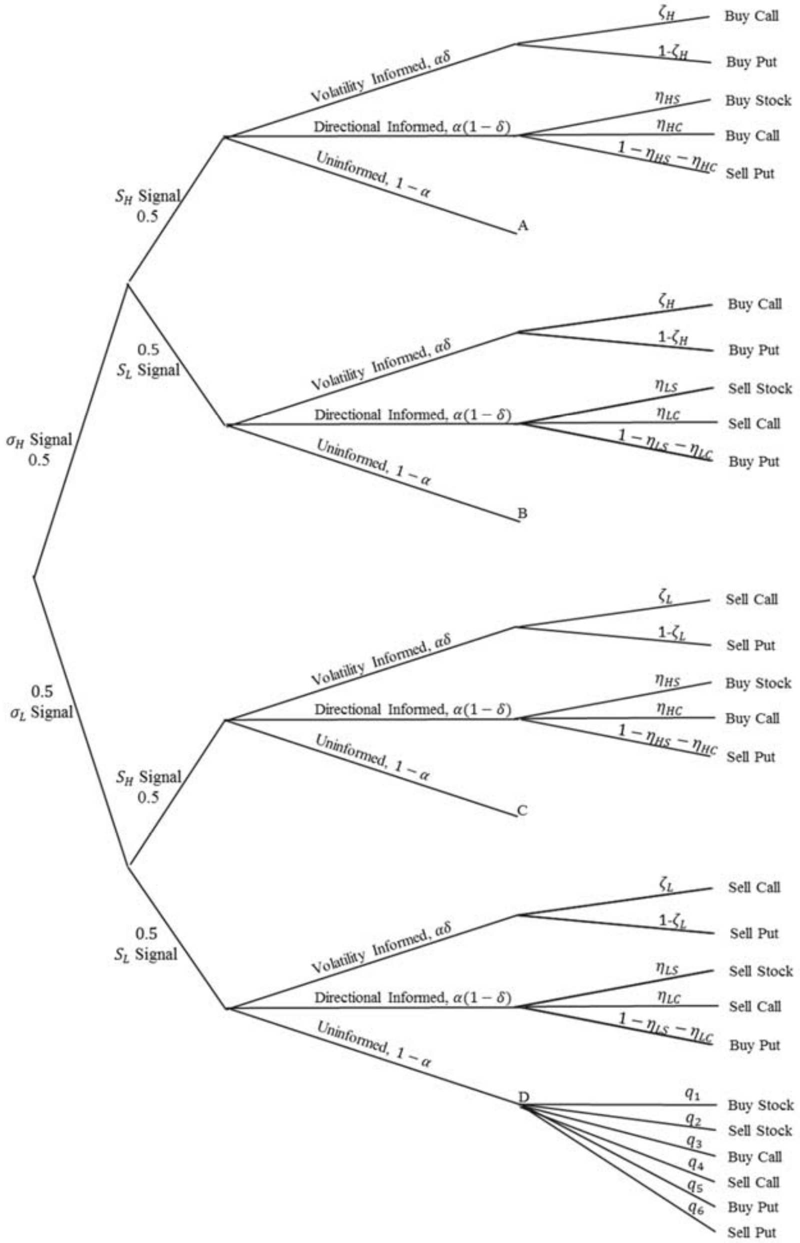
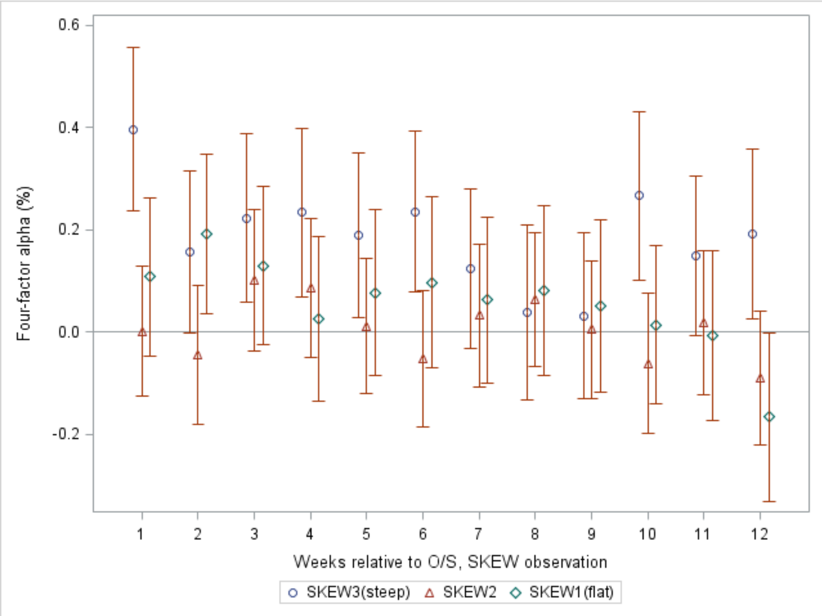


Fig. 2. Trading structure at the initial time point

The tree diagram represents the probabilistic structure of trading at the initial time point. The first two nodes reflect nature's draw for volatility and directional information events. Subsequent nodes reflect trader selection probabilities. The variable α is the fraction of the universe of traders who are informed, and $1-\alpha$ are uninformed; δ is the fraction of the universe of informed traders who have the volatility information, and $1-\delta$ are informed of directional information; ζ_v is the fraction of the volatility informed who choose to trade calls, and $1-\zeta_v$ choose to trade puts; η_{dS} is the fraction of the directional informed who choose to trade in the stock market, η_{dC} choose to trade calls, and $1-\eta_{dS}-\eta_{dC}$ choose to trade puts; q_1, q_2, q_3, q_4, q_5, and q_6 are the factions of the uninformed to buy or sell the stock, calls, or puts. The probabilities of trades are the same at each uninformed node A, B, C, and D.



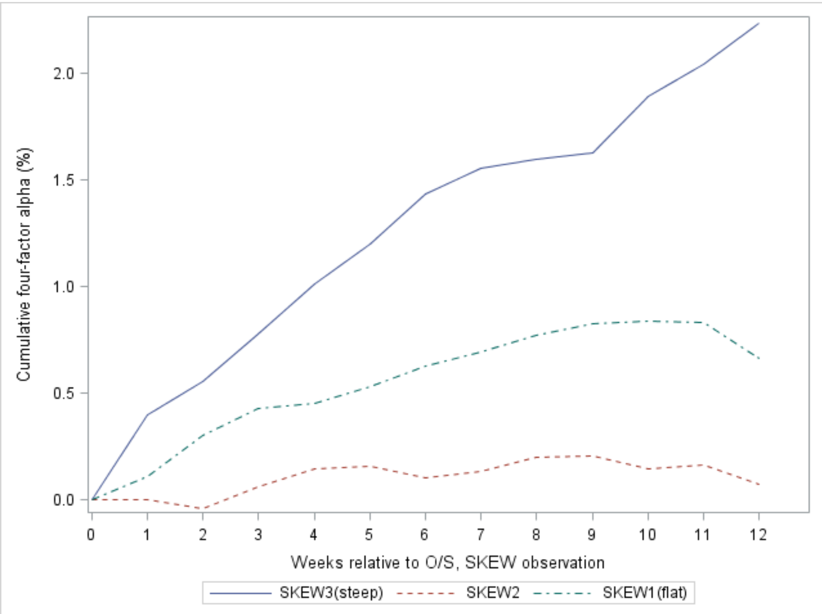
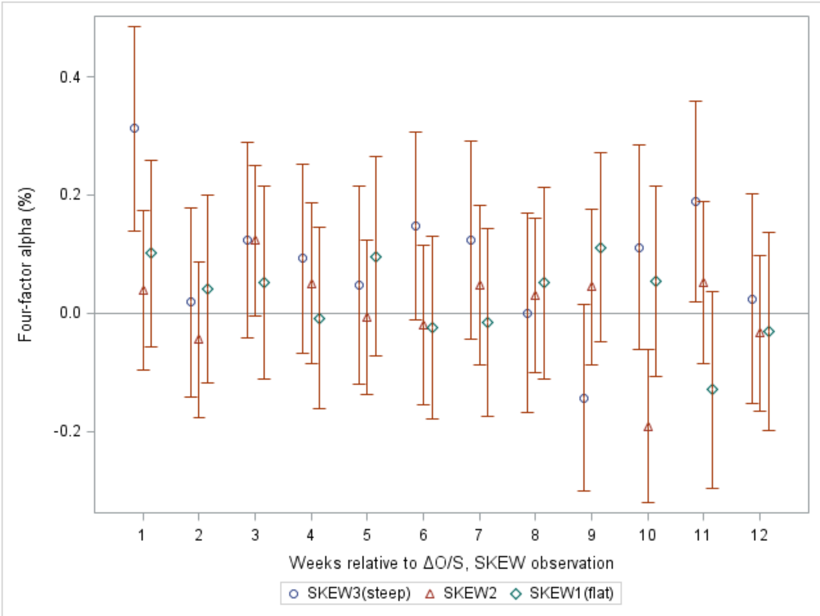


Fig. 3. Persistence of O/S-return relation by SKEW tercile.

This figure shows for each SKEW tercile S1 to S3, the four-factor alphas of the O/S long-short strategies over a twelve week period after portfolio formation. SKEW is the difference between the implied volatilities of an OTM put and an ATM call. O/S equals the ratio of options volume to stock volume. Portfolios are formed based on an independent sort by the three SKEW and ten O/S groups, as in Panel B of Table 1. Stocks in S1 have the lowest SKEW, while stocks in S3 have the highest SKEW. Stocks in V1 have the lowest O/S, while stocks in V10 have the highest O/S. The O/S long-short strategy involves buying the lowest O/S decile (V1) and selling the highest O/S decile (V10). The top graph shows weekly alphas, along with the 95% confidence interval. The bottom graph shows cumulative alphas. Alphas are shown as percentages.



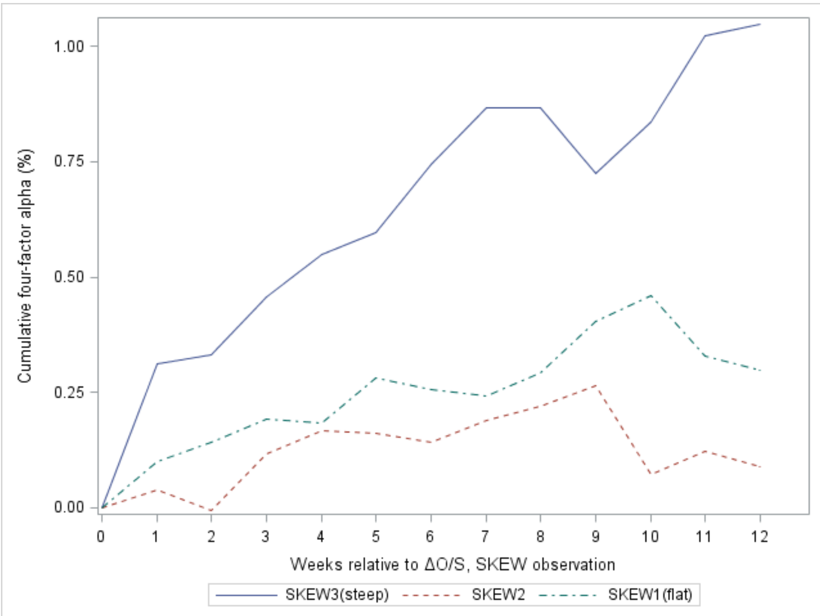


Fig. 4. Persistence of ΔO/S-return relation by SKEW tercile.

This figure presents for each SKEW tercile S1 to S3, the four-factor alphas of the ΔO/S long-short strategies over a twelve week period after portfolio formation. SKEW is the difference between the implied volatilities of an OTM put and an ATM call. O/S is the ratio of options volume to stock volume and ΔO/S equals the deviation of O/S from its historical average over the previous six months. Portfolios are formed based on an independent sort by the three SKEW and ten ΔO/S groups. Stocks in S1 have the lowest SKEW, while stocks in S3 have the highest SKEW. Stocks in V1 have the lowest ΔO/S, while stocks in V10 have the highest ΔO/S. The ΔO/S long-short strategy involves buying the lowest ΔO/S decile (V1) and selling the highest ΔO/S decile (V10). The top graph shows weekly alphas, along with the 95% confidence interval. The bottom graph shows cumulative alphas. Alphas are shown as percentages.