The Idiosyncratic Volatility Puzzle and its Interplay with Sophisticated and Private Investors

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We establish a direct link between the idiosyncratic volatility (IVol) puzzle and the behavior of sophisticated and private investors. To do so, we employ three option-based measures of informed trading and attention data from Google Trends. Our analyses show that the IVol puzzle is particularly driven by a group of overpriced stocks that can be identified by the use of sophisticated trader opinion. Since IVol is no perfect mispricing indicator, the option measures can help to distinguish high-IVol stocks that are overvalued from high-IVol stocks that are not exposed to mispricing. We link the origin of the anomaly to the trading activity of irrational private investors. This supports the intuitive idea that noise trading leads to mispricing which can be exploited by sophisticated investors at the option market.

Keywords: Demand-Based Option Pricing, Idiosyncratic Volatility, Investor Attention

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1. Introduction

Market anomalies tend to be weaker when sophisticated investors trade against mispricing, while they tend to be stronger when many irrational traders are present (De Long et al., 1990; Shleifer and Vishny, 1997; Brav and Heaton, 2002). We find support for these theoretical conjectures, combining three informed trading measures calculated from option prices and the investor attention measure by Da et al. (2011). We show that the strength of the idiosyncratic volatility (IVol) puzzle depends on the opinion of sophisticated informed investors while the origin of the anomaly can be linked to the attention of irrational private investors. So far, research has paid surprisingly little attention to the relation between the trading behavior of different investor types and the well-known IVol puzzle. In conclusion, our findings support and extend behavioral explanations for the IVol puzzle.

The IVol puzzle dates back to Ang et al. (2006) who were the first documenting a negative relation between idiosyncratic volatility and subsequent stock returns. Our analysis reveals that the IVol puzzle is also statistically and economically significant in a weekly sample of liquidly traded firms between 1996 and 2016. Although the precise origin of the IVol puzzle is subject to a controversial debate, the puzzle's relation to behavioral explanations is the prevalent opinion. For example, Boyer et al. (2010) and Bali et al. (2011) relate the IVol puzzle to investors' preferences for lottery-like payoffs (Barberis and Huang, 2008). Using several skewness proxies, Hou and Loh (2016) confirm that lottery preferences can explain the highest fraction of the return premiums associated with idiosyncratic volatility.[1] Another behavioral explanation is provided by Stambaugh et al. (2015) who relate the IVol puzzle's origin to arbitrage asymmetry. They show that the IVol puzzle only emerges if a combination of eleven mispricing proxies points at a stock's overvaluation. Although the proposed behavioral approaches are rather different, they all ultimately suggest that idiosyncratic volatility represents an indicator for overvaluation. We therefore examine whether the IVol puzzle indeed only exists among stocks that are considered as overvalued by a presumably informed group of investors.

[1]One of these proxies is the maximum daily return of the previous month (MAX) as suggested by Bali et al. (2011). Although MAX and IVol are highly correlated, we show that the IVol puzzle is not subsumed by MAX in our sample. On the contrary, in our weekly sample of comparably large firms, the subsequent return impact of MAX can be fully explained by IVol and short-term reversal. However, we show that our empirical analyses would yield similar results if we use MAX instead of IVol.

In order to do so, we use option market data to measure sophisticated investor opinion inspired by the demand-based option pricing framework of Garleanu et al. (2009). They argue that option prices can contain superior information not immediately reflected in stock prices since informed investors might choose to trade in the option market first. Relying on this theoretical foundation, we employ three measures to capture informed option demand: the volatility spread VS_{CW} following Cremers and Weinbaum (2010) who show that their measure captures demand differences in call versus put options; the volatility spread VS_{BH} introduced by Bali and Hovakimian (2009) who also link their measure to the opinion of sophisticated option market participants; and the SMIRK-measure of Xing et al. (2010) which reflects investors' demand for out-of-the-money (OTM) puts as an indicator for negative expectations. We run Fama-MacBeth regressions which show that, though the three measures of sophisticated trading are highly correlated, each of them has a significant incremental value in explaining subsequent stock returns.

Turning to the interplay between sophisticated investors and the IVol puzzle, conditional double sorts show that subsequent returns mutually depend on sophisticated trader opinion and idiosyncratic volatility. On the one hand, the return predictability associated with the informed trading measures increases in idiosyncratic volatility. This shows that sophisticated option trading is more likely to prove successful if the stock is prone to mispricing. On the other hand, the IVol puzzle is especially pronounced for those stocks with negative sophisticated trader opinion. This finding is in line with the hypothesis that the IVol puzzle is driven by those stocks that are perceived as overvalued by sophisticated option traders. Since IVol is no perfect mispricing indicator, the option measures can help to distinguish high-IVol stocks that are overvalued from high-IVol stocks that are not exposed to mispricing. For example, these fairly priced stocks might simply have experienced a fundamental news shock which is correctly reflected in the stock price but which leads to an increase in idiosyncratic volatility. We show that sophisticated investors are apparently able to identify the overvalued high-IVol stocks which enables them to successfully trade on the existing return predictability.

We then turn from the exploitation of the mispricing to its origin. Kumar et al. (2017) show that the IVol puzzle only exists among those stocks that show up on newspapers' winner and loser stock rankings, i.e., stocks with a presumably high level of investor attention. The empirical findings are in line with a model proposed by Barber and Odean

(2008). Accordingly, attention shocks can lead to net buying pressure by sentiment-driven uninformed private investors which cause temporary overvaluations. We apply Google Trends as a direct measure of investor attention as proposed by Da et al. (2011). They provide evidence that stock-related Google search volume mainly reflects the attention paid by private (not sophisticated) investors as they gather information most likely using Google. Thus, Google search volume indices provide a timely measure of firm-level, private investor attention. We show that this direct attention measure positively predicts the IVol puzzle's magnitude. We can therefore link the origin of high-IVol stocks' overvaluation to the attention of private investors and thereby contribute to several strands of literature.

For example, Han and Kumar (2013) show that the IVol puzzle is particularly pronounced if a stock's retail trading proportion is high. Moreover, our findings add to the analyses of Stambaugh et al. (2015) who show that the IVol puzzle is stronger in times of high market-wide investor sentiment. However, our attention measure is stock-specific and therefore allows for clear cross-sectional inference. Furthermore, our findings support theoretical considerations by De Long et al. (1990) implying that higher noise trader activity increases the probability that prices diverge from their fundamental value (also see empirical application in Aabo et al., 2017). In the model of Shleifer and Vishny (1997), return predictability can arise if private investors send sentiment shocks to a stock although a group of sophisticated investors is aware of the mispricing. We therefore expect that the IVol puzzle is particularly pronounced for stocks with both high private investor attention and negative sophisticated investor opinion. Our conjecture is supported by conditional triple sorts that jointly investigate the interplay of investor attention, sophisticated trading, and idiosyncratic volatility. During low attention periods the IVol puzzle disappears. In high investor attention periods on the contrary, we observe a pronounced IVol puzzle only for those stocks with negative sophisticated trader opinion.

Lastly, to support our behavioral line of argument, we investigate the role of liquidity and short-sell constraints. First, mispricing is more likely to persist if limits to arbitrage are high, that is if liquidity is low (Shleifer and Vishny, 1997). Second, Black (1975) argues that informed investors especially prefer to trade in the option market if stock market trading is constrained. Combining these two arguments, we expect that the option-based sophisticated trading measures are particularly successful in identifying overvalued stocks if stock liquidity is low and short-sale constraints are strong. Moreover, mispricing induced by attention-based trading of private investors is less likely to be corrected in this case. Employing the Amihud (2002) illiquidity measure and residual institutional ownership (Nagel, 2005), we show that the impact of sophisticated investor opinion and investor attention on the IVol puzzle becomes stronger for constrained stocks.[2] This finding extends previous theoretical conjectures in two directions: First, mispricing emerging from the trading behavior of sentiment-driven uninformed private investors is stronger if limits to arbitrage are strong. Second, the option-implied measures also have higher predictability in this case because sophisticated traders especially turn to the option market if short-selling is expensive or restricted. Thus, our findings point out that – at least with respect to the IVol puzzle – overvaluation can persist although a group of investors recognizes the mispricing.

2. Data and Summary Statistics

2.1. Data and Variable Construction

Sophisticated Trading Measures. The three sophisticated trading measures are based on implied volatility data from OptionMetrics (IvyDB). We take the last trading day of each week (usually Friday) for all individual stock options maturing within 10 to 180 days from January 1996 to April 2016.[3] The moneyness is restricted to be between 0.5 and 1.5; we only consider options that have positive open interest and positive bid prices. To ensure sufficient option availability and liquidity, we consider only those maturities with at least four options – two OTM put options and two OTM call options of the same maturity – and discard options with nonstandard settlement. Strictly speaking, to calculate a measure of sophisticated investor opinion, only two options are necessary, however we do not want to base our results on very extreme observations and therefore require a higher liquidity.[4] If

[2] Nagel (2005) argues that a low level of institutional ownership reduces the number of shares available for short-selling. He also puts forward that fewer institutional investors imply a lower investor sophistication. However, Edelen et al. (2016) provide empirical evidence that institutional owners are not necessarily sophisticated since they often exhibit a strong propensity to buy overvalued stocks. That is why we do not rely on the rather heterogeneous group of institutional investors as our measure for sophisticated investors, but use option market data instead.

[3] The choice of maturities is similar to the option set in Bali and Hovakimian (2009), Xing et al. (2010) or Stilger et al. (2017). We calculated the correlation between sophisticated trading measures and maturity, finding no indications that our results are biased due to interference with the term structure of implied volatility.

[4] In a robustness test, we take the model-free implied skewness (MFIS) as a control for skewness (Bakshi et al., 2003). To calculate this, it is necessary to extract the entire risk-neutral density. This requires at least four available options.

different option maturities are available for a given stock, we choose the option set with the shortest time to maturity.

The volatility spread measure VS_{CW} by Cremers and Weinbaum (2010) is calculated as the difference between the option-implied volatilities of call and put options that have identical strike prices and maturities. These spreads are weighted across strike prices using the level of open interest. Cremers and Weinbaum (2010) show that their measure captures demand differences in call versus put options, which reflects informational price pressure in the option market.

A similar finding is put forward in Bali and Hovakimian (2009), who show that call-put option implied volatility differences are a proxy for option traders' superior information. The corresponding volatility spread VS_{BH} is computed as the difference in average implied volatilities between near-the-money call and put options. Thereby, near-the-money options are defined to have a log-moneyness that is below 0.1 in absolute terms.

The last measure we take is the implied volatility SMIRK based on Xing et al. (2010) who attribute their results to the idea that informed traders with negative information prefer to trade OTM put options. They buy OTM puts to either hedge or speculate on the potential return. Thus, this argument is similar to the ideas underlying the demand-based option pricing model. SMIRK is the difference between at-the-money (ATM) call and OTM put implied volatility. The estimation of SMIRK follows Xing et al. (2010) but is inverted to allow for simple comparison with VS_{CW} and VS_{BH}. The ATM call is defined as the call option that has the lowest deviation from a moneyness of 1. The OTM put option is the put option with a moneyness closest to, but below 0.95. All three measures are signed measures, thus negative outcomes imply an overhang of negative information.

Stock Market Measures and Control Variables. Data on stock returns, market capitalization, and trading volume are sourced from the Center of Research in Security Prices (CRSP). IVol is the annualized idiosyncratic return volatility of the previous week based on Fama-French-Carhart (FFC) adjusted returns. These adjusted returns are calculated as the difference between realized daily returns and fitted daily returns based on the FFC-model. The required factor loadings are estimated over the previous year skipping one month.[5] Daily

[5]Note, that this methodology differs from the standard IVol estimation procedure in Ang et al. (2006). On a monthly basis, IVol is conventionally set to the volatility of residuals from time-series factor regressions over the previous month. However, we do not proceed identically on a weekly basis since this would imply

data on the risk-free rate and the FFC-factors are obtained from Kenneth R. French's homepage.

The market value (MV) is calculated as the closing share price times the number of shares outstanding. The book value of equity is calculated based on COMPUSTAT data and in accordance with Fama and French (1993), i.e., we exclude firms with negative book values and use the annual balance sheet data not before the beginning of July of the subsequent year. Book-to-market (BM) is set to the ratio of book equity and the most recent market value of equity. We also include the momentum return measured over the previous year skipping the previous month (MOM) and the stock return of the previous week (REV) as a proxy for short-term reversal. As a further control, we also take the maximum daily return of the previous week (MAX) into account.

To account for market frictions we construct the following control variables. We estimate the illiquidity measure, ILLIQ, following Amihud (2002): ILLIQ is the ratio of the absolute daily return to daily dollar trading volume averaged over the previous year. In many other studies, estimated shorting fees or short interest are an important variable to capture market frictions. However, short interest is also employed to identify the opinions of investors about overvaluation. Moreover, for estimating shorting-fees the availability of options is an important dummy variable which would be one for all companies in our analysis (Boehme et al., 2006) and makes large parts of the proxy meaningless. Instead, we use residual institutional ownership following Nagel (2005) to account for the level of professional institutional investors. These investors might reduce the amount of mispricing per se or provide a sufficient number of lendable shares to enable short-selling. Data on institutional holdings come from the Thomson Financial Institutional Holdings (13F) database. The calculation of residual institutional ownership follows Nagel (2005): first, the fraction of shares held by institutional investors is winsorized at 0.01% and 99.99%. Second, the logit transformation of this fraction is regressed on log-size and squared log-size. Each week's cross-sectional residuals constitute the residual institutional ownership measure resIO.

Our analyses make use of all common ordinary shares trading on NYSE, AMEX, or NASDAQ for which empirical VS_{CW}-, VS_{BH}-, SMIRK-, and IVol-estimates are available. In total we end up with 797,169 firm-week-observations from January 1996 to April 2016.

regressions with at maximum five observations and four explanatory variables which would imply very unreliable factor loading estimates.

Investor Attention. To examine the impact of private investors on the IVol puzzle, we apply Google Trends to identify those stocks that receive the highest amount of investor attention. Google provides weekly data of relative search frequency (https://trends.google.com/) from 2004 on. According to Da et al. (2011), these search volume indices provide a timely measure of firm-level investor attention. Moreover, they consider Google searches to reflect in particular private investor behavior, such that we can use the data to test our hypothesis that the documented anomalies are related to uninformed private investors. We use COMPUSTAT firm names as Google search terms and base our analysis on the sample period from January 2005 to April 2016. Notice that we adjust the COMPUSTAT firm names: we delete the legal form of the entity and share class codes. Moreover, we undo abbreviations. Based on this data set, the abnormal search volume index (ASVI) is calculated as the log-difference between the Google Search Volume Index of one week and the median Google Search Volume Index of the previous eight weeks (see equivalent calculation methodology in Da et al., 2011).

2.2. Summary Statistics

Table 1 presents summary statistics on our three sophisticated trading measures, the two short-term anomaly measures (IVol, MAX), the illiquidity measure of Amihud (2002), residual institutional ownership, short-term reversal, log firm size, book-to-market, momentum, and abnormal search volume index.

Several points are noteworthy. The distributions of VS_{CW} and VS_{BH} are very similar and both measures are on average negative implying that sophisticated investors disproportionably often use the options market either to express their negative opinion or to hedge positions. The volatility spreads implied by SMIRK are more negative on average since SMIRK does not solely reflect implied volatility differences between calls and puts, but also the negative slope of the implied volatility curve, i.e., it also takes the skewness of the risk-neutral density into account. Not surprisingly, as all three measures are used to proxy sophisticated trading behavior, the correlation between VS_{CW}, VS_{BH}, and SMIRK is strongly positive indicating a substantial similarity of these three measures. Moreover, we find a strong positive correlation of 0.75 between IVol and MAX, which supports the positive relationship (also correlation coefficient of 0.75) reported by Bali et al. (2011) in

Table 1. Summary Statistics and Correlation Coefficients

This table reports sample mean, standard deviation, 0.05-quantile, median, 0.95-quantile, and correlation coefficients for our main variables for the sample period from January 1996 to April 2016 on a weekly basis. VS_{CW} and VS_{BH} are the implied volatility spreads following Cremers and Weinbaum (2010) and Bali and Hovakimian (2009), respectively. The estimation of SMIRK follows Xing et al. (2010). IVol is the stock's idiosyncratic volatility. It is estimated over the previous week based on FFC-adjusted returns where factor loadings are estimated over the previous year skipping one month. MAX is the maximum daily return of the previous week. ILLIQ corresponds to the illiquidity measure of Amihud (2002) in billion estimated over the previous year. resIO is residual institutional ownership following Nagel (2005). REV denotes the stock return of the previous week. MV is the market capitalization of the stock. BM refers to the stock's book-to-market-ratio. MOM is the momentum return measured over the previous year skipping one month. ASVI is the abnormal search volume index calculated as log Google search volume of the previous week minus the median log Google search volume of the preceding eight weeks. ASVI summary statistics refer to a truncated sample period from January 2005 to April 2016.

	VS_{CW}	VS_{BH}	SMIRK	IVol	MAX	ILLIQ	resIO	REV	ln(MV)	BM	MOM	ASVI
mean	-0.009	-0.010	-0.050	0.303	0.029	2.629	0.000	0.002	22.169	0.404	0.263	-0.003
SD	0.056	0.052	0.056	0.266	0.032	96.070	3.955	0.062	1.488	0.438	0.848	0.263
$q_{0.05}$	-0.086	-0.078	-0.138	0.076	0.002	0.034	-9.649	-0.089	19.924	0.038	-0.428	-0.379
$q_{0.5}$	-0.006	-0.007	-0.042	0.229	0.021	0.467	0.438	0.001	22.059	0.308	0.135	0.000
$q_{0.95}$	0.057	0.049	0.011	0.771	0.083	8.502	6.949	0.096	24.803	1.107	1.253	0.357

Correlation Coefficients												
VS_{CW}	1.000											
VS_{BH}	0.878	1.000										
SMIRK	0.589	0.609	1.000									
IVol	-0.090	-0.069	-0.045	1.000								
MAX	-0.115	-0.096	-0.086	0.746	1.000							
ILLIQ	-0.002	-0.003	-0.001	0.018	0.011	1.000						
resIO	0.014	0.013	0.006	-0.020	-0.018	-0.007	1.000					
REV	-0.122	-0.111	-0.088	0.102	0.540	-0.001	-0.002	1.000				
ln(MV)	0.075	0.063	0.064	-0.287	-0.192	-0.036	-0.000	0.011	1.000			
BM	-0.021	-0.027	-0.085	-0.037	-0.011	-0.014	-0.025	-0.016	-0.051	1.000		
MOM	0.001	0.007	0.075	0.147	0.090	0.036	-0.029	-0.036	-0.041	-0.199	1.000	
ASVI	-0.009	-0.009	0.003	0.131	0.103	0.002	-0.019	0.027	0.003	-0.008	0.009	1.000

their monthly sample. Finally, IVol and investor attention are also positively correlated (0.13), indicating a higher investor attention for stocks with high idiosyncratic volatility.

3. Empirical Results

3.1. The IVol Puzzle

Previous literature uses idiosyncratic volatility to proxy a bunch of different variables. Stambaugh et al. (2015) consider IVol to represent arbitrage risk, that is, the risk that arbitrage opportunities are deterred by noise traders such that mispricing persists. IVol is also supposed to be connected to asymmetric information and disagreement in beliefs (see for example Boehme et al., 2009). A long list of articles argues that IVol reflects preferences for lottery-like stocks (Boyer et al., 2010; Bali et al., 2011; Han and Kumar, 2013) such that investors perceive stocks with high idiosyncratic volatility as attractive and therefore exert buying pressure on these stocks which leads to overpricing. More recently, Kumar et al. (2017) link idiosyncratic volatility to attention shocks occurring to stocks ranked as daily winners or losers which then results in mispricing. In summary, uncoupled from the question what IVol represents exactly, the common ground of these studies is its relation to mispricing. Consequently, we do not want to stick to one particular behavioral driving force in our analyses. Instead, we focus on the link between two different investor groups and IVol.

Before analyzing the behavior of these two investor groups, we examine whether the IVol puzzle is a robust phenomenon in our sample of large and liquidly traded stocks. More specifically, we want to ensure that the predictability of IVol is not subsumed by other determinants of cross-sectional return differences. For example, Bali et al. (2011) argue that IVol is merely a weak proxy for skewness and that accounting for MAX resolves the IVol puzzle. Using a monthly sample of US stocks from 1962 to 2005, they show that the puzzling negative relation between IVol and subsequent returns turns positive if MAX is included in their regression analyses. They conclude that MAX is a superior skewness proxy as investors judge a stock's attractiveness based on the maximum return spikes over the previous month. On the contrary, Hou and Loh (2016) consider MAX as another (range-based) proxy for volatility; they argue that the previous findings are rather mechanical due to near perfect collinearity (see correlation of 0.75 between IVol and MAX in Table 1).

To examine the cross-sectional relation between MAX, IVol, and subsequent stock returns, we run regressions following Fama and MacBeth (1973) presented in Table 2. Regression (1) supports the negative relation between IVol and subsequent returns in our weekly sample. This finding strengthens the evidence on the IVol puzzle's robustness, since our sample consists of large and liquidly traded firms only, due to our option market sample restrictions.[6] In line with previous literature, MAX is also negatively related to the returns of the following week, see regression (2). Due to the high correlation between IVol and MAX, the coefficient magnitude is substantially reduced if both variables are included in regression (3). Interestingly, if we further control for short-term reversal REV, the MAX effect becomes insignificant indicating that it is merely a joint proxy for the return patterns associated with IVol and REV. We attribute this contrary finding in comparison to Bali et al. (2011) to our sample of comparably large stocks.[7] Recall, that explanations for the MAX effect are usually associated with preferences for positively skewed payoffs where a high maximum daily return in the previous month serves as an indicator for such lottery-like stocks. The MAX effect should thus be particularly strong in small firms where information on the past performance of the asset is more likely to be meaningful for assessing the asset's attractiveness. Contrary, for large firms other information about the company is more salient in general while MAX values and idiosyncratic volatility are comparably low rendering it difficult to infer skewness from a price chart. Thus, attention-driven trading and its relation to idiosyncratic volatility is probably more relevant for our sample of large stocks while the skewness aspect of MAX plays a minor role compared to the sample of Bali et al. (2011). We will examine this line of attention-driven mispricing further in Section 3.3.

Since IVol dominates MAX in predicting subsequent returns, the following analyses focus on IVol and its interplay with sophisticated and private investors.[8] We next turn to univariate quintile portfolio sorts to quantify the return spreads associated with IVol. At the

[6] If we would use the entire CRSP universe from 1996 to 2016 instead of our restricted sample, median market capitalization would drop from 3.8bn dollar to 0.2bn dollar while the median Amihud illiquidity measure would increase from 0.47 to 3.82.

[7] Note that we can rule out that our findings are driven by our weekly framing or our shorter sample period beginning in 1996. Our Online Appendix shows that in monthly Fama-MacBeth-regressions using CRSP data since 1960, MAX is also dominated by IVol and REV if the sample is restricted to large firms. If small firms are included in the regressions, the predictive power of MAX improves at the expense of IVol.

[8] However, one might still argue that MAX is another short-term anomaly influenced by a heterogenous investor base. Therefore, we also conduct robustness tests in which we use MAX instead of IVol. The findings are reported in our Online Appendix and reveal that sophisticated investors behave similar towards MAX as towards IVol.

Table 2. Short-Term Anomalies

The table reports weekly Fama-MacBeth-regression estimates for the sample period from January 1996 to April 2016. The dependent variable is the stock return of the subsequent week. The explanatory variables are given in the first column. IVol is the stock's idiosyncratic volatility. It is estimated over the previous week based on FFC-adjusted returns where factor loadings are estimated over the previous year skipping one month. MAX is the maximum daily return of the previous week. REV denotes the stock return of the previous week. MV is the market capitalization of the stock. BM refers to the stock's book-to-market-ratio. MOM is the momentum return measured over the previous year skipping one month. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using five lags.

	(1)	(2)	(3)	(4)	(5)
intercept	0.0033	0.0029	0.0033	0.0031	0.0050
	(4.40)	(3.63)	(4.46)	(4.29)	(1.37)
IVOL	-0.0041		-0.0028	-0.0044	-0.0047
	(-3.73)		(-2.41)	(-4.12)	(-5.01)
MAX		-0.0316	-0.0137	0.0079	0.0058
		(-3.54)	(-1.58)	(0.62)	(0.48)
REV				-0.0134	-0.0147
				(-2.50)	(-2.96)
ln(MV)					-0.0001
					(-0.72)
BM					0.0004
					(0.61)
MOM					0.0005
					(0.92)

end of each week, the stocks are assigned to one quintile portfolio based on IVol. Table 3 presents the corresponding portfolio characteristics and the equally-weighted FFC-adjusted portfolio returns α_{FFC} of the subsequent week. Low-IVol stocks subsequently outperform high-IVol stocks by significant 0.23% per week (annualized return premium of 12.40%).[9] These findings are in contrast to the results of Bali and Cakici (2008) where the IVol puzzle does not exist for equally-weighted returns, i.e., when small firms are given higher weight in comparison to value-weighting. Recall that due to our option data restriction, our sample is disproportionately tilted towards large firms. This could explain why IVol remains significant also for equally-weighted returns.

Interestingly and consistent with a behavioral explanation for the IVol puzzle, the average portfolio returns do not decrease linearly from portfolio 1 to 5, but the effect is largely due to the negative returns of the high-IVol portfolio showing that the IVol puzzle is particularly driven by the most overvalued stocks.[10] In addition, these high-IVol stocks are less liquid,

[9]Untabulated analyses show that the return spread is also significant for unadjusted returns (-0.19% and t-statistic of -2.13) and value-weighted returns (-0.19% and t-statistic of -2.78).

[10]We formally test this nonlinearity and find an insignificant return difference between portfolios 3 and 1 while the return spread between portfolios 5 and 3 is highly significant (t-statistic of 4.01).

Table 3. Portfolio Sorts based on Idiosyncratic Volatility
The table reports equally-weighted weekly quintile portfolio sorts based on idiosyncratic volatility IVol for the sample period from January 1996 to April 2016. IVol is the stock's idiosyncratic volatility. It is estimated over the previous week based on FFC-adjusted returns where factor loadings are estimated over the previous year skipping one month. Corresponding portfolio averages are provided in the first column. The second column shows FFC-adjusted portfolio returns of the subsequent week. VS_{CW} and VS_{BH} are the implied volatility spreads following Cremers and Weinbaum (2010) and Bali and Hovakimian (2009), respectively. The estimation of SMIRK follows Xing et al. (2010). MAX is the maximum daily return of the previous week. ILLIQ corresponds to the illiquidity measure of Amihud (2002) in billion estimated over the previous year. resIO is residual institutional ownership following Nagel (2005). REV denotes the stock return of the previous week. MV is the market capitalization of the stock. BM refers to the stock's book-to-market-ratio. MOM is the momentum return measured over the previous year skipping one month. ASVI is the abnormal search volume index calculated as log Google search volume of the previous week minus the median log Google search volume of the preceding eight weeks. ASVI portfolio characteristics refer to a truncated sample period from January 2005 to April 2016. The t-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using five lags. Subsequent FFC-adjusted returns, VS_{CW}, VS_{BH}, SMIRK, MAX and REV are stated in %.

	IVol	α_{FFC}	VS_{CW}	VS_{BH}	SMIRK	MAX	ILLIQ	resIO	REV	ln(MV)	BM	MOM	ASVI
low	0.12	0.06	-0.73	-0.91	-4.90	1.53	1.07	-0.02	0.04	22.92	0.40	0.17	-0.01
2	0.19	0.06	-0.79	-0.89	-4.87	2.01	1.57	0.04	0.01	22.51	0.39	0.20	-0.01
3	0.26	0.02	-0.86	-0.90	-4.89	2.54	2.69	0.09	-0.01	22.13	0.38	0.25	-0.01
4	0.36	-0.03	-0.98	-0.98	-4.91	3.34	4.01	0.05	0.11	21.76	0.37	0.32	-0.01
high	0.66	-0.17	-1.52	-1.40	-5.34	5.87	5.71	-0.17	0.80	21.32	0.36	0.47	0.03
5-1	0.54	-0.23	-0.79	-0.50	-0.44	4.34	4.63	-0.15	0.76	-1.60	-0.04	0.30	0.04
t(5-1)		(-4.15)	(-13.02)	(-9.81)	(-7.53)	(36.01)	(14.75)	(-6.65)	(7.03)	(-76.69)	(-4.58)	(8.83)	(20.13)

smaller and receive more investor attention on average. Moreover, sophisticated investors have a more negative opinion about them indicating that they realize the overvaluation of high-IVol stocks. This interplay is further examined in the following section.

3.2. The IVol puzzle and Sophisticated Investors

It is well acknowledged that the three measures which we include in our analyses have predictive power for future stock returns and certain corporate events. Bali and Hovakimian (2009), Cremers and Weinbaum (2010), and Xing et al. (2010) find that their respective measures VS_{BH}, VS_{CW}, and SMIRK are able to predict returns in the equity market in line with the demand-based option pricing framework of Garleanu et al. (2009). They all argue that the information in the spreads and skews of implied volatilities reflects informed trading. The predictive power of the measures cannot solely be attributed to market frictions but is explicitly linked to demand effects of informed investors. Based on these findings, a second stream of literature examines whether sophisticated option market trading can also predict the timing and return impact of selected corporate events. Several papers, including Jin et al. (2012) and Atilgan (2014), consider earnings announcements and find that the option measures exhibit strong announcement return predictability. Lin and Lu (2015) analyze analyst recommendations and Chan et al. (2015) investigate mergers and acquisitions. Gharghori et al. (2017) look at stock splits and find that changes in implied volatility spreads significantly predict the level of stock volatility on the day after the announcement. However, none of these studies has examined whether the three measures also indicate informed trading on the IVol puzzle. We therefore expand the existing literature on specific events to the analysis of the IVol puzzle. Before we tackle this point and enlarge evidence on how different investor groups impact market efficiency, we want to assess the predictive power of the three sophisticated trading measures simultaneously. Thereby, we also answer the question whether they present complements or substitutes in predicting future stock returns (also see Fu et al., 2016).

Table 4 examines the relationship between option-based sophisticated trading measures and stock returns of the subsequent week using the regression approach of Fama and MacBeth (1973). Not surprisingly, all three measures, VS_{CW}, VS_{BH}, and SMIRK, positively predict future returns. Thus, these findings are in line with the positive relationship documented in the previous literature. Moreover, the results support the demand-based option pricing framework of Garleanu et al. (2009): Sophisticated traders with positive (negative) short-run return expectations demand calls (puts), push up call (put) prices, and increase (decrease) the value of the three measures. The return predictability arises since the opinion of these sophisticated investors does not seem to be correctly reflected in stock prices. Informed investors seem to trade in equity options rather than in the underlying stock because of short-sell constraints or because they might want to express their opinion in a levered way (Black, 1975; Easley et al., 1998). This implies that price pressure from uninformed investors can be so strong that sophisticated investors cannot eliminate the mispricing, but that their trading behavior predicts future returns. We will come to this point in our subsequent analysis, but first we will turn to the joint explanatory power of the three measures.

Table 4 shows that all three measures stay significant if they are jointly used as explanatory variables. Although the coefficient magnitude sharply declines due to multicollinearity (see correlation coefficients in Table 1), each of the three measures seems to take into account a slightly different part of the option universe and thus retains significant marginal explanatory power. This interpretation is not altered by the introduction of further well-known cross-sectional return determinants in regression (5).[11]

Table 4. Sophisticated Trading Measures and Subsequent Returns
The table reports Fama-MacBeth-regression estimates for the sample period from January 1996 to April 2016 based on weekly data. The dependent variable is the stock return of the subsequent week. The explanatory variables are given in the first column. VS_{CW} and VS_{BH} are the implied volatility spreads following Cremers and Weinbaum (2010) and Bali and Hovakimian (2009), respectively. The estimation of SMIRK follows Xing et al. (2010). REV denotes the stock return of the previous week. MV is the market capitalization of the stock. BM refers to the stock's book-to-market-ratio. MOM is the momentum return measured over the previous year skipping one month. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using five lags.

	(1)	(2)	(3)	(4)	(5)
intercept	0.0023	0.0023	0.0032	0.0028	0.0018
	(2.46)	(2.49)	(3.50)	(3.04)	(0.41)
VS_{CW}	0.0348			0.0138	0.0132
	(11.48)			(3.09)	(3.09)
VS_{BH}		0.0385		0.0181	0.0207
		(11.69)		(3.67)	(4.58)
SMIRK			0.0280	0.0114	0.0090
			(9.39)	(3.33)	(3.29)
REV					-0.0108
					(-3.26)
ln(MV)					0.0000
					(0.12)
BM					0.0007
					(0.91)
MOM					0.0003
					(0.50)

In order to illustrate the impact of the sophisticated trading measures on subsequent returns more tangibly, we also report portfolio sorts in the Appendix. We sort stocks at the end of each week in ascending order for each of the measures separately – VS_{CW}, VS_{BH}, or SMIRK – and assign them to quintile portfolios. Table 8 of the Appendix presents equally-weighted FFC-adjusted portfolio returns for the four subsequent weeks.[12] Accordingly,

[11] As Xing et al. (2010) point out, the measures of informed trading might also proxy for the implied skewness of the return distribution (also see Stilger et al., 2017). However, our robustness tests (see Online Appendix) show that the three measures remain significant if model-free implied skewness (MFIS) as proposed by Bakshi et al. (2003) is used as additional control variable. Moreover, we show that MFIS is less robust in predicting subsequent returns as a measure of sophisticated trading compared to VS_{CW}, VS_{BH}, and SMIRK. Due to this finding and since MFIS relies on potentially noisy extrapolation and interpolation techniques, we investigate its predictability in a robustness test only. In our Online Appendix, we also rule out that the return premiums are a compensation for option market illiquidity given that high absolute implied volatility spreads VS_{CW} and VS_{BH} might indicate illiquid options.

[12] In our robustness tests we also present the same analysis for unadjusted and value-weighted portfolio returns (see Online Appendix). The results remain qualitatively the same. Furthermore, potential nonsynchroneity issues raised by Battalio and Schultz (2006) cannot account for the return premiums either. Since the market for individual stock options closes at 4:02 PM while equity trading ceases at 4:00 PM, the option-implied

the difference between the extreme quintile portfolios ranges from 0.35% to 0.50% in the following week which corresponds to annualized returns of 19.99% and 29.56%. The predictive power of the three measures is still significant for the second next week, but considerably smaller in magnitude. For longer time horizons, the effect further attenuates. In conclusion, these findings show that sophisticated trading measures derived from option data can predict subsequent returns. Further, the results are particularly strong on a weekly horizon supporting the general presumption that sophisticated investors choose the option market to trade on especially short-run mispricing.

We proceed by testing how sophisticated investors relate their trading activity to the IVol puzzle. In particular, trading against high-IVol stocks should be attractive for sophisticated investors for the following three reasons: First, sophisticated traders can easily calculate IVol and trade accordingly. Second, the corresponding recent literature largely favors a behavioral explanation for IVol and does not suggest that respective trading strategies render unprofitable if systematic risk exposure is taken into account. Third, Li et al. (2016) suggest that a stock trading strategy based on IVol is unprofitable after costs, and thus sophisticated investors are likely to turn to the option market in order to exploit the anomaly on a levered basis. Referring to Table 3, we find support for these conjectures since it reports a consistent negative relationship between IVol and the three sophisticated trading measures: Each of the three measures is significantly higher for the low- compared to the high-IVol portfolio.[13] One rationale for this could be that sophisticated investors hedge against high-IVol stocks in the option market. However, we can rule out that the more negative trading measures are due to investors who buy puts simply because they want to hedge their positions due to the high level of IVol. This hedging demand should also exist for systematic volatility. But, we do not find a significant negative relationship between a stock's systematic volatility and

moments might not be available for stock market investors at market closure time. However, the relation between the three sophisticated trading measures and subsequent returns also remains significantly positive if the return measurement starts at the open price of the next trading day, that is, if we exclude the return over the weekend.

[13] Note that one might also suspect this relationship to be a consequence of investor disagreement: Considering IVol to be a proxy for investor disagreement (Boehme et al., 2009), high IVol should be associated with lower sophisticated trading measures if optimistic opinions are predominantly reflected in the stock price while pessimistic investors buy puts in the option market. The use of analyst dispersion data from IBES in the Online Appendix indeed supports the negative relation between disagreement and sophisticated trading measures. However, this effect cannot subsume the findings from Table 3 in the Fama-MacBeth-regressions.

the three trading measures.[14] Hence, the empirical evidence suggests that sophisticated option traders might indeed recognize the overvaluation associated with high IVol and trade accordingly in the option market.

As the return asymmetry in Table 3 indicates that the IVol puzzle is particularly driven by overpriced stocks, we further expect that the return effects are particularly strong if sophisticated investor trading also points towards an overvaluation. Vice versa, we would expect the return spreads associated with IVol to be smaller if the sophisticated trading measures indicate no overvaluation. For example, a correctly priced fundamental news shock increases the idiosyncratic volatility, but does not imply an overvaluation. Following this line of argument, we can use the sophisticated trading measures to identify those high-IVol stocks that are most likely prone to mispricing.

Table 5. Conditional Double Sorts on Sophisticated Trading Measures and Idiosyncratic Volatility

The table reports equally-weighted FFC-adjusted portfolio returns for the week after portfolio formation from January 1996 to April 2016. First, each stock is allocated to one tercile (columns) based on the implied volatility spread following Cremers and Weinbaum (2010), VS_{CW}, the implied volatility spread following Bali and Hovakimian (2009), VS_{BH}, or SMIRK based on Xing et al. (2010). Second, within each tercile, every stock is assigned to an IVol tercile (rows) based on its idiosyncratic volatility. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using five lags. Subsequent FFC-adjusted returns are stated in %.

	first sorting criterion VS_{CW}					first sorting criterion VS_{BH}					first sorting criterion SMIRK				
IVol	low	2	high	3-1	t(3-1)	low	2	high	3-1	t(3-1)	low	2	high	3-1	t(3-1)
low	-0.09	0.03	0.23	0.32	(9.26)	-0.08	0.05	0.22	0.30	(9.73)	-0.04	0.06	0.15	0.19	(6.99)
2	-0.16	0.03	0.19	0.36	(9.09)	-0.17	-0.00	0.20	0.37	(9.79)	-0.08	0.00	0.14	0.22	(5.59)
high	-0.34	-0.06	0.07	0.40	(8.17)	-0.36	-0.07	0.11	0.48	(8.85)	-0.33	-0.07	0.05	0.38	(7.06)
3-1	-0.24	-0.09	-0.16			-0.28	-0.12	-0.11			-0.29	-0.13	-0.10		
t(3-1)	(-4.37)	(-1.73)	(-2.91)			(-4.98)	(-2.59)	(-1.92)			(-5.11)	(-2.83)	(-1.87)		

Table 5 examines this reasoning empirically and presents cross-sectional conditional double sorts. First, every stock is allocated to a portfolio based on VS_{CW}, VS_{BH}, or SMIRK. Second, each of these portfolios is divided into three IVol terciles. Table 5 presents the equally-weighted FFC-adjusted portfolio returns of the subsequent week and the return differences between the extreme terciles.[15] The results support a behavioral explanation for the IVol puzzle since it is especially pronounced for those stocks that are considered

[14]Untabulated analyses applying sorts on systematic volatility show that the quintile differences are -0.0004, -0.0001, and +0.0002 for VS_{CW}, VS_{BH}, and SMIRK, respectively.

[15]The Online Appendix shows conditional double sorts for unadjusted returns and value-weighted returns. The results remain qualitatively the same.

to be overpriced by sophisticated investors in the option market. Instead, for stocks with positive sophisticated investor opinion the IVol puzzle is less strong since these stocks are apparently less prone to overvaluation. In addition, Table 5 shows that the return spreads associated with VS_{CW}, VS_{BH}, or SMIRK are particularly strong for high-IVol stocks.[16] This underpins our conjecture that sophisticated option trading is presumably most successful for the most mispriced stocks which offer the largest return opportunities.

To sum up, the IVol puzzle is most pronounced for the stocks which sophisticated investors perceive as overvalued and within high-IVol stocks we also identify the highest potential for exploitation in terms of return spreads. Thus, our findings are in line with Stambaugh et al. (2015) who also find a strong dependence of the IVol puzzle on the level of stock overpricing. However, they proxy mispricing through a combination of eleven market anomalies. Thus, their abstract measure of mispricing does not allow for a link to the opinion of informed investors and their trading on overvaluation. In the following, we want to gain more insights with respect to the question when exploitation of overvalued stocks at the option market is especially promising for informed investors and how this is related to the presence of sentiment-driven private investors.

3.3. The IVol puzzle and Private Investors

Tables 3 and 5 strongly suggest that sophisticated investors recognize the overvaluation of high-IVol stocks and trade accordingly in the option market. This raises the question why stock prices do not correctly reflect fundamental values in the first place given the existence of a seemingly well-informed investor group. Based on previous literature, the strength of the IVol puzzle is associated with the presence of market frictions and noise trader activity. When it comes to noise trading, the models introduced by De Long et al. (1990) and Shleifer and Vishny (1997) show that noise traders can generate stock mispricing even in the presence of rational market participants. If market power of sophisticated investors does not suffice to compensate demand effects of irrational private investors, they have the option market as a channel to express their opinion even in the presence of short-sell constraints.

[16] Strictly speaking, this second interpretation of Table 5 would require a conditional double sort where idiosyncratic volatility is the first sorting criterion and the sophisticated trading measures are the second sorting criterion. However, in our Online Appendix we show that the sorting criterion order does not affect the results in this case.

Stambaugh et al. (2015) show that market-wide sentiment has an impact on the IVol puzzle's magnitude. In particular, they show that mispricing has a considerably stronger impact following high periods of investor sentiment.[17] Kumar et al. (2017) argue that the IVol puzzle is driven by attention effects stemming from irrational investors overreacting to daily winner and loser rankings in the newspapers. Since sophisticated traders seem to recognize biased stock valuations, we expect that especially private sentiment-driven investors cause prices to deviate from their fundamental value. While this sentiment-driven investor group is often abstractly labeled as noise traders, measuring the impact of this group directly is not straight forward. We use private investor attention data from Google Trends to examine this line of argument, since Da et al. (2015) also relate internet search query volume to the behavior of noise traders.

We think that this stock-specific noise trading measurement enhances our understanding of the impact of different investor groups on the cross-section of stock returns.[18] We hypothesize that cross-sectional differences in noise trading activity also influence the IVol puzzle. High attention levels imply an increased stock market activity of these investors which could especially lead to stock price overvaluation as the group of noise traders is usually exposed to short-sale constraints. Since the idiosyncratic volatility puzzle is often explained by the lottery preferences of private investors (see Barberis and Huang, 2008 and Boyer et al., 2010 for theoretical and empirical evidence, respectively), the puzzle should depend on the attention of private investors. Only if they pay attention to a stock and its lottery-like features, they can exert buying pressure and trigger the stock's overvaluation. Our analyses on investor attention extend the work of Kumar et al. (2017) as we use a direct proxy for investor attention and do not rely on stock rankings as an indirect measure. Hence, our analysis also includes broader sources of investor attention such that we expect to gain new insights on the origin of the IVol puzzle.

Based on these considerations, we expect the IVol puzzle to be particularly pronounced for stocks with high average search volume. Table 6 reports conditional double sorts where we first sort on attention (stock's abnormal search volume) and then on IVol. The corresponding

[17]We provide an analysis of market wide sentiment in our Online Appendix.

[18]According to Da et al. (2011), changes in investor attention are able to predict subsequent returns. We cannot significantly support that finding which we assert to our sample of large and liquidly traded stocks given that Da et al. (2011) consider their findings to be mainly driven by smaller less liquid stocks.

Table 6. Conditional Double Sorts based on Attention
This table reports equally-weighted FFC-adjusted portfolio returns for the week after portfolio formation. The return impact of IVol is separately evaluated after each stock has been allocated to one tercile (columns) based on the stock's abnormal search volume index (ASVI). ASVI is calculated as the log-difference between the Google Search Volume of one week and the median Google Search Volume of the previous eight weeks. The sample period covers January 2005 to April 2016. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using five lags. Subsequent FFC-adjusted returns are stated in %.

	Investor Attention		
IVol	low	2	high
low	0.03	0.05	0.06
2	0.02	0.03	0.04
high	-0.06	-0.04	-0.10
3-1	-0.09	-0.09	-0.16
t(3-1)	(-1.91)	(-2.08)	(-3.37)

weekly return effect associated with IVol increases from insignificant 0.09% in the low-ASVI-tercile to significant 0.16% in the high-ASVI-tercile supporting our hypothesis.[19]

The natural follow-up question is how the IVol puzzle interacts with both private and sophisticated investor group. We expect that the IVol puzzle is most pronounced for stocks that are considered overvalued by informed investors and that exhibit a high private investor attention moving prices beyond fundamental value. According to conditional triple sorts in Table 7, the IVol puzzle is strongest if both attention is high and sophisticated trader opinion is low.[20] Interestingly, the high-IVol stocks with negative sophisticated investor opinion (judged by VS_{CW}), which are usually responsible for the IVol puzzle, earn subsequent abnormal returns of -0.25% in the high-attention tercile, but only -0.14% among low attention stocks. In particular, the IVol puzzle loses significance during low attention periods even if sophisticated trading opinion is negative for two of the three measures. These results strongly support a behavioral explanation of the return pattern associated with idiosyncratic volatility: private investor attention can cause an overvaluation of high-IVol stocks which is not eliminated by sophisticated investors due to insufficient market power but exploited at the option market.

[19]The results remain qualitatively the same for unadjusted and value-weighted returns; see our Online Appendix.
[20]In the Online Appendix, we provide similar findings for triple sorts based on value-weighted and unadjusted returns. The Online Appendix also provides the same analysis for market-wide investor sentiment yielding similar results.

Table 7. Triple Sorts based on Attention, Sophisticated Trading Measures, and Idiosyncratic Volatility
This table shows equally-weighted FFC-adjusted portfolio returns of weekly conditional triple sorts. First, each stock is allocated to a top- or bottom-tercile based on investor attention (abnormal search volume index based on Google Trends data). Second, within each tercile, every stock is allocated to one tercile (columns) based on the implied volatility spread following Cremers and Weinbaum (2010), VS_{CW}, the implied volatility spread following Bali and Hovakimian (2009), VS_{BH}, or SMIRK based on Xing et al. (2010). Third, within each tercile, every stock is assigned to an IVol tercile (rows) based on its idiosyncratic volatility. The sample period covers January 2005 to April 2016. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using five lags. The subsequent FFC-adjusted returns are stated in %.

Panel A: High Investor Attention

	VS_{CW}					VS_{BH}					SMIRK				
IVol	low	2	high	3-1	t(3-1)	low	2	high	3-1	t(3-1)	low	2	high	3-1	t(3-1)
low	-0.06	0.06	0.17	0.23	(3.99)	-0.01	0.04	0.16	0.17	(3.33)	-0.00	0.06	0.14	0.14	(2.96)
2	-0.01	0.04	0.13	0.14	(2.30)	-0.03	0.03	0.10	0.12	(2.04)	-0.03	0.05	0.09	0.12	(1.75)
high	-0.25	-0.02	-0.00	0.25	(3.17)	-0.25	-0.04	0.04	0.28	(3.41)	-0.26	-0.04	0.03	0.30	(3.44)
3-1	-0.20	-0.08	-0.17			-0.23	-0.08	-0.12			-0.26	-0.10	-0.10		
t(3-1)	(-2.66)	(-1.28)	(-2.82)			(-3.18)	(-1.35)	(-1.93)			(-3.82)	(-1.72)	(-1.46)		

Panel B: Low Investor Attention

	VS_{CW}					VS_{BH}					SMIRK				
IVol	low	2	high	3-1	t(3-1)	low	2	high	3-1	t(3-1)	low	2	high	3-1	t(3-1)
low	-0.01	0.01	0.09	0.11	(2.00)	-0.06	0.02	0.12	0.18	(3.55)	0.04	-0.03	0.11	0.07	(1.42)
2	-0.03	-0.04	0.11	0.14	(2.49)	-0.01	-0.05	0.10	0.11	(1.88)	0.01	0.02	0.04	0.03	(0.51)
high	-0.14	-0.02	-0.00	0.14	(1.83)	-0.17	-0.04	0.04	0.21	(2.65)	-0.13	-0.06	-0.01	0.12	(1.43)
3-1	-0.13	-0.03	-0.09			-0.11	-0.06	-0.08			-0.17	-0.03	-0.11		
t(3-1)	(-1.78)	(-0.54)	(-1.36)			(-1.51)	(-1.03)	(-1.22)			(-2.16)	(-0.52)	(-1.76)		

3.4. The impact of Short-Sell Constraints

Several articles including Boehme et al. (2009), Duan et al. (2010), and Stambaugh et al. (2015) document that short-sell impediments result in larger return spreads associated with IVol. Applied to our group of informed traders, the stocks with negative sophisticated investor opinion, high idiosyncratic volatility, and restricted short-selling should earn the lowest subsequent returns. Likewise, the stocks with highest private investor attention, high idiosyncratic volatility, and restricted short-selling, should earn the lowest subsequent returns. Fundamental price risk and market frictions such as trading costs and short-sell constraints can render arbitrage strategies unattractive (see for example Lam and Wei, 2011). As a consequence, the magnitude of potential mispricing should be higher if limits to arbitrage are more severe. In this case, we expect a stronger IVol puzzle.

Tables 9 and 10 of the Appendix examine this line of argument using conditional cross-sectional triple sorts. We include two proxies for market frictions and limits to arbitrage: the illiquidity measure of Amihud (2002) and residual institutional ownership as proposed by Nagel (2005).[21] He argues that limits to arbitrage especially exist in the absence of institutional investors. There are mainly two reasons why the latter is also a good proxy for market frictions in our analysis: first, a higher level of professional institutional investors might reduce the amount of mispricing. Second, the number of lendable shares depends on the availability of institutional shares such that short-sell constraints are assumed to be stronger for low levels of residual institutional ownership. Informed investors who are affected by these impediments are more likely to trade at the option market.

In our triple sort analyses, we first sort on one of the limits to arbitrage proxies, second on the sophisticated trading measures or investor attention, and third on idiosyncratic volatility. The empirical results in the Appendix support our line of argument: The most negative subsequent FFC-adjusted portfolio returns are obtained for those high-IVol stocks that are illiquid, short-sell constrained, and overvalued based on sophisticated investor opinion (see Table 9). On the contrary, for the most liquid stocks with positive sophisticated investor opinion, the IVol puzzle largely disappears. Thus, the strength of the IVol puzzle depends on both the opinion of sophisticated investors about the stock's overpricing and the stock's degree of illiquidity. Next, we asses the origin of the IVol puzzle by relating it to attention-driven investors (see Table 10). The IVol puzzle is strongest for those stocks that are illiquid/short-sell-constrained and exposed to high investor attention. For example, the tercile return spread associated with IVol is -0.04% for low-attention- and low-ILLIQ-stocks while it is -0.17% for high-attention- and high-ILLIQ-stocks. These findings are in line with our conjecture that the IVol puzzle particularly emerges if private noise traders are active and informed investors cannot eliminate the mispricing due to illiquidity and short-sell constraints.

4. Conclusion

The paper provides an in-depth analysis of the impact of different investor groups on the IVol puzzle. Our results support behavioral explanations for the IVol puzzle and also

[21]Our Online Appendix also reports similar triple sorts using model-free option-implied volatility and bid-ask-spreads as limits to arbitrage proxies.

shed new light on how anomalies are driven by private investor attention and exploited by sophisticated investors in the option market. We show that the IVol puzzle is statistically and economically meaningful in our sample of large liquidly traded firms. Quintile sorts on idiosyncratic volatility reveal that the subsequent portfolio returns do not decrease linearly from portfolio 1 to 5, but that the effect is largely due to the negative returns of overpriced high-IVol stocks which is in line with behavioral explanations for the IVol puzzle.

We employ three sophisticated trading measures calculated from option data as proxies for sophisticated investor opinion and show that all of these measures have incremental value in forecasting stock returns. These findings provide further support to the demand-based option pricing framework of Garleanu et al. (2009). Moreover, compared to conventional trading measures, our approach has several advantages. While other measures like institutional holdings merely cover the presence of one investor group, the option market also allows to derive their opinion. In addition, option data are available on daily frequencies and can thus reflect short-term changes in sophisticated investor opinion. This seems especially suitable given the short-term variation in idiosyncratic volatility. We find support that sophisticated investors try to exploit the apparent mispricing in the option market. Furthermore, return spreads associated with sophisticated trading measures are stronger for high-IVol stocks. This supports our conjecture that sophisticated option trading is particularly successful for the most mispriced stocks which offer the largest return opportunities. In addition, the IVol puzzle is particularly pronounced if the sophisticated trading measures indicate an overvaluation lending further support to a behavioral explanation of the anomaly.

We are not only interested in the interplay of sophisticated investors and the IVol puzzle but also want to dig deeper into its underlying sources. We therefore include a proxy for attention-driven private investors in our analyses: the return spreads associated with idiosyncratic volatility strongly increase if attention is high which directly links noise traders to the mispricing's origin. The magnitude of these effects further increases among illiquid and short-sell-constrained stocks. Overall, the analyses point out the following conclusion: Attention-driven noise traders seem to generate mispricing which leads to return predictability and corresponding option trading by sophisticated investors. These empirical findings imply that different investor groups have a different impact on financial markets and that the acknowledgement of a very heterogeneous investor base is a necessary condition to fully understand capital market phenomena.

Appendix

Table 8. Portfolio Sorts based on Sophisticated Trading Measures
The table reports the equally-weighted FFC-adjusted returns of quintile portfolios for the subsequent four weeks. The sample period covers January 1996 to April 2016. Portfolios are constructed using the implied volatility spread following Cremers and Weinbaum (2010), VS_{CW}, the implied volatility spread following Bali and Hovakimian (2009), VS_{BH}, and SMIRK based on Xing et al. (2010). The t-statistics in parentheses are based on standard errors following Newey and West (1987) using five lags. FFC-adjusted subsequent returns are stated in %.

	Portfolios sorted by VS_{CW}				Portfolios sorted by VS_{BH}				Portfolios sorted by SMIRK			
	t+1	t+2	t+3	t+4	t+1	t+2	t+3	t+4	t+1	t+2	t+3	t+4
low	-0.27	-0.07	-0.09	-0.08	-0.26	-0.06	-0.08	-0.07	-0.19	-0.09	-0.08	-0.03
2	-0.08	-0.05	-0.00	0.01	-0.09	-0.03	0.00	0.02	-0.09	-0.01	0.02	-0.01
3	-0.01	0.01	0.02	0.03	-0.02	0.00	0.03	0.01	0.00	0.02	-0.01	0.01
4	0.08	0.03	-0.01	-0.01	0.08	0.01	-0.01	0.00	0.05	0.01	0.00	-0.01
high	0.21	-0.01	-0.03	-0.02	0.23	-0.01	-0.05	-0.03	0.16	-0.02	-0.04	-0.03
5-1	0.48	0.06	0.06	0.06	0.50	0.06	0.03	0.04	0.35	0.08	0.04	0.00
t(5-1)	(11.62)	(2.07)	(1.95)	(1.72)	(12.35)	(1.99)	(0.88)	(1.27)	(9.50)	(2.38)	(1.37)	(0.09)

Table 9. Triple Sorts based on Short Sale Constraints, Sophisticated Trading Measures, and Idiosyncratic Volatility

This table reports equally-weighted FFC-adjusted subsequent returns for weekly conditional triple sorts. First, each stock is allocated to a top- or bottom-tercile based on Amihud illiquidity (Panels A and B) and residual institutional ownership (Panels C and D). Second, within each portfolio, every stock is allocated to one tercile (columns) based on the implied volatility spread following Cremers and Weinbaum (2010), VS_{CW}, the implied volatility spread following Bali and Hovakimian (2009), VS_{BH}, or SMIRK based on Xing et al. (2010). Third, within each tercile, every stock is assigned to an IVol tercile (rows) based on its idiosyncratic volatility. The sample period covers January 1996 to April 2016. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using five lags. The subsequent FFC-adjusted returns are stated in %.

Panel A: High Amihud Illiquidity

	VS_{CW}					VS_{BH}					SMIRK				
IVol	low	2	high	3-1	t(3-1)	low	2	high	3-1	t(3-1)	low	2	high	3-1	t(3-1)
low	-0.22	-0.05	0.25	0.46	(7.68)	-0.20	-0.03	0.25	0.45	(7.72)	-0.18	-0.01	0.17	0.34	(5.69)
2	-0.23	-0.08	0.15	0.38	(5.07)	-0.32	-0.08	0.20	0.52	(7.40)	-0.16	-0.11	0.13	0.30	(4.34)
high	-0.45	-0.17	0.06	0.51	(6.16)	-0.50	-0.19	0.12	0.61	(6.86)	-0.47	-0.19	0.09	0.56	(6.11)
3-1	-0.23	-0.12	-0.19			-0.29	-0.15	-0.13			-0.29	-0.17	-0.07		
t(3-1)	(-3.04)	(-1.64)	(-2.53)			(-3.90)	(-2.07)	(-1.87)			(-3.73)	(-2.43)	(-1.02)		

Panel B: Low Amihud Illiquidity

	VS_{CW}					VS_{BH}					SMIRK				
IVol	low	2	high	3-1	t(3-1)	low	2	high	3-1	t(3-1)	low	2	high	3-1	t(3-1)
low	-0.03	0.04	0.19	0.23	(6.32)	0.00	0.04	0.18	0.17	(4.94)	0.01	0.07	0.14	0.13	(3.61)
2	-0.13	0.07	0.23	0.36	(7.00)	-0.12	0.05	0.23	0.34	(7.04)	0.01	0.02	0.16	0.16	(3.11)
high	-0.20	-0.03	0.18	0.37	(6.54)	-0.18	-0.02	0.14	0.32	(4.95)	-0.16	0.00	0.06	0.22	(3.61)
3-1	-0.16	-0.08	-0.02			-0.18	-0.06	-0.04			-0.18	-0.07	-0.08		
t(3-1)	(-2.66)	(-1.35)	(-0.31)			(-2.91)	(-1.12)	(-0.58)			(-2.82)	(-1.21)	(-1.29)		

Panel C: Low Residual Institutional Ownership

	VS_{CW}					VS_{BH}					SMIRK				
IVol	low	2	high	3-1	t(3-1)	low	2	high	3-1	t(3-1)	low	2	high	3-1	t(3-1)
low	-0.11	0.02	0.26	0.37	(7.04)	-0.13	0.03	0.26	0.39	(7.91)	-0.06	0.02	0.16	0.22	(4.64)
2	-0.19	0.01	0.16	0.35	(5.98)	-0.21	-0.02	0.19	0.41	(6.77)	-0.12	0.03	0.13	0.25	(3.93)
high	-0.42	-0.17	0.03	0.45	(5.49)	-0.46	-0.14	0.06	0.52	(6.36)	-0.41	-0.10	-0.06	0.35	(4.56)
3-1	-0.30	-0.19	-0.23			-0.33	-0.17	-0.20			-0.35	-0.13	-0.21		
t(3-1)	(-3.63)	(-2.65)	(-3.19)			(-3.97)	(-2.35)	(-2.64)			(-4.50)	(-1.77)	(-2.73)		

Panel D: High Residual Institutional Ownership

	VS_{CW}					VS_{BH}					SMIRK				
IVol	low	2	high	3-1	t(3-1)	low	2	high	3-1	t(3-1)	low	2	high	3-1	t(3-1)
low	-0.08	0.02	0.21	0.29	(5.76)	-0.06	0.04	0.16	0.22	(4.57)	-0.03	0.04	0.13	0.15	(3.62)
2	-0.16	0.02	0.14	0.30	(5.38)	-0.16	-0.00	0.17	0.32	(6.17)	-0.08	0.02	0.08	0.16	(2.79)
high	-0.37	-0.05	0.07	0.45	(6.57)	-0.39	-0.06	0.08	0.47	(6.50)	-0.31	-0.12	0.05	0.36	(4.99)
3-1	-0.30	-0.08	-0.14			-0.33	-0.10	-0.08			-0.28	-0.16	-0.07		
t(3-1)	(-4.43)	(-1.28)	(-2.09)			(-5.24)	(-1.66)	(-1.18)			(-4.33)	(-2.81)	(-1.12)		

Table 10. Triple Sorts based on Short Sale Constraints, Investor Attention, and Idiosyncratic Volatility
This table reports equally-weighted FFC-adjusted subsequent returns for weekly conditional triple sorts. First, each stock is allocated to a top- or bottom-tercile based on Amihud illiquidity (ILLIQ in Panels A and B) and residual institutional ownership (resIO in Panels C and D). Second, each observation is allocated to one tercile (columns) based on investor attention. For investor attention, allocation depends on the stock's abnormal search volume index (ASVI). ASVI is calculated as the log-difference between the Google Search Volume of one week and the median Google Search Volume of the previous eight weeks. Third, within each tercile, every stock is assigned to an IVol tercile (rows) based on its idiosyncratic volatility. The sample period covers January 2005 to April 2016. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using five lags. Subsequent FFC-adjusted returns are stated in %.

	Panel A: High Amihud Illiquidity			Panel B: Low Amihud Illiquidity		
	Investor Attention			Investor Attention		
IVol	low	2	high	low	2	high
low	-0.03	0.05	0.08	0.02	0.07	0.01
2	-0.00	0.02	0.06	0.02	0.02	0.03
high	-0.04	-0.09	-0.09	-0.01	-0.01	-0.15
3-1	-0.01	-0.14	-0.17	-0.04	-0.08	-0.16
t(3-1)	(-0.20)	(-1.82)	(-2.05)	(-0.59)	(-1.63)	(-2.74)

	Panel C: Low Residual Inst. Ownership			Panel D: Residual Inst. Ownership		
	Investor Attention			Investor Attention		
IVol	low	2	high	low	2	high
low	0.01	0.06	0.10	0.04	0.05	0.04
2	0.05	0.01	-0.04	-0.03	-0.01	0.05
high	-0.13	-0.04	-0.14	-0.08	-0.07	-0.11
3-1	-0.14	-0.10	-0.24	-0.12	-0.13	-0.15
t(3-1)	(-1.80)	(-1.39)	(-3.34)	(-1.95)	(-2.34)	(-2.38)

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Online-Appendix for "The Idiosyncratic Volatility Puzzle and its Interplay with Sophisticated and Private Investors"

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This Online Appendix provides additional analyses for ”The Idiosyncratic Volatility Puzzle and its Interplay with Sophisticated and Private Investors”. It comprises the main analyses provided in the original article for unadjusted and value-weighted returns (Tables 1 to 8). Moreover, we investigate the MAX effect (Bali et al., 2011) in addition to the IVol puzzle. First, we run Fama-MacBeth-regressions showing that IVol dominates MAX in predicting subsequent returns among large stocks (Table 9). Nonetheless, the behavior of sophisticated and private investors might interact similarly with MAX as with IVol. Tables 10 to 13 support this conjecture empirically.

Further, we provide Fama-MacBeth-regressions including analyst forecast dispersion data from IBES that support a negative relation between idiosyncratic volatility and sophisticated trading measures (Table 14). In Table 15, we show that the three sophisticated trading measures we use in our main analyses remain meaningful after controlling for option-implied model-free skewness. Morevoer, we provide an additional double sort to demonstrate that sorting criterion order does not affect the results with respect to the interaction of IVol and sophisticated trading measures (Table 16). Furthermore, to mitigate potential non-synchroneity concerns, we show that the relation between sophisticated trading measures and subsequent returns also remains significantly positive if the return measurement starts with the open price of the next trading day, that is, if we exclude the return over the weekend (Table 17).

Table 18 examines whether the return predictability associated with the sophisticated trading measures might be driven by their ability to proxy for option market illiquidity. High absolute implied volatility spreads might indicate violations of put-call-parity, market inefficiency, and illiquidity. We therefore also include absolute values of VS_{CW} and VS_{BH} in our regression analyses. Note that we do not run this analysis for SMIRK for two reasons. First, SMIRK also reflects the slope of the implied volatility curve and is therefore not linked to potential violations of put-call-parity. Second, SMIRK is negative for most observations of our sample such that the resulting high multicollinearity of SMIRK and abs(SMIRK) does not allow for reasonable regression analyses. In addition, we shed further light on our findings' relation with market frictions: Beside the Amihud (2002) illiquidity measure and residual institutional ownership (Nagel, 2005), we use option-implied model-free volatility and bid-ask-spreads as proxies for market constraints (Tables 19 and 20).

Finally, we rerun our analyses using the market-wide investor sentiment index of Baker and Wurgler (2006) as an alternative variable to measure the impact of sentiment-driven private investors in Tables 21 and 22. Monthly data from January 1996 to September 2015 are sourced from Jeffrey Wurgler's page http://people.stern.nyu.edu/jwurgler/. Baker and Wurgler (2006) argue that the index captures systematic waves of sentiment that influence the cross-section of stock returns. To merge sentiment data with our original data set, we adapt the period in time covered and assume that during one month sentiment levels remain the same. Since the sentiment index refers to the entire market, it cannot identify those stocks that are particularly influenced by the sentiment waves.

Analyses based on Unadjusted Returns

Table 1. Portfolio Sorts based on Sophisticated Trading Measures – Unadjusted Returns
This table reports equally-weighted portfolio raw returns for the subsequent four weeks after portfolio formation. Portfolios are constructed using the implied volatility spread following Cremers and Weinbaum (2010), VS_{CW}, the implied volatility spread following Bali and Hovakimian (2009), VS_{BH}, and SMIRK based on Xing et al. (2010). The sample period covers January 1996 to April 2016. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using five lags. Subsequent returns are stated in %.

	Portfolios sorted by VS_{CW}				Portfolios sorted by VS_{BH}				Portfolios sorted by SMIRK			
	t+1	t+2	t+3	t+4	t+1	t+2	t+3	t+4	t+1	t+2	t+3	t+4
low	-0.06	0.15	0.13	0.14	-0.06	0.15	0.13	0.14	0.01	0.11	0.13	0.18
2	0.12	0.16	0.20	0.22	0.11	0.18	0.21	0.22	0.11	0.19	0.22	0.19
3	0.19	0.22	0.23	0.24	0.19	0.21	0.24	0.22	0.20	0.23	0.20	0.22
4	0.29	0.23	0.19	0.19	0.28	0.21	0.19	0.21	0.26	0.22	0.21	0.20
high	0.41	0.19	0.17	0.18	0.43	0.19	0.15	0.17	0.38	0.20	0.17	0.19
5-1	0.47	0.05	0.05	0.04	0.49	0.04	0.01	0.03	0.37	0.09	0.04	0.01
t(5-1)	(11.21)	(1.60)	(1.39)	(1.20)	(12.00)	(1.52)	(0.38)	(0.76)	(8.95)	(2.49)	(1.30)	(0.29)

Table 2. Conditional Double Sorts on Sophisticated Trading Measures and Idiosyncratic Volatility – Unadjusted Returns
This table reports equally-weighted portfolio raw returns for the week after portfolio formation. First, each stock is allocated to one tercile (columns) based on the implied volatility spread following Cremers and Weinbaum (2010), VS_{CW}, the implied volatility spread following Bali and Hovakimian (2009), VS_{BH}, or SMIRK based on Xing et al. (2010). Second, within each tercile, every stock is assigned to an IVol tercile (rows) based on its idiosyncratic volatility. The sample period covers January 1996 to April 2016. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using five lags. Subsequent returns are stated in %.

	first sorting criterion VS_{CW}					first sorting criterion VS_{BH}					first sorting criterion SMIRK				
IVol	low	2	high	3-1	t(3-1)	low	2	high	3-1	t(3-1)	low	2	high	3-1	t(3-1)
low	0.10	0.21	0.42	0.31	(9.03)	0.11	0.23	0.41	0.30	(9.54)	0.15	0.25	0.34	0.20	(6.97)
2	0.04	0.24	0.40	0.35	(8.91)	0.04	0.21	0.40	0.36	(9.68)	0.11	0.21	0.36	0.25	(5.76)
high	-0.12	0.16	0.28	0.40	(7.72)	-0.14	0.14	0.33	0.47	(8.48)	-0.12	0.14	0.27	0.39	(6.77)
3-1	-0.22	-0.05	-0.14			-0.25	-0.09	-0.08			-0.26	-0.11	-0.07		
t(3-1)	(-2.70)	(-0.70)	(-1.61)			(-3.02)	(-1.26)	(-0.96)			(-3.11)	(-1.42)	(-0.86)		

Table 3. Conditional Double Sorts based on Investor Attention – Unadjusted Returns
This table reports equally-weighted portfolio raw returns for the week after portfolio formation. Each stock is first allocated to one tercile (columns) based on the stock's abnormal search volume index (ASVI). ASVI is calculated as the log-difference between the Google Search Volume of one week and the median Google Search Volume of the previous eight weeks. Second, within each tercile, every stock is assigned to a tercile (rows) based on idiosyncratic volatility IVol. The sample period covers January 2005 to April 2016. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using five lags. Subsequent returns are stated in %.

	Investor Attention		
IVol	low	2	high
low	0.21	0.23	0.24
2	0.22	0.22	0.24
high	0.17	0.17	0.13
3-1	-0.04	-0.06	-0.11
t(3-1)	(-0.63)	(-0.99)	(-1.91)

Table 4. Triple Sorts based on Attention, Sophisticated Trading Measures, and Idiosyncratic Volatility – Unadjusted Returns
This table shows equally-weighted portfolio raw returns of weekly conditional triple sorts. First, each stock is allocated to a top- or bottom-tercile based on investor attention (abnormal search volume index based on Google Trends data). Second, within each tercile, every stock is allocated to one tercile (columns) based on the implied volatility spread following Cremers and Weinbaum (2010), VS_{CW}, the implied volatility spread following Bali and Hovakimian (2009), VS_{BH}, or SMIRK based on Xing et al. (2010). Third, within each tercile, every stock is assigned to an IVol tercile (rows) based on its idiosyncratic volatility. The sample period covers January 2005 to April 2016. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using five lags. The subsequent returns are stated in %.

Panel A: High Investor Attention

	VS_{CW}					VS_{BH}					SMIRK				
IVol	low	2	high	3-1	t(3-1)	low	2	high	3-1	t(3-1)	low	2	high	3-1	t(3-1)
low	0.13	0.23	0.35	0.22	(4.06)	0.17	0.22	0.34	0.17	(3.39)	0.18	0.24	0.32	0.14	(2.62)
2	0.19	0.23	0.33	0.15	(2.44)	0.17	0.23	0.30	0.13	(2.18)	0.17	0.24	0.30	0.13	(1.76)
high	-0.03	0.20	0.22	0.25	(3.18)	-0.02	0.18	0.26	0.28	(3.47)	-0.04	0.17	0.25	0.29	(3.27)
3-1	-0.16	-0.03	-0.13			-0.19	-0.04	-0.08			-0.22	-0.07	-0.06		
t(3-1)	(-1.95)	(-0.47)	(-1.93)			(-2.27)	(-0.55)	(-1.12)			(-2.68)	(-1.02)	(-0.81)		

Panel B: Low Investor Attention

	VS_{CW}					VS_{BH}					SMIRK				
IVol	low	2	high	3-1	t(3-1)	low	2	high	3-1	t(3-1)	low	2	high	3-1	t(3-1)
low	0.18	0.18	0.27	0.10	(1.86)	0.13	0.20	0.30	0.18	(3.58)	0.22	0.14	0.29	0.07	(1.52)
2	0.17	0.15	0.32	0.14	(2.52)	0.19	0.15	0.30	0.11	(1.89)	0.20	0.21	0.25	0.05	(0.68)
high	0.08	0.20	0.23	0.15	(1.85)	0.06	0.18	0.27	0.22	(2.72)	0.09	0.16	0.22	0.13	(1.53)
3-1	-0.10	0.02	-0.05			-0.07	-0.02	-0.03			-0.13	0.02	-0.07		
t(3-1)	(-1.08)	(0.27)	(-0.57)			(-0.76)	(-0.27)	(-0.33)			(-1.31)	(0.32)	(-0.84)		

Analyses based on Value-Weighted Returns

Table 5. Portfolio Sorts based on Sophisticated Trading Measures – Value-Weighted Returns
This table reports the value-weighted FFC-adjusted returns of quintile portfolios for the subsequent four weeks after portfolio formation. Portfolios are constructed using the implied volatility spread following Cremers and Weinbaum (2010), VS_{CW}, the implied volatility spread following Bali and Hovakimian (2009), VS_{BH}, and SMIRK based on Xing et al. (2010). The sample period covers January 1996 to April 2016. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using five lags. Subsequent FFC-adjusted returns are stated in %.

	Portfolios sorted by VS_{CW}				Portfolios sorted by VS_{BH}				Portfolios sorted by SMIRK			
	t+1	t+2	t+3	t+4	t+1	t+2	t+3	t+4	t+1	t+2	t+3	t+4
low	-0.26	0.01	-0.03	-0.08	-0.25	-0.02	-0.04	-0.05	-0.08	0.03	-0.01	0.01
2	-0.08	-0.07	0.01	0.00	-0.10	-0.02	0.01	0.01	-0.06	0.02	0.07	0.01
3	-0.02	0.05	0.04	0.07	-0.00	0.02	0.04	0.04	0.02	0.02	-0.01	0.00
4	0.08	0.04	0.01	0.03	0.07	0.04	0.01	0.05	0.05	0.00	0.01	0.03
high	0.26	0.04	-0.00	-0.01	0.25	0.02	0.00	-0.01	0.19	-0.05	-0.00	0.03
5-1	0.53	0.03	0.03	0.07	0.50	0.04	0.04	0.05	0.27	-0.08	0.01	0.01
t(5-1)	(9.93)	(0.56)	(0.57)	(1.51)	(8.93)	(0.90)	(0.83)	(0.95)	(5.06)	(-1.60)	(0.12)	(0.22)

Table 6. Conditional Double Sorts on Sophisticated Trading Measures and Idiosyncratic Volatility – Value-Weighted Returns
This table reports value-weighted FFC-adjusted portfolio returns for the week after portfolio formation. First, each stock is allocated to one tercile (columns) based on the implied volatility spread following Cremers and Weinbaum (2010), VS_{CW}, the implied volatility spread following Bali and Hovakimian (2009), VS_{BH}, or SMIRK based on Xing et al. (2010). Second, within each tercile, every stock is assigned to an IVol tercile (rows) based on its idiosyncratic volatility. The sample period covers January 1996 to April 2016. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using five lags. Subsequent FFC-adjusted returns are stated in %.

	first sorting criterion VS_{CW}					first sorting criterion VS_{BH}					first sorting criterion SMIRK				
IVol	low	2	high	3-1	t(3-1)	low	2	high	3-1	t(3-1)	low	2	high	3-1	t(3-1)
low	-0.14	0.01	0.22	0.36	(7.41)	-0.10	0.01	0.21	0.31	(6.75)	-0.05	0.04	0.15	0.19	(4.82)
2	-0.19	-0.03	0.17	0.36	(6.16)	-0.20	-0.04	0.19	0.39	(6.22)	-0.09	0.01	0.10	0.19	(3.09)
high	-0.35	-0.02	0.08	0.43	(5.64)	-0.32	-0.07	0.09	0.41	(5.28)	-0.26	-0.04	0.00	0.26	(3.52)
3-1	-0.21	-0.03	-0.14			-0.22	-0.08	-0.12			-0.21	-0.08	-0.15		
t(3-1)	(-3.05)	(-0.55)	(-1.94)			(-3.32)	(-1.46)	(-1.72)			(-3.19)	(-1.44)	(-2.11)		

Table 7. Conditional Double Sorts based on Investor Attention – Value-Weighted Returns
This table reports value-weighted FFC-adjusted portfolio returns for the week after portfolio formation. Each stock is first allocated to one tercile (columns) based on the stock's abnormal search volume index (ASVI). ASVI is calculated as the log-difference between the Google Search Volume of one week and the median Google Search Volume of the previous eight weeks. Second, within each tercile, every stock is assigned to a tercile (rows) based on idiosyncratic volatility IVol. The sample period covers January 2005 to April 2016. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using five lags. Subsequent FFC-adjusted returns are stated in %.

	Investor Attention		
IVol	low	2	high
low	0.02	0.02	0.02
2	0.01	-0.01	-0.06
high	-0.02	-0.05	-0.15
3-1	-0.04	-0.07	-0.17
t(3-1)	(-0.65)	(-1.18)	(-2.92)

Table 8. Triple Sorts based on Attention, Sophisticated Trading Measures, and Idiosyncratic Volatility – Value-Weighted Returns
This table shows value-weighted FFC-adjusted portfolio returns of weekly conditional triple sorts. First, each stock is allocated to a top- or bottom-tercile based on investor attention (abnormal search volume index based on Google Trends data). Second, within each tercile, every stock is allocated to one tercile (columns) based on the implied volatility spread following Cremers and Weinbaum (2010), VS_{CW}, the implied volatility spread following Bali and Hovakimian (2009), VS_{BH}, or SMIRK based on Xing et al. (2010). Third, within each tercile, every stock is assigned to an IVol tercile (rows) based on its idiosyncratic volatility. The sample period covers January 2005 to April 2016. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using five lags. The subsequent FFC-adjusted returns are stated in %.

	Panel A: High Investor Attention														
	VS_{CW}					VS_{BH}					SMIRK				
IVol	low	2	high	3-1	t(3-1)	low	2	high	3-1	t(3-1)	low	2	high	3-1	t(3-1)
low	-0.09	-0.01	0.20	0.29	(3.82)	-0.05	-0.01	0.12	0.17	(2.24)	-0.01	-0.05	0.15	0.15	(2.67)
2	-0.05	-0.04	-0.03	0.02	(0.19)	-0.03	-0.01	-0.02	0.02	(0.21)	-0.02	-0.04	0.01	0.03	(0.38)
high	-0.38	-0.08	0.00	0.38	(3.37)	-0.30	-0.13	-0.04	0.26	(2.26)	-0.38	-0.08	0.01	0.39	(3.02)
3-1	-0.28	-0.07	-0.20			-0.25	-0.13	-0.16			-0.37	-0.03	-0.14		
t(3-1)	(-3.03)	(-0.89)	(-2.38)			(-2.88)	(-1.63)	(-1.75)			(-4.14)	(-0.39)	(-1.44)		

	Panel B: Low Investor Attention														
	VS_{CW}					VS_{BH}					SMIRK				
IVol	low	2	high	3-1	t(3-1)	low	2	high	3-1	t(3-1)	low	2	high	3-1	t(3-1)
low	-0.07	0.00	0.08	0.14	(2.27)	-0.07	-0.00	0.14	0.21	(3.97)	0.04	-0.05	0.10	0.06	(0.93)
2	-0.03	-0.04	0.17	0.20	(2.01)	-0.05	-0.07	0.20	0.25	(2.77)	0.07	0.02	0.04	-0.03	(-0.29)
high	-0.11	-0.03	0.07	0.18	(1.89)	-0.08	-0.03	0.07	0.15	(1.37)	-0.09	0.02	0.03	0.12	(1.19)
3-1	-0.05	-0.03	-0.01			-0.00	-0.03	-0.07			-0.13	0.07	-0.07		
t(3-1)	(-0.49)	(-0.43)	(-0.07)			(-0.05)	(-0.39)	(-0.82)			(-1.26)	(0.97)	(-0.78)		

Analyses based on MAX as Short-Term Anomaly

Table 9. Explanatory Power of MAX and IVol in Monthly Fama-MacBeth-regressions
This table reports Fama-MacBeth-regression estimates for a monthly CRSP sample from January 1960 to April 2016. The dependent variable is the stock return of the subsequent month. The explanatory variables are given in the first column. IVol is the stock's idiosyncratic volatility based on the previous month. MAX is the maximum daily return of the previous month. REV denotes the stock return of the previous month. Panel A presents regression estimates if the entire sample is used. In Panel B, the sample is restricted to those stocks that have above-median market capitalization in each month. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using five lags.

	Panel A: entire sample				Panel B: sample of large stocks			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
intercept	0.0143	0.0146	0.0133	0.0134	0.0156	0.0143	0.0155	0.0153
	(7.37)	(6.81)	(7.03)	(6.84)	(9.05)	(7.78)	(9.07)	(8.90)
IVOL	-0.0099		0.0100	-0.0055	-0.0193		-0.0133	-0.0211
	(-3.43)		(2.23)	(-1.30)	(-4.84)		(-2.85)	(-4.84)
MAX		-0.0574	-0.1020	-0.0075		-0.0835	-0.0318	0.0234
		(-5.18)	(-8.43)	(-0.73)		(-5.30)	(-2.72)	(2.00)
REV				-0.0485				-0.0247
				(-11.85)				(-5.35)

Table 10. Portfolio Sorts based on MAX

The table reports equally-weighted weekly quintile portfolio sorts based on the maximum return of the previous week MAX for the sample period from January 1996 to April 2016. Corresponding portfolio averages are provided in the first column. The second column shows FFC-adjusted portfolio returns of the subsequent week. VS_{CW} and VS_{BH} are the implied volatility spreads following Cremers and Weinbaum (2010) and Bali and Hovakimian (2009), respectively. The estimation of SMIRK follows Xing et al. (2010). IVol is the stock's idiosyncratic volatility. It is estimated over the previous week based on FFC-adjusted returns where factor loadings are estimated over the previous year skipping one month. ILLIQ corresponds to the illiquidity measure of Amihud (2002) in billion estimated over the previous year. resIO is residual institutional ownership following Nagel (2005). REV denotes the stock return of the previous week. MV is the market capitalization of the stock. BM refers to the stock's book-to-market-ratio. MOM is the momentum return measured over the previous year skipping one month. ASVI is the abnormal search volume index calculated as log Google search volume of the previous week minus the median log Google search volume of the preceding eight weeks. ASVI portfolio characteristics refer to a truncated sample period from January 2005 to April 2016. The t-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using five lags. Subsequent FFC-adjusted returns, VS_{CW}, VS_{BH}, SMIRK, MAX and REV are stated in %.

	MAX	α_{FFC}	VS_{CW}	VS_{BH}	SMIRK	IVol	ILLIQ	resIO	REV	ln(MV)	BM	MOM	ASVI
low	0.65	0.12	-0.50	-0.65	-4.73	0.23	2.45	-0.01	-3.26	22.42	0.40	0.21	-0.01
2	1.63	0.04	-0.71	-0.84	-4.81	0.22	2.24	0.03	-1.07	22.46	0.39	0.21	-0.01
3	2.45	0.02	-0.90	-0.97	-4.92	0.26	2.63	0.07	-0.06	22.27	0.39	0.25	-0.01
4	3.59	-0.07	-1.10	-1.10	-5.03	0.33	2.96	0.05	1.06	21.97	0.38	0.31	-0.01
high	6.97	-0.17	-1.66	-1.52	-5.43	0.57	4.78	-0.13	4.28	21.51	0.37	0.43	0.02
5-1	6.31	-0.30	-1.16	-0.88	-0.70	0.34	2.33	-0.12	7.54	-0.91	-0.03	0.21	0.03
t(5-1)		(-4.45)	(-18.93)	(-16.22)	(-12.43)	(37.76)	(8.16)	(-5.78)	(43.91)	(-49.10)	(-4.33)	(8.39)	(14.15)

Table 11. Conditional Double Sorts on Sophisticated Trading Measure and Short-Term Anomalies

This table reports equally-weighted FFC-adjusted portfolio returns for the week after portfolio formation from January 1996 to April 2016. First, each stock is allocated to one tercile (columns) based on the implied volatility spread following Cremers and Weinbaum (2010), VS_{CW}, the implied volatility spread following Bali and Hovakimian (2009), VS_{BH}, or SMIRK based on Xing et al. (2010). Second, within each tercile, every stock is assigned to an idiosyncratic volatility or MAX tercile (rows). The t-statistics in parentheses are based on standard errors following Newey and West (1987) using five lags. Subsequent FFC-adjusted returns are stated in %.

Panel A: VS_{CW} as first sorting criterion

	low	2	high	3-1	t(3-1)		low	2	high	3-1	t(3-1)
low IVOL	-0.05	0.07	0.27	0.32	(9.26)	low MAX	-0.06	0.15	0.29	0.35	(9.68)
2	-0.12	0.07	0.24	0.36	(9.09)	2	-0.14	0.03	0.24	0.39	(9.91)
high IVOL	-0.29	-0.02	0.11	0.40	(8.17)	high MAX	-0.27	-0.05	0.09	0.35	(7.62)
3-1	-0.24	-0.09	-0.16			3-1	-0.21	-0.21	-0.20		
t(3-1)	(-4.37)	(-1.73)	(-2.91)			t(3-1)	(-3.41)	(-3.76)	(-3.20)		

Panel B: VS_{BH} as first sorting criterion

	low	2	high	3-1	t(3-1)		low	2	high	3-1	t(3-1)
low IVOL	-0.04	0.09	0.27	0.30	(9.73)	low MAX	-0.03	0.14	0.30	0.33	(9.25)
2	-0.13	0.04	0.24	0.37	(9.79)	2	-0.15	0.03	0.24	0.39	(9.62)
high IVOL	-0.32	-0.03	0.16	0.48	(8.85)	high MAX	-0.31	-0.07	0.12	0.43	(9.45)
3-1	-0.28	-0.12	-0.11			3-1	-0.28	-0.21	-0.18		
t(3-1)	(-4.98)	(-2.59)	(-1.92)			t(3-1)	(-4.50)	(-3.79)	(-2.86)		

Panel C: SMIRK as first sorting criterion

	low	2	high	3-1	t(3-1)		low	2	high	3-1	t(3-1)
low IVOL	0.01	0.11	0.20	0.19	(6.99)	low MAX	0.04	0.14	0.23	0.20	(6.29)
2	-0.04	0.05	0.18	0.22	(5.59)	2	-0.09	0.06	0.16	0.25	(6.50)
high IVOL	-0.28	-0.03	0.09	0.38	(7.06)	high MAX	-0.27	-0.07	0.07	0.34	(7.34)
3-1	-0.29	-0.13	-0.10			3-1	-0.31	-0.21	-0.16		
t(3-1)	(-5.11)	(-2.83)	(-1.87)			t(3-1)	(-4.73)	(-3.90)	(-2.77)		

Table 12. Conditional Double Sorts based on Attention and MAX
This table reports equally-weighted FFC-adjusted portfolio returns for the week after portfolio formation. The return impact of MAX is separately evaluated after each stock has been allocated to one tercile (columns) based on the stock's abnormal search volume index (ASVI). ASVI is calculated as the log-difference between the Google Search Volume of one week and the median Google Search Volume of the previous eight weeks. The sample period covers January 2005 to April 2016. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using five lags. Subsequent FFC-adjusted returns are stated in %.

	Investor Attention		
MAX	low	2	high
low	0.03	0.07	0.07
2	0.01	-0.01	0.01
high	-0.05	-0.02	-0.07
3-1	-0.09	-0.08	-0.14
t(3-1)	(-1.54)	(-1.79)	(-2.43)

Table 13. Triple Sorts based on Attention, Sophisticated Trading Measures, and MAX
This table shows equally-weighted FFC-adjusted portfolio returns of weekly conditional triple sorts. First, each stock is allocated to a top- or bottom-tercile based on investor attention (abnormal search volume index based on Google Trends data). Second, within each tercile, every stock is allocated to one tercile (columns) based on the implied volatility spread following Cremers and Weinbaum (2010), VS_{CW}, the implied volatility spread following Bali and Hovakimian (2009), VS_{BH}, or SMIRK based on Xing et al. (2010). Third, within each tercile, every stock is assigned to a MAX tercile (rows) based on its maximum daily return in the previous week. The sample period covers January 2005 to April 2016. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using five lags. The subsequent FFC-adjusted returns are stated in %.

Panel A: High Investor Attention

	VS_{CW}					VS_{BH}					SMIRK				
IVol	low	2	high	3-1	t(3-1)	low	2	high	3-1	t(3-1)	low	2	high	3-1	t(3-1)
low	-0.03	0.06	0.17	0.20	(3.53)	-0.02	0.06	0.14	0.16	(2.70)	0.03	0.09	0.11	0.09	(1.60)
2	-0.11	0.04	0.15	0.26	(4.51)	-0.05	0.05	0.13	0.18	(3.18)	-0.08	0.02	0.10	0.18	(2.67)
high	-0.19	-0.02	-0.02	0.17	(2.09)	-0.22	-0.07	0.02	0.24	(2.81)	-0.23	-0.03	0.05	0.29	(3.34)
3-1	-0.16	-0.08	-0.19			-0.20	-0.13	-0.12			-0.26	-0.12	-0.06		
t(3-1)	(-2.07)	(-1.08)	(-2.50)			(-2.45)	(-1.86)	(-1.52)			(-3.21)	(-1.77)	(-0.71)		

Panel B: Low Investor Attention

	VS_{CW}					VS_{BH}					SMIRK				
IVol	low	2	high	3-1	t(3-1)	low	2	high	3-1	t(3-1)	low	2	high	3-1	t(3-1)
low	-0.06	0.04	0.11	0.17	(3.27)	-0.05	0.01	0.12	0.17	(3.45)	0.05	-0.01	0.05	0.00	(0.05)
2	-0.03	-0.04	0.11	0.14	(2.29)	-0.08	-0.02	0.16	0.23	(3.59)	-0.04	-0.01	0.10	0.14	(1.98)
high	-0.10	-0.04	-0.02	0.08	(1.03)	-0.11	-0.06	-0.01	0.10	(1.22)	-0.09	-0.06	-0.01	0.08	(1.06)
3-1	-0.05	-0.07	-0.13			-0.06	-0.07	-0.13			-0.14	-0.05	-0.06		
t(3-1)	(-0.64)	(-1.19)	(-1.69)			(-0.73)	(-0.98)	(-1.80)			(-1.96)	(-0.74)	(-0.91)		

Further Fama-MacBeth Regressions

Table 14. Sophisticated Trading Measures, Idiosyncratic Volatility, and Analyst Forecast Dispersion

This table provides weekly Fama-MacBeth-regression estimates. The dependent variable is one of the three sophisticated trading measures: VS_{CW} and VS_{BH} are the implied volatility spreads following Cremers and Weinbaum (2010) and Bali and Hovakimian (2009), respectively; the estimation of SMIRK follows Xing et al. (2010). IVol is the stock's idiosyncratic volatility. It is estimated over the previous week based on FFC-adjusted returns where factor loadings are estimated over the previous year skipping one month. Analyst forecast dispersion (DISP) data are sourced from the Institutional Brokers Estimate System (IBES) detail file using a forecast period of one year. For each firm-week, we measure the analyst dispersion as the standard deviation of all earnings per share forecasts, divided by the current stock price. MV is the market capitalization of the stock. BM refers to the stock's book-to-market-ratio. MOM is the momentum return measured over the previous year skipping one month. The sample period covers January 1996 to April 2016. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using five lags.

	VS_{CW}	VS_{BH}	SMIRK	VS_{CW}	VS_{BH}	SMIRK	VS_{CW}	VS_{BH}	SMIRK
intercept	-0.0056	-0.0072	-0.0469	-0.0058	-0.0074	-0.0468	-0.0461	-0.0422	-0.0730
	(-9.77)	(-15.10)	(-56.00)	(-9.77)	(-15.12)	(-55.84)	(-13.65)	(-13.31)	(-16.59)
IVOL	-0.0154	-0.0111	-0.0105	-0.0113	-0.0073	-0.0059	-0.0049	-0.0019	-0.0028
	(-13.40)	(-11.45)	(-11.47)	(-11.76)	(-9.18)	(-7.49)	(-5.43)	(-2.40)	(-3.36)
DISP				-0.1457	-0.1254	-0.3326	-0.1450	-0.1093	-0.2670
				(-5.95)	(-5.92)	(-11.40)	(-5.66)	(-4.50)	(-9.20)
REV							-0.0968	-0.0815	-0.0608
							(-23.92)	(-22.03)	(-17.32)
ln(MV)							0.0017	0.0015	0.0011
							(12.28)	(11.43)	(6.19)
BM							0.0024	0.0018	-0.0007
							(5.39)	(4.30)	(-1.21)
MOM							-0.0003	-0.0000	0.0028
							(-0.89)	(-0.17)	(7.76)

Table 15. Sophisticated Trading Measures and MFIS
The table provides weekly Fama-MacBeth-regression estimates. The dependent variable is the stock return of the subsequent week. The explanatory variables are given in the first column. VS_{CW} and VS_{BH} are the implied volatility spreads following Cremers and Weinbaum (2010) and Bali and Hovakimian (2009), respectively. The estimation of SMIRK follows Xing et al. (2010). REV denotes the stock return of the previous week. MV is the market capitalization of the stock. BM refers to the stock's book-to-market-ratio. MOM is the momentum return measured over the previous year skipping one month. The model-free option-implied skewness, MFIS, following Bakshi et al. (2003) is applied as additional control variable. The sample period covers January 1996 to April 2016. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using five lags.

	(1)	(2)	(3)	(4)	(5)
intercept	0.0030	0.0030	0.0036	0.0032	0.0008
	(2.80)	(2.85)	(3.53)	(3.14)	(0.18)
VS_{CW}	0.0338			0.0151	0.0130
	(10.97)			(3.38)	(3.06)
VS_{BH}		0.0371		0.0181	0.0210
		(11.06)		(3.65)	(4.61)
SMIRK			0.0259	0.0088	0.0070
			(7.82)	(2.35)	(2.37)
REV					-0.0107
					(-3.25)
ln(MV)					0.0001
					(0.48)
BM					0.0007
					(0.90)
MOM					0.0003
					(0.56)
MFIS	0.0010	0.0011	0.0007	0.0007	0.0006
	(2.57)	(2.74)	(1.68)	(1.62)	(2.03)

Further Portfolio Sorts

Table 16. Conditional Double Sorts on Idiosyncratic Volatility and Sophisticated Trading Measures
This table reports equally-weighted FFC-adjusted portfolio returns for the week after portfolio formation. First, each stock is allocated to one tercile (rows) based on its idiosyncratic volatility IVol. Second, within each tercile, every stock is assigned to a tercile portfolio (columns) based on the implied volatility spread following Cremers and Weinbaum (2010), VS_{CW}, the implied volatility spread following Bali and Hovakimian (2009), VS_{BH}, or SMIRK based on Xing et al. (2010). The sample period covers January 1996 to April 2016. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using five lags. Subsequent FFC-adjusted returns are stated in %.

	second sorting criterion VS_{CW}					second sorting criterion VS_{BH}					second sorting criterion SMIRK				
IVol	low	2	high	3-1	t(3-1)	low	2	high	3-1	t(3-1)	low	2	high	3-1	t(3-1)
low	-0.08	0.04	0.22	0.31	(9.58)	-0.08	0.05	0.21	0.29	(9.59)	-0.03	0.06	0.15	0.19	(7.17)
2	-0.13	0.00	0.21	0.34	(9.07)	-0.14	0.01	0.21	0.36	(9.34)	-0.09	0.01	0.16	0.24	(6.22)
high	-0.35	-0.12	0.10	0.45	(8.78)	-0.36	-0.13	0.12	0.48	(9.04)	-0.30	-0.14	0.07	0.37	(7.36)
3-1	-0.27	-0.16	-0.12			-0.28	-0.17	-0.09			-0.27	-0.20	-0.08		
t(3-1)	(-5.02)	(-3.00)	(-2.31)			(-5.18)	(-3.36)	(-1.68)			(-4.80)	(-3.96)	(-1.48)		

Table 17. Portfolio Sorts based on Sophisticated Trading Measures – Open-to-Close-Returns
This table reports the FFC-adjusted returns of quintile portfolios for the subsequent four weeks. For the first week, return measurement starts with the open price of the next trading day after portfolio formation. Portfolios are constructed using the implied volatility spread following Cremers and Weinbaum (2010), VS_{CW}, the implied volatility spread following Bali and Hovakimian (2009), VS_{BH}, and SMIRK based on Xing et al. (2010). The sample period covers January 1996 to April 2016. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using five lags. Subsequent FFC-adjusted returns are stated in %.

	Portfolios sorted by VS_{CW}				Portfolios sorted by VS_{BH}				Portfolios sorted by SMIRK			
	t+1	t+2	t+3	t+4	t+1	t+2	t+3	t+4	t+1	t+2	t+3	t+4
low	-0.22	-0.07	-0.09	-0.08	-0.21	-0.06	-0.08	-0.07	-0.16	-0.09	-0.08	-0.03
2	-0.08	-0.05	-0.00	0.01	-0.10	-0.03	0.00	0.02	-0.10	-0.01	0.02	-0.01
3	-0.04	0.01	0.02	0.03	-0.04	0.00	0.03	0.01	-0.03	0.02	-0.01	0.01
4	0.02	0.03	-0.01	-0.01	0.01	0.01	-0.01	0.00	-0.00	0.01	0.00	-0.01
high	0.05	-0.01	-0.03	-0.02	0.07	-0.01	-0.05	-0.03	0.02	-0.02	-0.04	-0.03
5-1	0.27	0.06	0.06	0.06	0.28	0.06	0.03	0.04	0.19	0.08	0.04	0.00
t(5-1)	(8.00)	(2.07)	(1.95)	(1.72)	(8.45)	(1.99)	(0.88)	(1.27)	(5.70)	(2.38)	(1.37)	(0.09)

Liquidity Analyses

Table 18. Absolute Sophisticated Trading Measures and Subsequent Returns
The table reports Fama-MacBeth-regression estimates for the sample period from January 1996 to April 2016 based on weekly data. The dependent variable is the stock return of the subsequent week. The explanatory variables are given in the first column. VS_{CW} and VS_{BH} are the implied volatility spreads following Cremers and Weinbaum (2010) and Bali and Hovakimian (2009), respectively. REV denotes the stock return of the previous week. MV is the market capitalization of the stock. BM refers to the stock's book-to-market-ratio. MOM is the momentum return measured over the previous year skipping one month. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using five lags.

	(1)	(2)	(3)	(4)
intercept	0.0024	0.0024	0.0018	0.0016
	(2.75)	(2.70)	(0.43)	(0.38)
VS_{CW}	0.0371		0.0359	
	(10.71)		(10.82)	
abs(VS_{CW})	0.0004		0.0003	
	(0.09)		(0.09)	
VS_{BH}		0.0422		0.0415
		(10.50)		(10.94)
abs(VS_{BH})		0.0026		0.0020
		(0.54)		(0.50)
REV			-0.0108	-0.0113
			(-3.27)	(-3.42)
ln(MV)			0.0000	0.0000
			(0.02)	(0.08)
BM			0.0006	0.0007
			(0.87)	(0.91)
MOM			0.0003	0.0003
			(0.55)	(0.50)

Table 19. Triple Sorts based on Short Sale Constraints, Sophisticated Trading Measures, and Idiosyncratic Volatility – Bid-Ask-Spread and MFIV
This table reports equally-weighted FFC-adjusted subsequent returns for weekly conditional triple sorts. First, each stock is allocated to a top- or bottom-tercile based on the stock's average relative bid-ask-spread of the previous year (Panels A and B) and model-free implied volatility following Bakshi et al. (2003) (Panels C and D). Second, within each portfolio, every stock is allocated to one tercile (columns) based on the implied volatility spread following Cremers and Weinbaum (2010), VS_{CW}, the implied volatility spread following Bali and Hovakimian (2009), VS_{BH}, or SMIRK based on Xing et al. (2010). Third, within each tercile, every stock is assigned to an IVol tercile (rows) based on its idiosyncratic volatility. The sample period covers January 1996 to April 2016. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using five lags. The subsequent FFC-adjusted returns are stated in %.

Panel A: High Bid-Ask-Spread

	VS_{CW}					VS_{BH}					SMIRK				
IVol	low	2	high	3-1	t(3-1)	low	2	high	3-1	t(3-1)	low	2	high	3-1	t(3-1)
low	-0.18	-0.04	0.29	0.47	(8.41)	-0.16	-0.04	0.29	0.45	(8.68)	-0.12	0.02	0.19	0.31	(6.03)
2	-0.26	-0.02	0.18	0.44	(6.92)	-0.31	-0.02	0.19	0.50	(8.40)	-0.14	-0.11	0.12	0.26	(3.95)
high	-0.39	-0.15	0.08	0.47	(5.82)	-0.45	-0.09	0.09	0.54	(6.93)	-0.42	-0.08	0.05	0.47	(5.69)
3-1	-0.21	-0.11	-0.21			-0.29	-0.05	-0.20			-0.30	-0.10	-0.14		
t(3-1)	(-2.82)	(-1.67)	(-2.96)			(-4.02)	(-0.81)	(-2.77)			(-3.86)	(-1.58)	(-1.96)		

Panel B: Low Bid-Ask-Spread

	VS_{CW}					VS_{BH}					SMIRK				
IVol	low	2	high	3-1	t(3-1)	low	2	high	3-1	t(3-1)	low	2	high	3-1	t(3-1)
low	-0.05	0.01	0.19	0.24	(4.90)	-0.05	0.05	0.18	0.23	(5.40)	-0.01	0.06	0.12	0.12	(3.12)
2	-0.04	0.06	0.19	0.23	(4.21)	-0.06	0.02	0.23	0.29	(4.95)	-0.04	0.05	0.16	0.20	(3.62)
high	-0.18	-0.03	0.12	0.30	(4.25)	-0.17	-0.02	0.09	0.26	(3.79)	-0.15	-0.00	0.08	0.23	(3.21)
3-1	-0.13	-0.04	-0.07			-0.12	-0.07	-0.09			-0.14	-0.06	-0.03		
t(3-1)	(-1.96)	(-0.67)	(-0.94)			(-1.85)	(-1.02)	(-1.20)			(-2.05)	(-0.96)	(-0.39)		

Panel C: High Model-Free Implied Volatility

	VS_{CW}					VS_{BH}					SMIRK				
IVol	low	2	high	3-1	t(3-1)	low	2	high	3-1	t(3-1)	low	2	high	3-1	t(3-1)
low	-0.22	-0.07	0.23	0.45	(6.00)	-0.29	-0.05	0.26	0.55	(7.35)	-0.17	-0.05	0.23	0.40	(5.29)
2	-0.30	-0.03	0.18	0.48	(5.93)	-0.26	-0.05	0.19	0.45	(5.46)	-0.24	-0.05	0.10	0.33	(4.23)
high	-0.53	-0.28	-0.02	0.51	(5.93)	-0.57	-0.28	-0.01	0.56	(6.25)	-0.58	-0.25	-0.03	0.55	(5.99)
3-1	-0.31	-0.21	-0.25			-0.28	-0.23	-0.27			-0.41	-0.20	-0.26		
t(3-1)	(-3.65)	(-2.78)	(-3.04)			(-3.33)	(-3.09)	(-3.28)			(-4.90)	(-2.42)	(-3.13)		

Panel D: Low Model-Free Implied Volatility

	VS_{CW}					VS_{BH}					SMIRK				
IVol	low	2	high	3-1	t(3-1)	low	2	high	3-1	t(3-1)	low	2	high	3-1	t(3-1)
low	-0.03	0.05	0.16	0.19	(5.83)	-0.02	0.07	0.16	0.18	(5.90)	0.02	0.09	0.09	0.07	(2.41)
2	-0.01	0.06	0.20	0.21	(6.35)	-0.00	0.06	0.18	0.18	(5.70)	0.02	0.06	0.15	0.13	(4.42)
high	-0.08	0.00	0.12	0.21	(6.11)	-0.10	0.00	0.14	0.24	(6.92)	-0.03	-0.02	0.11	0.14	(4.10)
3-1	-0.06	-0.05	-0.04			-0.08	-0.07	-0.01			-0.05	-0.11	0.01		
t(3-1)	(-1.79)	(-1.42)	(-1.09)			(-2.24)	(-2.01)	(-0.43)			(-1.74)	(-3.51)	(0.35)		

Table 20. Triple Sorts based on Short Sale Constraints, Investor Attention, and Idiosyncratic Volatility – Bid-Ask-Spread and MFIV

This table reports equally-weighted FFC-adjusted subsequent returns for weekly conditional triple sorts. First, each stock is allocated to a top- or bottom-tercile based on the stock's average relative bid-ask-spread of the previous year (Panels A and B) and model-free implied volatility following Bakshi et al. (2003) (Panels C and D). Second, each observation is allocated to one tercile (columns) based on investor attention. For investor attention, allocation depends on the stock's abnormal search volume index (ASVI). ASVI is calculated as the log-difference between the Google Search Volume of one week and the median Google Search Volume of the previous eight weeks. Third, within each tercile, every stock is assigned to an IVol tercile (rows) based on its idiosyncratic volatility. The sample period covers January 2005 to April 2016. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using five lags. Subsequent FFC-adjusted returns are stated in %.

	Panel A: High Bid-Ask-Spread			Panel B: Low Bid-Ask-Spread		
	Investor Attention			Investor Attention		
IVol	low	2	high	low	2	high
low	-0.00	0.05	0.09	0.08	0.09	0.04
2	-0.05	-0.01	-0.03	0.02	0.04	0.05
high	-0.03	-0.04	-0.13	-0.03	-0.05	-0.04
3-1	-0.03	-0.09	-0.22	-0.11	-0.14	-0.09
t(3-1)	(-0.36)	(-1.23)	(-2.70)	(-2.28)	(-2.75)	(-1.66)

	Panel C: High Model-Free Implied Volatility			Panel D: Low Model-Free Implied Volatility		
	Investor Attention			Investor Attention		
IVol	low	2	high	low	2	high
low	-0.02	0.05	0.05	0.05	0.07	0.09
2	-0.03	-0.03	-0.03	0.05	0.06	0.07
high	-0.13	-0.11	-0.19	0.01	0.03	0.02
3-1	-0.11	-0.16	-0.24	-0.04	-0.03	-0.08
t(3-1)	(-1.21)	(-2.06)	(-2.60)	(-0.91)	(-0.96)	(-2.43)

Market-Wide Sentiment

Table 21. Conditional Double Sorts based on Sentiment
This table reports equally-weighted FFC-adjusted portfolio returns for the week after portfolio formation. Each week is first classified as high-, medium-, or low-sentiment week (columns). The terciles are constructed using the monthly market-wide investor sentiment index of Baker/Wurgler (2006). Second, within each tercile, every stock is assigned to a tercile (rows) based on idiosyncratic volatility IVol. The sample period covers January 1996 to September 2015. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using five lags. Subsequent FFC-adjusted returns are stated in %.

	Investor Sentiment		
IVol	low	2	high
low	0.03	0.05	0.08
2	0.02	0.03	0.06
high	-0.09	-0.04	-0.15
3-1	-0.12	-0.06	-0.24
t(3-1)	(-1.88)	(-0.97)	(-2.62)

Table 22. Triple Sorts based on Sentiment, Sophisticated Trading Measures, and Idiosyncratic Volatility

This table shows equally-weighted FFC-adjusted portfolio returns of weekly conditional triple sorts. First, each week is allocated to one tercile based on the monthly investor sentiment index of Baker and Wurgler (2006). Panel A shows high- and Panel B low-sentiment weeks. Second, for each week, every stock is allocated to one tercile (columns) based on the implied volatility spread following Cremers and Weinbaum (2010), VS_{CW}, the implied volatility spread following Bali and Hovakimian (2009), VS_{BH}, or SMIRK based on Xing et al. (2010). Third, within each tercile, every stock is assigned to an IVol tercile (rows) based on its idiosyncratic volatility. The sample period covers January 1996 to September 2015. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using five lags. The subsequent FFC-adjusted returns are stated in %.

Panel A: High Investor Sentiment

	VS_{CW}					VS_{BH}					SMIRK				
IVol	low	2	high	3-1	t(3-1)	low	2	high	3-1	t(3-1)	low	2	high	3-1	t(3-1)
low	-0.15	0.03	0.35	0.50	(7.64)	-0.15	0.08	0.35	0.50	(8.64)	-0.11	0.11	0.24	0.35	(7.02)
2	-0.30	0.08	0.36	0.67	(8.16)	-0.31	-0.02	0.40	0.71	(9.63)	-0.17	0.05	0.27	0.44	(5.12)
high	-0.44	-0.10	0.15	0.59	(5.49)	-0.53	-0.07	0.22	0.75	(6.23)	-0.46	-0.05	0.11	0.58	(4.79)
3-1	-0.29	-0.13	-0.20			-0.38	-0.15	-0.13			-0.35	-0.16	-0.13		
t(3-1)	(-2.41)	(-1.30)	(-1.81)			(-3.21)	(-1.63)	(-1.09)			(-2.90)	(-1.57)	(-1.29)		

Panel B: Low Investor Sentiment

	VS_{CW}					VS_{BH}					SMIRK				
IVol	low	2	high	3-1	t(3-1)	low	2	high	3-1	t(3-1)	low	2	high	3-1	t(3-1)
low	-0.08	0.00	0.15	0.22	(4.52)	-0.07	0.03	0.15	0.22	(4.81)	0.00	0.01	0.07	0.07	(1.74)
2	-0.06	-0.01	0.13	0.19	(3.83)	-0.06	-0.03	0.11	0.17	(3.74)	-0.00	-0.03	0.08	0.08	(1.59)
high	-0.28	-0.03	0.06	0.34	(5.69)	-0.25	-0.06	0.06	0.32	(5.54)	-0.19	-0.05	-0.01	0.18	(2.84)
3-1	-0.20	-0.03	-0.09			-0.18	-0.08	-0.09			-0.19	-0.06	-0.08		
t(3-1)	(-2.91)	(-0.54)	(-1.06)			(-2.64)	(-1.16)	(-1.13)			(-2.66)	(-0.96)	(-0.98)		

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